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Abstract

In this paper we examine the extent of time-varying correlations between stock markets returns and policy uncertainty based on a newly introduced uncertainty index by Baker et al. (2012). We identify several empirical regularities: (1) the dynamic correlations of policy uncertainty and stock market returns are consistently negative. (2) Increased stock market volatility increases policy uncertainty and dampens stock markets returns. (3) Increases in the volatility of policy uncertainty lead to negative stock market returns and increased uncertainty. (4) Oil specific demand shocks and domestic shocks (price and income shocks) lead to further increase in the negative correlation between policy uncertainty and stock market returns.

Keywords: Policy uncertainty, dynamic correlation, stock market return, oil shock

JEL codes: C32; E60; E66; G10; G18

1. Introduction

The foundations of the effects of policy uncertainty on the economy have been placed for more than 30 years now (see, inter alia, Marcus, 1981; Bernanke, 1983; Aizenman and Marion, 1991; Rodrik, 1991). Nevertheless, the interest in the effects of policy has resurged especially after the advent of the 2007 financial crisis. Authors mainly focus their attention on the examination of the effects of policy uncertainty on macroeconomic variables, such as growth, inflation and investment (see, Bloom, 2009; Baum et al., 2010; Bachmann et al., 2010; Jones and Olson, 2013, among

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others). Arguably, in the presence of uncertainty regarding the effectiveness of the macroeconomic policies, rational agents will withhold their investment decision (considering that these investments are either completely or partly irreversible) until the uncertainty is removed. Thus, the general consensus is that uncertainty has a negative effect on the level of growth and investment. The effect of uncertainty on inflation is less clear-cut as it depends on international shocks, such as oil price shocks, according to Jones and Olson (2013).

The aim of this paper is to contribute towards the study of the effects of macroeconomic policy uncertainty on the economy, focusing on its effects on stock market performance. In particular, we explore the dynamic co-movements between macroeconomic policy uncertainty and stock market returns using the newly introduced index of macroeconomic uncertainty by Baker et al. (2012) and a more elaborate measure of correlations.

To achieve that, we construct a time-varying measure of policy uncertainty and stock market returns correlations based on the dynamic conditional correlation (DCC) model of Engle (2002). Taking into account both time variation and conditional heterogeneity in correlations, the proposed measure has several advantages compared to other commonly used measures. 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 m consecutive periods, with m being the window span. In addition, under the proposed measure there is neither need to set a window span, nor loss of observations, nor is there a requirement for subsample estimation.

Our results based on monthly data between January 1997 and September 2012 suggest that dynamic correlations between policy uncertainty and stock market returns are consistently negative. In addition, increased stock market volatility increases policy uncertainty and dampens stock markets returns, while increases in the volatility of policy uncertainty lead to negative stock market returns and increased uncertainty. Finally, oil specific demand shocks and domestic shocks (price and income shocks) lead to further increase in the negative correlation between policy uncertainty and stock market returns.

The remainder of the paper is organized as follows. Section 2 discusses the methodology and describes the data used. Section 3 presents the empirical findings, and Section 4 summarizes and concludes the paper.

2. Methodology and Data

Let $y_t = [y_{1t}, y_{2t}]'$ be a 2×1 vector of policy uncertainty index series and S&P500 returns. The former series comes from Baker et al. (2012) and measures policy-related economic uncertainty in the United States. In particular, it's a constructed index based on three components. The first component quantifies newspaper coverage of policy-related economic uncertainty. The second component reflects the number of federal tax code provisions set to expire in future years. The third component uses disagreement among economic forecasters as a proxy for uncertainty. The S&P500 returns series is obtained from FRED database and defined as the annualized monthly change of the natural logarithm of S&P500 index, and given by: $1200 \times (\log(S\&P500_t) - \log(S\&P500_{t-1}))$. Our sample ranges from January 1997 to September 2012 (189 observations).

Figure 1 shows the evolution of the policy uncertainty index of Baker et al. (2012) and the S&P500 returns. According to this figure, we observe that peaks of the uncertainty index to be associated with abrupt changes in stock market returns. A feature which we explore further below. In addition, there is an increasing pattern – regarding the policy uncertainty index – beginning to emerge since the outbreak of the financial crisis in mid-2007.

Table 1 presents descriptive statistics of the uncertainty index and the S&P500 returns series. According to this table, we observe large variability in both variables. The augmented Dickey-Fuller (ADF) test with just a constant indicates that S&P500 returns are stationary (as the null hypothesis of a unit root process is rejected), while uncertainty contains a unit root. Nevertheless, uncertainty is trend stationary as the ADF test with a constant and a trend rejects the null of a unit root – a fact that was also observed informally by looking at Figure 1. The fact that the ARCH-LM test rejects the null hypothesis of homoskedasticity for both variables suggests that it is appropriate to model these series as an ARCH-type process. Finally, the unconditional correlation of -0.1853 indicates that when policy uncertainty increases, stock market returns decline, and vice versa.

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

The conditional mean equations are represented by:

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

where A is a matrix, 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 models and $R_t = \rho_{ij_t}$ where $i, j = 1, 2$ is the 2×2 matrix comprising the conditional correlations. The standard deviations in matrix D_t follow a univariate process of:

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

The DCC model of Engle (2002) has the following structure:

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

where

$$Q_t = (1 - \sum_{k=1}^{K} a_k - \sum_{l=1}^{L} b_l)\bar{Q} + \sum_{k=1}^{K} a_k(\varepsilon_{t-k}\varepsilon_{t-k}) + \sum_{l=1}^{L} b_l Q_{t-l}, \tag{5}$$

$\bar{Q}$ is the unconditional variance-covariance matrix from estimating the model in equation 3, and Q_t^* is a 2×2 diagonal matrix containing the square root of the diagonal elements of Q_t. Our main focus is on the time-varying conditional correlations $\rho_{ij} = \frac{q_{ij,t}}{\sqrt{q_{ii,t}q_{jj,t}}}$, where $i, j = 1, 2$, in matrix R_t.

The DCC model is estimated using the quasi-maximum likelihood estimator.

3. 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 multivariate Portmanteau statistics. Based on the Akaike information criterion (AIC) and Schwarz Bayesian criterion (BIC), the conditional mean (CM) of uncertainty is modeled as an autoregressive process of order nine, AR(9), and a trend, $Trend$, is included to account for the upward movement of uncertainty, while no lags of S&P500 returns were necessary for the CM of uncertainty or S&P500 returns. However, up to nine lags of uncertainty were included in the CM of returns to correctly capture the return process in our model and to filter any remaining serial correlation in the standardized residuals. Indeed the estimated DCC model is well specified, as the multivariate versions of the Portmanteau statistic of Hosking (1980) and Li and McLeod (1981) do not reject the null hypothesis of no serial correlation in the standardized and squared-standardized residuals, respectively, up to 10 lags.

Note that we include the conditional variances of uncertainty, h_{unc_t}, and S&P500 returns, $h_{S\&P500\_Ret_t}$ in the CM equations in 1. The estimated parameters are correctly signed and significant. Specifically, increased stock market volatility increases policy uncertainty and dampens stock markets returns, while increases in the volatility of policy uncertainty lead to negative stock market returns (significant at the 10% level) and increased uncertainty.

In Figure 2, we present the dynamic conditional correlation between uncertainty and stock market returns along with the 90% confidence intervals. The time-varying correlation between uncertainty and stock market returns is consistently negative over time. We observe an increasing trend in correlation (i.e. it becomes less negative) since the later part of the 2007-2008 global financial crisis, and it remains in lower negative correlation levels throughout the latter period of our sample, although with a downward trend. Interestingly, there is a heterogeneous behaviour of the correlation during the two recessions which are covered by our sample. A plausible explanation why the correlation in the later part of the financial crisis did not behave as expected can be found in the unprecedented bailout package for the US banking sector of 2008 and the stimulus package of 2009. Even though the policy uncertainty remains high after these two packages, the stock market responded favourably, considering that in the later part of the financial crisis the market was experiencing positive returns.

An important question that arises is why correlations between stock market returns and uncertainty fluctuate in that manner? Put differently, what explains the evolution of conditional correlations between stock market returns and macroeconomic uncertainty?

In order to tackle this issue, we apply a Fisher transform on the estimated time-varying correlations, ρ_t, between uncertainty and stock market returns according to $DC_t = log((1+\rho_t)/(1-\rho_t))$, so as to ensure our dependent variable is not confined to the interval $[-1, 1]$,[1] and estimate various specifications of the following model:

$$DC_t = \alpha + \beta DC_{t-1} + \gamma Oil\_Shocks_t + \delta Domestic\_Shocks_t + \epsilon_t, \tag{6}$$

where α is a constant, Oil_Shocks_t is a vector of three oil price shocks[2], $Domestic\_Shocks_t$ is a vector of domestic shocks, namely, US industrial production growth and inflation so as to account for changes in the real economy not captured by the oil shock variables, and ϵ_t is the innovation. Finally, one lag of the dependent variable, DC_{t-1}, is included to account for first-order serial correlation in our transformed variable.

[1] The results are not sensitive to this transformation though.

[2] Oil price shocks have been estimated using the framework developed by Kilian (2009). Kilian (2009) identifies three oil price shocks (namely, supply-side shocks, aggregate demand shocks and oil specific demand shocks). Supply-side shocks are associated with changes in the world oil production, aggregate demand shocks are associated with changes in the global economic activity and oil specific demand shocks are associated with concerns about the future availability of oil.

Table 3 presents the results of the various forms of model (6). Under Columns (1)–(4) we examine the effects of the oil price shocks without including any of the domestic shocks. We find that only the oil specific demand shocks (OSS) have a negative and significant effect on dynamic correlation, suggesting that this specific oil price shock pushes the correlation to lower values. This is expected as positive oil specific demand shocks (which drive oil prices in higher levels) would increase the uncertainty of the macroeconomic policies and decrease stock returns. Under Columns (5)–(12) we also add the domestic shocks to account for changes in the real economy not captured by international factors. We find that once domestic factors are accounted for, the oil price shocks do not exercise any significant effect on the correlation level. On the contrary, a significant negative effect is observed from both inflation and industrial production. We maintain that the results are expected considering that an increase in inflation (industrial production) would impose greater (lower) uncertainty in the macroeconomic policies, whereas stock prices would experience a bearish (bullish) period, thus the correlation between the two variables will become more negative.

4. Conclusion

The focal point of this study is the extent of time-varying correlations between stock market returns and macroeconomic policy uncertainty. In particular, we employ S&P500 index returns and the policy uncertainty index of Baker et al. (2012) that has recently gained considerable attention, and construct a measure of their underlying correlation based on the DCC model of Engle (2002). Results show that the dynamic correlation between policy uncertainty and stock market returns is consistently negative over time. Pertaining to increased stock market volatility, this appears to increase policy uncertainty and to dampen stock market returns. We also provide evidence that rises in the volatility of policy uncertainty lead to negative stock market returns and increased uncertainty. Particularly worthy of mention is the fact that only oil specific demand shocks have a significantly negative effect on dynamic correlations.

On a final note, an important question that deserves further research, is why correlations between stock market returns and uncertainty behave heterogeneously during extreme economic conditions?

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Figure 1: Baker et al. (2012) Uncertainty index and S&P500 Returns

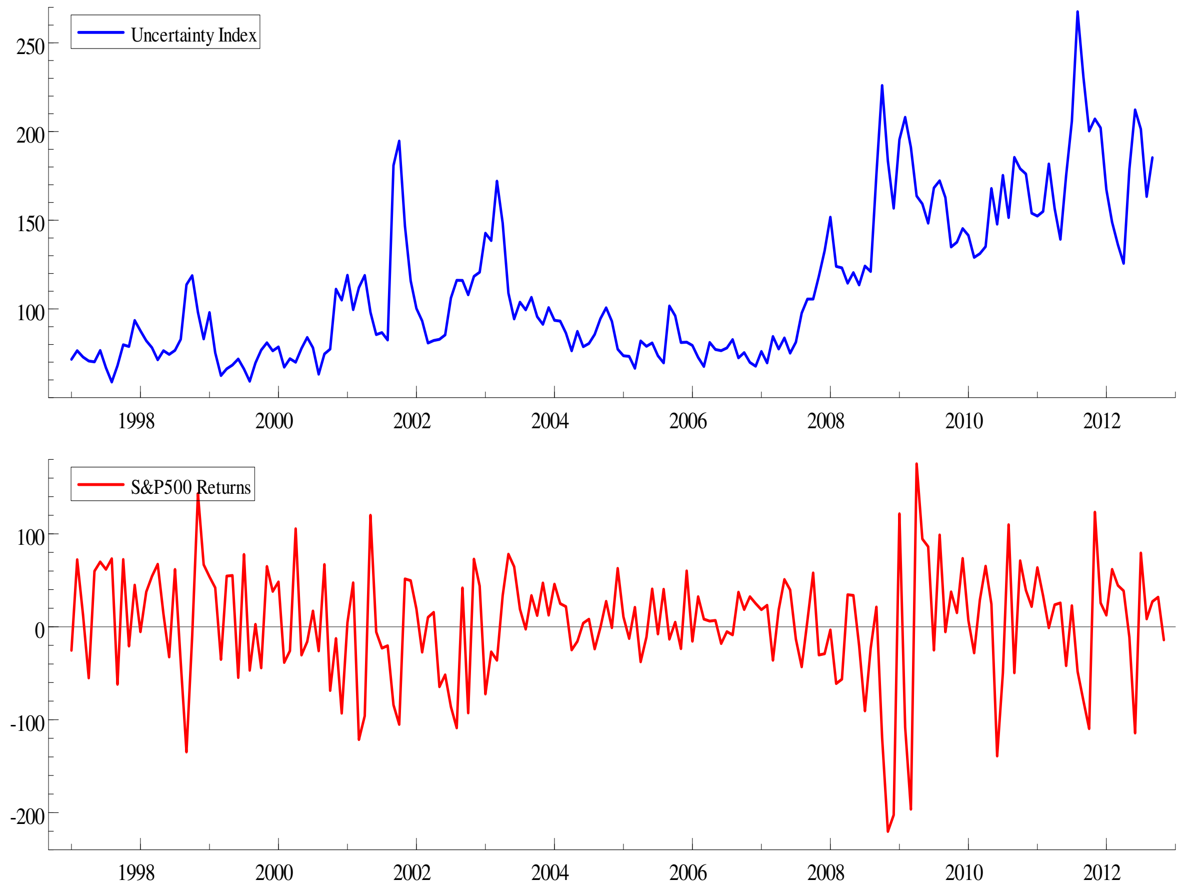
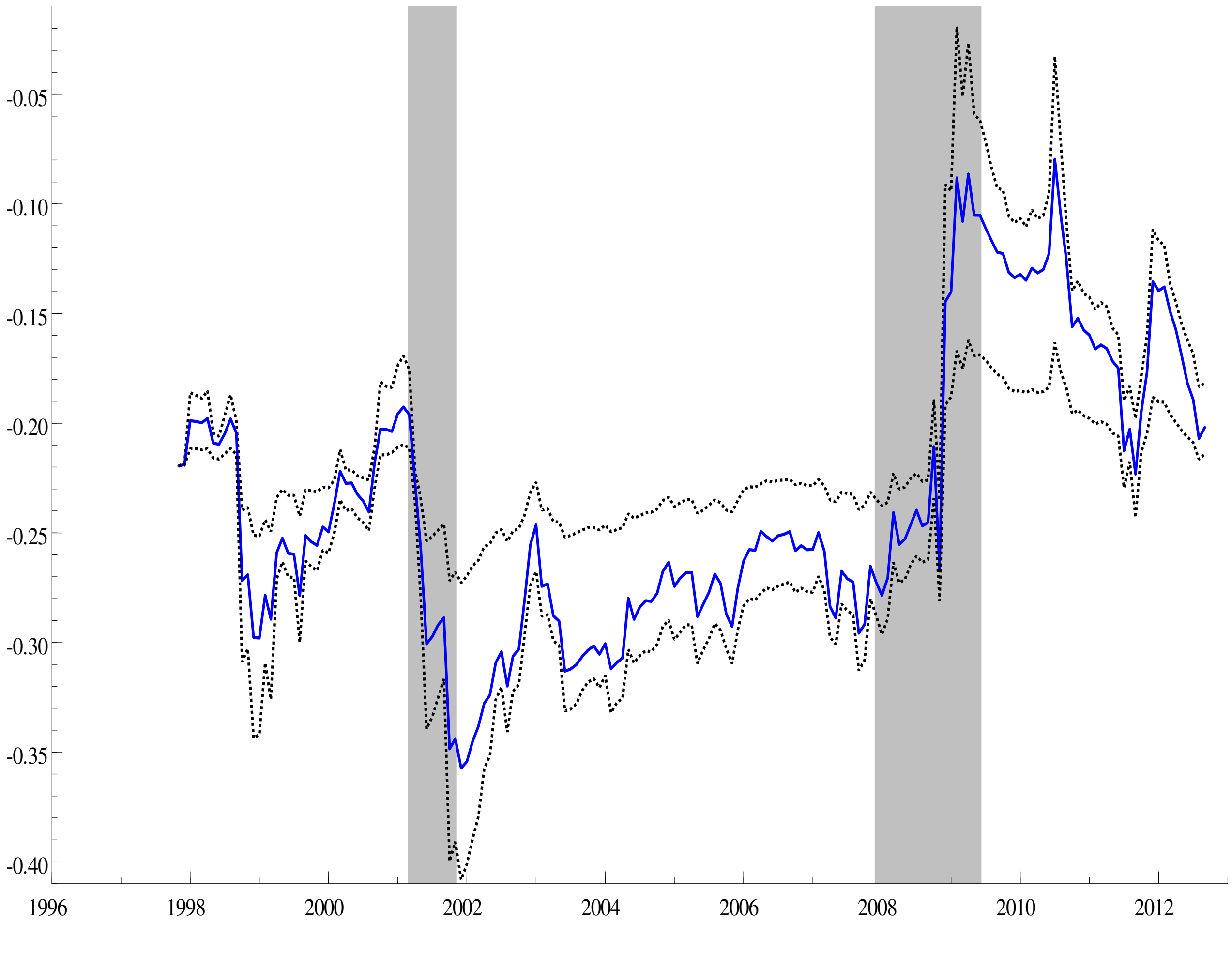


Figure 2: Dynamic conditional correlations of Uncertainty and S&P500 Returns



Notes: Dotted lines are the 90% confidence intervals. Shading denotes US recessions as defined by NBER.

Table 1: Descriptive statistics

	Uncertainty	S&P500 Returns
Min	58.8071	-220.3415
Mean	112.2421	4.9937
Max	267.5631	175.3441
Std	43.3294	59.8821
ADF[a] (constant)	-2.8022	-12.1120**
ADF[b] (constant & trend)	-4.1110**	
ARCH(12) LM Test	56.1950**	8.2454**
	Unconditional Correlations	
Uncertainty	1.0000	
S&P500 Returns	-0.1853	1.0000

Notes:

[a] The 5% and 1% critical values are -2.88 and -3.47, respectively.

[b] The 5% and 1% critical values are -3.44 and -4.01, respectively.

* and ** indicate significance at 5% and 1% level, respectively.

Table 2: Estimation results of DCC-GARCH models, Period: 1997M1 – 2012M9

	(1)		(2)	
Panel A: Conditional mean				
	Unc_t	$S\&P500\ Ret_t$	Unc_t	$S\&P500\ Ret_t$
$Constant$	0.7338*** (0.0378)	6.7539** (3.1610)	0.7139 (1.2393)	2.7692 (3.5430)
Unc_{t-1}	0.0411*** (0.0026)	-0.0540*** (0.0202)	0.7661*** (0.0087)	-0.0773*** (0.0263)
Unc_{t-2}	-0.1491*** (0.0245)	-0.0056 (0.0229)	0.0265*** (0.0094)	-0.0005 (0.0275)
Unc_{t-3}	-0.2919*** (0.0912)	0.0305 (0.0219)	-0.0474*** (0.0099)	0.2436*** (0.0284)
Unc_{t-4}	-0.0816*** (0.0215)	0.0041 (0.0216)	0.0736*** (0.0099)	-0.0110 (0.0302)
Unc_{t-5}	-0.2583*** (0.0534)	0.0276 (0.0203)	-0.0015 (0.0097)	-0.0154 (0.0300)
Unc_{t-6}	-0.0182*** (0.0054)	-0.0016 (0.0226)	-0.0220** (0.0100)	0.0405 (0.0291)
Unc_{t-7}	-0.1498*** (0.0416)	-0.0004 (0.0230)	-0.0509*** (0.0100)	-0.0158 (0.0294)
Unc_{t-8}	-0.0506*** (0.0111)	0.0077 (0.0176)	0.1427*** (0.0094)	0.0255 (0.0297)
Unc_{t-9}	-0.1075*** (0.0325)	-0.0030*** (0.0007)	0.0546*** (0.0096)	-0.0068*** (0.0022)
$Trend$	0.0617*** (0.0197)		0.0878*** (0.0243)	
h_{unc_t}			0.0111*** (0.0040)	-0.0115* (0.0065)
$h_{S\&P500\ Ret_t}$			0.0012*** (0.0004)	-0.0020** (0.0009)
Panel B: Conditional variance				
ω	16.4521*** (2.0345)	57.6895*** (5.6487)	20.8821*** (1.2795)	97.3991*** (7.4955)
α_1	0.0779*** (0.0008)	0.1559*** (0.0499)	0.1968*** (0.0198)	0.1816*** (0.0167)
β_2	0.8964*** (0.0943)	0.6642*** (0.1134)	0.2671*** (0.0366)	0.5632*** (0.0256)
a	0.0144*** (0.0025)		0.1050*** (0.0065)	
b	0.9480*** (0.1287)		0.8336*** (0.0407)	
Panel C: Misspecification tests				
Standardized residuals				
$H(12)$	41.5823 [0.1283]		45.2128 [0.3283]	
$Li-McL(12)$	41.4399 [0.1396]		45.0743 [0.3289]	
Squared standardized residuals				
$H^2(12)$	30.6188 [0.7969]		50.2984 [0.3071]	
$Li-McL^2(12)$	30.7626 [0.7915]		50.3989 [0.3037]	

Notes: $H(12)$, $H^2(12)$ and $Li-McL(12)$, $Li-McL^2(12)$ are the multivariate Portmanteau statistics of Hosking (1980) and Li and McLeod (1981), respectively, up to 10 lags. Standard Errors in parenthesis and p-values in square brackets. ***, ** and * denote statistical significance at the 1 percent, 5 percent and the 10 percent level, respectively.

Table 3: Dynamic correlations and the role of shocks

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$Constant$	-0.0113	-0.0099	-0.0103	-0.0109	-0.0074	-0.0068	-0.0066	-0.0075	-0.0065	-0.0058	-0.0057	-0.0064
	(0.0086)	(0.0085)	(0.0086)	(0.0085)	(0.0084)	(0.0084)	(0.0084)	(0.0085)	(0.0083)	(0.0083)	(0.0083)	(0.0084)
DC_{t-1}	0.9763***	0.9791***	0.9783***	0.9770***	0.9767***	0.9779***	0.9778***	0.9770***	0.9775***	0.9784***	0.9785***	0.9776***
	(0.0166)	(0.0165)	(0.0167)	(0.0166)	(0.0162)	(0.0162)	(0.0162)	(0.0163)	(0.0160)	(0.0160)	(0.0160)	(0.0161)
ADS	-0.1497			-0.1504	-0.0748			-0.0800	-0.0707			-0.0712
	(0.0935)			(0.0932)	(0.0941)			(0.0954)	(0.0927)			(0.0941)
OSS		-0.0368*		-0.0370*		-0.0104		-0.0124		-0.0013		-0.0031
		(0.0202)		(0.0202)		(0.0216)		(0.0219)		(0.0216)		(0.0219)
SS			0.0559	-0.0087			0.1908	0.1436			0.1726	0.1430
			(0.6562)	(0.6496)			(0.6371)	(0.6411)			(0.6278)	(0.6323)
π_t					-0.1530***	-0.1525***	-0.1633***	-0.1412***	-0.1499***	-0.1576***	-0.1596***	-0.1476***
					(0.0478)	(0.0507)	(0.0465)	(0.0532)	(0.0471)	(0.0501)	(0.0458)	(0.0525)
y_t									-0.0602**	-0.0602**	-0.0604**	-0.0595**
									(0.0242)	(0.0246)	(0.0242)	(0.0247)
R^2	0.9522	0.9524	0.9515	0.9531	0.9548	0.9547	0.9547	0.9549	0.9564	0.9563	0.9563	0.9564

Note: In each specification, the dependent variable, DC_t, is the transformed correlation based on the Fisher transformation. ***, ** and * denote statistical significance at the 1 percent, 5 percent and the 10 percent level, respectively.