Stock Market Volatility, Risk Attitude and the Demand for Money in the UK

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Abstract

Is stock market volatility an important determinant of money demand in the UK? If yes, what is the driving force behind that effect? In a cointegration framework, we find that volatility in share prices is an important positive determinant of money demand, alongside standard variables and the stock price level. By studying different stock market indexes effects, we find that the risk aversion of investors is an important force behind the effect, implying that the effect is due to investors' flight to safer assets in times of volatile stock prices.

Keywords: money demand, share prices, volatility, risk attitude, cointegration

1. Introduction

Friedman (1988) argued that increasing stock prices on the one hand can have a positive impact on money demand as it (1) increases nominal wealth; (2) reflects increasing expected return, and hence increases the risk of the stocks, which can induce reallocation to safer assets; (3) increases the money demanded to carry out financial transactions. On the other hand, Friedman argued, increasing stock prices can increase the relative attractiveness of equities to other portfolio components, and thus have a negative effect on money demand. The net effect of stock prices on demand for real money balances may be positive or negative, depending on which of the two is more dominant. According to Friedman's investigation, the net effect was positive. Evidence for the existence of a stationary long-run relationship between money demand and real stock prices has later been found both for the US (Choudhry 1996) and for the UK (Bissoondeeal, Mullineux and Binner 2009). A review of the literature that studies the effect of the stock market on money demand is provided by Stern and Stern (2008). [1]

Given that stock prices have been found to be an important determinant of money demand, it is reasonable to ask whether uncertainty in the form of volatility in the stock market affects the demand for money as well. Similar to stock market price levels, stock market volatility may have a positive or negative impact on the demand for money. We postulate that if individuals are risk averse, stock market uncertainty should have a positive impact on demand for money. Investors are likely to reallocate some stock holdings to safer monetary assets holdings in times of high volatility. If on the other hand, individuals' attitude towards risk is risk seeking, then we would expect stock market volatility to have a negative impact on the demand for money. As the level of uncertainty increases, investors typically demand higher returns for assets carrying greater risks. Motivated by higher expected returns, investors willing to undertake high risks, may reallocate from safer assets to stocks holdings. Here also the net impact of stock prices volatility on the demand for money may be positive or negative, depending on which of the two is more dominant that the other. There are surprisingly few studies examining the impact of stock price volatility on the demand for money. Among the notable few is the study of Carpenter and Lange (2003), who identify a positive link between money demand and stock market volatility for the US economy.

In this study, we elaborate further on the relation between stock market volatility and money demand. In an application to the UK economy, we model the relationship along with standard variables and the stock price level in a cointegration framework. Our first objective is to investigate whether the relation between stock volatility can be shown to hold for the UK as well. We find that, using the general stock price index FTSE ALL, both the level and the volatility of stock prices influence money demand positively. As we discussed earlier, the positive relationship between money demand and stock price volatility is due to the net attitude of individuals being risk averse. To give more credence to this claim, we estimate the money demand/stock price volatility relationship across sub-indexes of the general stock market. The idea behind this exercise is that the degree of risk aversion should be dependent on the size of the companies considered in the index. Small companies typically trade at greater risk than large companies (Banz 1981). Hence large (small) companies should have more (less) risk averse investors. By substituting the index used in the money demand equation to its different sub-indexes, we find that the magnitude of reallocation from stock to safer monetary assets falls as company size decreases. The clear trend identified here indicates that more risk averse investors are associated with larger companies while less risk averse investors are associated with smaller firms. Interestingly, along this trend, for the index with the smallest companies, and arguably the index with least risk averse investors, the impact of stock volatility on money demand turns negative. This implies, on aggregate, that risk seeking behaviour induces investors to reallocate funds from safe to risky assets.

Thus, the results we obtain in this study indicate that the increase in money demand, in times of stock price volatility, is primarily due to risk aversion. That is, the increase is due to a precautionary motive rather than a transaction motive. Such an observation has very important implications for money as an indicator for future economic activity.

Money is a variable whose importance in policy making has traditionally been high, but it is currently out of fashion. Both the UK and the US have moved away from monetary targeting, where it is necessary to employ some sort of money demand function in order to correctly interpret the movements in targeted monetary aggregates (Knell and Stix 2006). The abandonment of monetary targeting has often been linked with substantial financial innovations occurring in the 1980s which created instabilities in money demand functions (see for example Binner, Gazely and Chen 2002; Drake, Chrystal and Binner 2000; Friedman 1996). However, policymakers continue to pay attention to monetary aggregates. For example, the ECB monitors Euro area M3 for its monetary policy strategy aimed to assess medium to long-term inflation trends (ECB 2003). Golinelli and Pastorello (2002) emphasise the importance of money demand stability in the monetary transmission mechanism and the role of monetary policy in the Euro area. Mervyn King, the Governor of the Bank of England, believes that the absence of monetary aggregates in the standard models which economist use will cause problems in the future and there will be profitable developments from future research into the way in which monetary aggregates affect economic behaviour (see King 2002). By improving the understanding of the link between money and financial markets, and hence the understanding of money demand in general, this study aims to contribute to these developments. Given that we find money demand and stock price volatility have a positive relationship, this indicates that an increase in money demand, in times of stock price volatility, has a precautionary motive, rather than a transaction motive, behind it. This finding sheds some light on the important debate on why money demand has a stable relationship with inflation in the long-run but a very erratic relationship in the short-run.

The remainder of the paper proceeds as follows. Section 2 describes the econometric method that will be used to investigate the objectives of this paper. Section 3 describes the data and carries out some preliminary analysis. Section 4 presents the results and discussions.

2. Econometric methodology

As shown in Equation (1), we model money demand M_t to be related to income level Y_t ; an opportunity cost variable OPC_t ; stock price level SP_t ; and stock price volatility VOL_t. The alphas are coefficients and ε_{1t} is the residual term.

$$\ln M_t = \alpha_0 + \alpha_1 \ln Y_t + \alpha_2 OPC_t + \alpha_3 \ln SP_t + \alpha_4 \ln VOL_t + \varepsilon_{1t} \tag{1}$$

We estimate this relationship in a cointegrated vector autoregressive (VAR) model framework based on Johansen's (1988) maximum likelihood method. Let z_t denote a $p \times 1$ set of variables that are not integrated of an order higher than one. Then the cointegrated VAR may be represented in vector error correction form as:

$$\Delta z_t = \sum_{i=1}^{m-1} \Gamma_i \Delta z_{t-i} + \Pi z_{t-1} + \text{deterministic components} + \varepsilon_{2t} \tag{2}$$

where Γ_i s and Π are coefficient matrices and ε_{2t} is a vector of Gaussian error terms. Let $r = rank(\Pi)$. Then, if $0 < r < p$ the matrix Π can be partitioned into $p \times r$ matrices α and β such that $\Pi = \alpha\beta'$ and $\beta' z_t$ is I(0) (Johansen and Juselius 1990). The number of cointegrating relationships is r and each column of β is a cointegrating vector. We use the trace test and the $\lambda - \max$ test (Johansen 1995) to determine the number of cointegrating relationships.

3. Data, variables, and preliminary analysis

For the analysis in this article, we cover the period 1986Q1 to 2006Q4. The starting period corresponds to the earliest time where data are available on all the variables under investigation: real M4, real income, an opportunity cost variable, real stock prices and stock price volatility. Data on nominal income, gross domestic product (GDP), stock price indices and consumer price index (CPI) were obtained from Datastream. CPI is used to convert the nominal variables - income, M4, stock price indices and stock price volatility - to real variables.

For measuring money we use the official measure M4 for our analysis, which is in keeping with the relevant literature (Choudhry 1996, Carpenter and Lange 2003). The monetary aggregate M4 is the sum of notes and coins, non-interest bearing sight deposits, interest bearing sight deposits, interest bearing time deposits and building society deposits (all downloaded from the Bank of England's website). In addition to these assets, TESSA deposits and cash ISA deposits are included in the construction of the official UK M4 aggregate; however, these are omitted here since they are only available for a short period [2].

The opportunity cost variable we use is a dual price index, constructed as the spread between the rate of return on 'alternative asset', *R*, and the own rate on the monetary aggregate *M4*. *R* is constructed using an envelope approach in which R_t is set to the highest return of all the assets at time *t* (see for example Drake, Chrystal and Binner 2000 and Hancock 2005 for a discussion on choice of benchmark rate). The own rate on the monetary aggregate M4 is constructed as $\sum r_i \, {}^{m_i}\!/_{M4}$, where r_i is the return on asset m_i (Stracca, 2004).

In the first instance, we are interested in establishing whether volatility in the stock market in general has an impact on the demand for money. For stock price level and volatility we then use the FTSE ALL index, which is a market-capitalisation based index of about 800 companies of the London Stock Exchange companies (about 40% of the companies with >98% of the market capitalisation). In the subsequent analysis, we also investigate the relationship between sub-indexes to FTSE ALL and money demand. The sub-indices to FTSE ALL are FTSE 100, which comprises of the 100 largest companies on the London Stock Exchange; FTSE 250 with the 250 largest companies excluding the FTSE 100; FTSE 350, which is the companies of the first two indexes together; and finally FTSE Smallcap, containing 300 companies smaller than those in FTSE 350 index.[3] We model stock price volatility using a generalised autoregressive conditional heteroscedasticity model, GARCH(1,1) model (see Bollerslev 1986, and Engle 1982), described in Equations 3 - 5, where r_t is the first difference of the logarithm of share prices; ν is the mean of r_t; and u_t is a variable containing innovations in r_t. Ω_{t-1} denotes all information available at time t-1, and $N(0, h_t)$ defines conditional normal density with zero mean and conditional variance h_t .

$$r_t = \nu + u_t \tag{3}$$

$$u_t \mid \Omega_{t-1} \sim N(0, h_t) \tag{4}$$

$$h_t = \omega + \beta_1 h_{t-1} + \alpha_1 u_{t-1}^2 \tag{5}$$

According to a survey by Bollerslev, Chou and Kroner (1992), the GARCH(1,1) specification is widely held as an appropriate model for estimating conditional volatility of financial data. In Table 1 we give the results from the GARCH(1,1) model estimation for FTSE ALL, along with the corresponding results for four sub-indexes that we use in the subsequent analysis. The logarithm of the estimated conditional variance, h_t , is denoted VOL_t and applied to Equation 1.

[Table 1: around here]

In order to use the cointegration framework set out for the analysis, we need to verify the order of integration for each variable. We apply the augmented Dickey and Fuller test (ADF) by Said and Dickey (1984). The results, reported in Table 2, show that apart from volatility in small caps, all the variables are nonstationary I(1) variables. Usually I(1) variables are used in searching for cointegration relationships, but as argued in Hansen and Juselius (2000), stationary variables can also be allowed in cointegration relationships as long as two of the variables in a cointegration vector are nonstationary I(1) variables. Thus, in order to maintain consistency with other money demand equations, volatility in small caps is also included in the money demand equation involving small caps.

[Table 2: around here]

4. Results and Discussion

We now turn to estimation of the cointegration relationship modelled in Equation 2. We set the lag length of the model to 3. This specification is tested using a Lagrange Multiplier test for autocorrelation of order 1 and 4. As shown in Table 3, this test does not suggest any misspecification problem with this lag length.

[Table 3: around here]

Results from the trace and $\lambda-\max$ tests, investigating the number of cointegration relationships, are reported in Table 4; and normalised long run cointegration relationships are given in Table 5.

[Table 4: around here]

[Table 5: around here]

4.1 General stock market volatility effect on demand for money

To study whether stock price volatility influences the demand for money in the UK, we are looking at the model sketched in Equation 2, using the broadest stock market index, FTSE ALL, as basis for share price level and volatility. Results from the trace and $\lambda-\max$ tests are reported in Table 4. For each model at least one of the tests provides evidence for the existence of a cointegration vector on the basis of the 95% significance level. Thus, the results suggest that along with standard variables, stock price volatility has an impact on money demand. As seen in Table 5, the standard variables have the expected signs: real income has a positive effect with a coefficient around 1.3 and opportunity cost has a negative effect. These observations conform to the findings in the literature (see for example Binner et al. 2005). Stock prices have a positive impact on money demand, which is also in line with previous empirical literature such as Bissoondeeal, Mullineux and Binner (2009) as well as Friedman's (1988) theoretical line of argument.

Stock price volatility has a positive influence on the demand for money. This corresponds to the US finding of Carpenter and Lange (2003). Our result indicates that in times of volatility in the stock market, the demand for money increases. As discussed earlier, this may be due to the fact that the net attitude of investors in the UK is risk aversion – when stocks appear more risky investors are turning to safer assets.

4.2 Stock market volatility effect on demand for money across company sizes

To ascertain that increases in money demand are due to risk aversion, that is, investors increase their demand for money because of a precautionary motive rather than a transaction motive in times of stock market volatility, we examine the relationship between stock price volatility and money demand across sub-indexes of the general stock market.

As mentioned earlier, it is reasonable to believe that small companies have less risk-averse investors. This reasoning is based on the size effect (Banz 1981), saying that small firms yield excess returns. This small firm risk can in turn be related to liquidity risk (Amihud and Mendelson 1986) which comes in the form of smaller trading activity and larger spreads, possibly due to asymmetric information effects (that small firms are less transparent as they are not followed by as many analysts). Thus, if large (small) firms have more (less) risk averse investors, then we can hypothesise that, in times of volatility, more risk averse investors will be more concerned by the uncertain environment than less risk averse investors. Therefore, we would expect the magnitude of reallocation from risky assets to safer assets to fall as the company size decreases and volatility increases. If, on the other hand, the transaction motive is the driving force behind increases in money demand then the magnitude of reallocation from stocks to monetary assets should not be much different across the different tiers of the stock market or at least there should not be any discernable trend. Thus, we now rerun the model above using different sub-indexes of the FTSE ALL index. The sub-indexes are categorised by the market capitalisation of their constituent companies, with FTSE 100 being the largest and FTSE Smallcap the smallest.

The results of our tests are again found in Tables 4 and 5. In the former, we see that for each model at least one of the tests provides evidence for the existence of one cointegration vector at 95% significance level. These results suggest that, along with standard variables, the share price volatility is an important determinant of the demand for money, regardless of which tier of the market we are focusing on. Also, the standard variables in the money demand equation are relatively stable across the sub-indexes, and no consistent trend in the differences with respect to constituent company size can be seen. The stock price level effect remains positive for all indexes tested, though substantially smaller for the FTSE Smallcap than for other indexes.

In the effect of stock price volatility on money demand we see a clear trend. The relationship is clearly positive for FTSE 100, and much stronger than for FTSE ALL. As the size of constituent firms is falling, however, so does the impact of their volatility. In the case of FTSE Smallcap, the relation even turns negative. We interpret this as an indication of investors' risk aversion falling with company size, even turning to be risk-seeking in the case of FTSE Smallcap. When the volatility in this category increases, the demand for money tends to decrease.

The fact that the coefficient on the volatility variable is so dependent on which index is being used is an indication of that the driving motive behind the money demand effect is portfolio reallocation – when volatility increases investors take refuge in safer assets. This motive, rather than a transaction motive, appears to be the main reason behind money demand increases during periods of stock market volatility.

4.3 Money demand, stock price volatility and policy implications

What are the policy implications of this finding? It is generally accepted that there is a stable long-run relationship between money growth and inflation and money growth is a good indicator of inflation in the long run. However, the money growth and inflation relationship is not stable in the short-run, which is a reason for money being less attractive as a policy tool. The findings from this study could provide some explanation for this erratic relationship in the short-run. As discussed earlier, in times of stock price volatility money demand increases due to a portfolio reallocation driven by risk aversion, thus it is a precautionary move. For policy purposes, money demand increases due to transaction motives are more important as they are likely to contribute to inflation. Thus, our study shows that during times of stock price volatility money may not have a very stable relationship with inflation. If money is monitored for policy purposes as it is the case with the ECB, then changes in the level of money demand should be given more weight when the stock market is fairly calm. On the other hand, a smaller weight should be attached to money demand in times of high stock price volatility as investors are essentially seeking refuge in safer assets during such times.

5. Summary and Conclusions

In this paper we investigate whether volatility in the stock market affects the demand for money in the UK. We find that along with standard variables such as interest rates and income, share prices and their volatility are also important determinants of the demand of money in the UK. Our results suggest that money demand increases in times of stock price volatility. We argue that this is due to risk aversion where investors are seeking refuge in safer monetary assets during such periods. To ascertain this claim we examine the relationship between money demand and different sub-indexes of the stock market, where the market capitalisation of the constituent firms varies across indexes. We find that the relation between money demand and stock market volatility is highly dependent on the firm size considered. We interpret this size effect as a sign that risk aversion of investors is important.

The finding in this study has important policy implications for policy makers, such as the ECB, who monitor changes in the demand for money as an indicator for future economic activity such as inflation. Given that during periods of stock price volatility money demand increases because of risk aversion, money demand will not reliably indicate inflation risks and thus should be given smaller weights during periods of stock price volatility and more weight when the stock market is relatively calm.

References

Amihud Y. and H. Mendelson 1986. Asset pricing and the bid-ask spread. *Journal of Financial Economics* 17(2): 223-250.

Banz R.W. 1981. The relationship between return and market value of common stocks. *Journal of Financial Economics* 9(1): 3-18.

Binner J.M., A.M. Gazely, and S. Chen. 2002. Financial Innovation and Divisia Monetary Indices: A Neural Network Approach. *The European Journal of Finance* 8: 238-247.

Binner J.M., R.K. Bissoondeeal, T. Elger, A.M. Gazely, and A.W. Mullineux. 2005. A Comparison of Linear Forecasting Models and Neural Networks: An Application to Euro Inflation and Euro Divisia. *Applied Economics* 37: 665-680.

Bissoondeeal R.K., A.W. Mullineux, and J.M. Binner. 2009. Stock Market Effect on Money Demand in the UK. Working Paper, Aston Business School.

Bollerslev T. 1986. Generalized Autoregressive Conditional Heteroscedasticity. *Journal of Econometrics* 31: 301-327.

Bollerslev T., R.Y. Chou, and K.F. Kroner. 1992. Arch Modeling in Finance: A review of the Theory and Empirical Evidence. *Journal of Econometrics* 52: 5-59.

Carpenter S.B. and J. Lange. 2003. Money Demand and Equity Markets. US Federal Reserve Board's Finance & Economic Discussion Series. 2003-3. Washington: Board of Governors of the Federal Reserve System. February.

Choudhry T. 1996. Real Stock Prices and the Long-run Money Demand Function: Evidence from Canada and the USA. *Journal of International Money and Finance* 15: 1–17.

Choudhry T. 1999. Does Interest Rate Volatility Affect the US M1 Demand Function? Evidence from cointegration. *The Manchester School* 67: 621-648.

Drake L., K.A. Chrystal and J.M. Binner. 2000. Weighted monetary aggregates for the UK. In *Divisia Monetary Aggregates: Theory and Practice*, ed. M.T. Belongia and J.M. Binner, 47-78. New York: Palgrave.

Drake L., A. Fleissig, and A.W. Mullineux. 1999. Are Risky Assets Substitutes for Monetary Assets? *Economic Inquiry* 37: 510-526.

ECB. 2003. *The Outcome of the ECB's Evaluation of its Monetary Policy Strategy*. ECB Monthly Bulletin, June: 87-102.

Engle R.F. 1982. Autoregressive Conditional Heteroscedasticity with Estimates of the Variances of the UK Inflation. *Econometrica* 50: 987-1017.

Friedman M. 1988. Money and the Stock Market. *Journal of Political Economy* 96: 221-245.

Friedman B.M. 1996. The Rise and Fall of Money Growth Targets as Guidelines for U.S. Monetary Policy. NBER Working Paper 5465.

Golinelli R. and Pastorello S. 2002. Modelling the demand for M3 in the Euro area. *European Journal of Finance* 8: 371-401.

Hansen H. and K. Juselius. 2000. *Cats in Rats: Cointegration Analysis of Time Series*. Evaston, IL: Estima.

Hancock M. 2005. Divisia Money. *Bank of England Quarterly Bulletin*, 45: 39-47.

Johansen S. 1988. Statistical Analysis of Cointegration Vectors. *Journal of Economic Dynamics and Control* 12: 231-54.

Johansen S. 1995. *Likelihood-Based Inference in Cointegrated Vector Autoregressive Models*. Oxford: Oxford University Press.

Johansen S. and K. Juselius. 1990. Maximum Likelihood Estimation and Inference on Cointegration with Application to the Demand for Money. *Oxford Bulletin of Economics and Statistics* 52: 169-209.

King M. 2002. No money, No inflation - The Role of Money in the Economy. Bank of England Quarterly Bulletin, Summer 2002.

Knell M. and H. Stix. 2006. Three Decades of Money Demand Studies: Differences and Similarities. *Applied Economics* 38: 805-818.

MacKinnon J.G. 1996. Numerical Distribution Functions for Unit Root and Cointegration Tests. *Journal of Applied Econometrics* 11: 601-618.

Nelson D.B. and C.O. Cao. 1992. Inequality Constraints in the Univariate GARCH Model. *Journal of Business and Economic Statistics* 10: 229–235.

Said E.S. and D.A. Dickey 1984. Testing for unit roots in autoregressive-moving average models of unknown order. *Biometrika* 71(3): 599-607.

Sriram S.S. 2001. A Survey of Recent Empirical Money Demand Studies. IMF Staff Papers 47: 334–365.

Stern L.V. and M.L. Stern. 2008. Expected Equity Returns and the Demand for Money. *The B.E. Journal of Macroeconomics* 8: Article 18.

Stracca, L., 2004. Does liquidity matter: properties of a synthetic Divisia monetary aggregate in the Euro area. Oxford Bulletin of Economics and Statistics 66 (3), 309–331.

Footnotes

[1] For a recent survey of the huge literature on money demand, see Sriram (2001).

[2] Bissoondeeal, Mullineux and Binner (2009) compare the effect of the stock market on money demand using the official measure and a weighted measure of money supply.

[3] In the exposition below, these indexes are ordered by company size, putting FTSE 350 between the FTSE 100 and FTSE 250 indexes.

Table Captions

Table 1: Test results from GARCH(1,1) models

Equity index	*Regression coefficients*			
	v	ω	h_{t-1}	u_{t-1}^2
FTSE ALL	0.008	3.10E-04	1.03	-0.09
	-1.01	-4.86	-29.12	(-3.534)
FTSE 100	0.01	7.00E-07	1.05	-0.05
	-1.77	-0.01	-109.51	(-34.54)
FTSE 350	0.013	4.2E-05	1.06	-0.06
	(1.63)	(0.03)	(25.31)	(-3.02)
FTSE 250	0.017	6.3E-05	1.05	-0.06
	(1.95)	(1.11)	(172.01)	(-43.53)
FTSE SmallCap	0.004	5.0E-03	0.39	-0.10
	(0.35)	(0.52)	(0.35)	(0.44)

This table presents results from GARCH analysis in accordance with Equations (3)-(5). Values within parentheses are z statistics. FTSE ALL, FTSE 100, FTSE 350, FTSE 250, FTSE SmallCap are stock price indexes..

Table 2: Unit root tests

	ADF test statistics	
Variable	Level	First difference
M	-2.69	-3.59 *
Y	-2.33	-4.21 *
OPC	-3.12	-9.20 *
FTSE ALL	-2.37	-9.01 *
FTSE 100	-2.00	-9.95 *
FTSE 350	-2.22	-10.16 *
FTSE 250	-2.91	-10.38 *
FTSE SmallCap	-2.74	-8.87 *
VOL FTSE ALL	-2.55	-7.95 *
VOL FTSE 100	-2.54	-8.55 *
VOL FTSE 350	-2.77	-8.17 *
VOL FTSE 250	-2.12	-8.02 *
VOL FTSE SmallCap	-5.31 *	-

All variables except OPC are given in natural logarithms. The null hypothesis of the ADF test is that the series tested has a unit root. Critical values at the 1% significance level are approximately -4.07 for levels and -3.51 for first differences (MacKinnon 1996). A star (*) indicates when the null hypothesis can be rejected at the 1% level. Lag lengths for the ADF test were chosen using the Schwarz information criterion (not reported). A constant and a trend were included for tests on level series; a constant was included for tests on first differences. *M* is real money (M4); *Y* is real GDP; *OPC* is the opportunity cost dual price index as constructed by Stracca (2004); FTSE ALL, FTSE 100, FTSE 350, FTSE 250, FTSE SmallCap are stock price indexes given in real terms; and VOL is the conditional volatility of these stock price indexes calculated in a GARCH(1,1) model.

Table 3: Lagrange Multiplier tests for autocorrelation

	Lag length	
VAR model	1	4
FTSE ALL	23.96 (0.52)	22.60 (0.60)
FTSE 100	28.90 (0.27)	28.41 (0.29)
FTSE 350	27.20 (0.35)	28.36 (0.29)
FTSE 250	25.37 (0.44)	27.35 (0.34)
FTSE SmallCap	33.01 (0.13)	32.88 (0.13)

VAR models based on Equation (2), with stock price variables SP(t) and VOL(t) based on the variable named in the first column of the table, are tested for autocorrelation at different lag length specifications. The null hypothesis is that there is autocorrelation in the residuals. For each test, test statistic and corresponding *p*-value (within parenthesis) are given. The LM test statistic is asymptotically distributed as chi-square of order 25. FTSE ALL, FTSE 100, FTSE 350, FTSE 250, FTSE SmallCap are stock price indexes.

Table 4: Cointegration tests

Panel A: Trace test

	r (number of cointegrating relationships)				
VAR model	0	1	2	3	4
FTSE ALL	67.29 *	32.10	14.36	4.16	0.06
FTSE 100	73.03	30.19 *	15.13	4.73	0.24
FTSE 350	71.54	30.93 *	16.38	6.24	0.09
FTSE 250	66.20 *	31.87	15.04	6.08	0.01
FTSE SmallCap	78.41	44.86 *	18.79	7.59	0.33
Trace critical value (95%)	69.82	47.86	29.80	15.49	3.84

Panel B: λ-max test

	r (number of cointegrating relationships)				
VAR model	0	1	2	3	4
FTSE ALL	35.19	17.73 *	10.20	4.10	0.06
FTSE 100	42.84	15.06 *	10.39	4.49	0.24
FTSE 350	40.61	14.55 *	10.15	6.14	0.09
FTSE 250	34.33	16.83 *	8.96	6.07	0.01
FTSE SmallCap	33.55 *	26.07	11.20	7.26	0.33
λ-max critical value (95%)	33.88	27.58	21.13	14.26	3.84

VAR models based on Equation (2), with stock price variables SP(t) and VOL(t) based on the variable named in the first column of the table, are tested for number of cointegrating vectors. In Panel A, results for the trace test are given, and in Panel B results for the λ-max test are given. Both tests are based on Johansen (1995). A star (*) indicates the existence of *r* cointegration vectors. FTSE ALL, FTSE 100, FTSE 350, FTSE 250, FTSE SmallCap are stock price indexes.

Table 5: Cointegration relationships

	Variable coefficients			
VAR model	Y	OPC	SP	VOL
FTSE ALL	1.330	-0.008	0.044	0.063
FTSE 100	1.321	-0.014	0.106	0.207
FTSE 350	1.126	-0.010	0.150	0.094
FTSE 250	1.048	-0.005	0.168	0.044
FTSE SmallCap	1.280	-0.005	0.004	-0.253

The table reports the coefficients of the cointegration relationship in Equation (1), with stock price variables SP(t) and VOL(t) based on the variable named in the first column of the table. All variables except OPC are given in natural logarithms. M is real money (M4); Y is real GDP; OPC is the opportunity cost dual price index as constructed by Stracca (2004); FTSE ALL, FTSE 100, FTSE 350, FTSE 250, FTSE SmallCap are stock price indexes given in real terms; and VOL is the conditional volatility of these stock price indexes calculated in a GARCH(1,1) model.