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“Volatility and volatility spillovers on financial markets”

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Komise pro obhajoby doktorských disertací v oboru ekonomické teorie a jejich dějiny

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Summary

The thesis consists of five parts and deals with issues of volatility and volatility spillovers on financial markets. The abstracts of the thesis bring forth the essential concept, methods, and results of the thesis.

The first part describes the analysis of comovements, interdependence, and spillovers among three stock markets (Hungary, the Czech Republic, and Poland) in Central and Eastern Europe (CEE) with respect to their Western European counterparts (Germany, France, and the United Kingdom). A component GARCH model is employed with five-minute-tick intraday price data to distinguish between short-term (transitory) and long-term (permanent) conditional volatility. In terms of spillovers, there are signs of short-term spillover effects both on stock returns and stock price volatility. Volatility spillover effects are identified among the CEE markets, among the Western markets, and from Western markets to CEE markets. An especially important result is the identification of volatility spillovers running from stock exchanges in Budapest and Warsaw to exchanges in Frankfurt and London, respectively. This result is the first of its kind published in the literature and shows that even smaller markets may impact dominant markets in terms of volatility spillovers.

The second part introduces an analysis of exchange rate volatility in the Visegrad Four countries during the period in which they abandoned tight regimes for more flexible ones. An augmented GARCH methodology accounts for path dependency, asymmetric shocks, and movements in interest rates. The overall findings are that path-dependent volatility has a limited effect on exchange rate developments and that the introduction of floating regimes tends to increase exchange rate volatility. When the countries had flexible regimes, volatility was mainly driven by surprises. Asymmetric effects of news tend to decrease volatility under a floating regime. Interest differentials impact exchange rate volatility contemporaneously under either regime, although no intertemporal effect of interest differentials is found. As a general observation, volatility is found to be driven primarily by country-specific effects, and budgetary imbalances correlate well with exchange rate volatility in these countries.

The third part addresses the issue of volatility-related foreign exchange risk and its macroeconomic determinants in several new EU members. The observable macroeconomic factors—consumption and inflation—are derived using the stochastic discount factor (SDF) approach. The joint distribution of excess returns in foreign exchange markets and the macroeconomic factors are modeled using a multivariate GARCH-in-mean specification. The findings show that both real and nominal factors play important roles in explaining the variability of the foreign exchange risk premium. Both types of factors should be included in monetary general equilibrium models employed to study excess returns despite the fact that the effect of the nominal factor is greater than that of the real factor. On a policy level, the results show that to contribute

to the further stability of domestic currencies, new EU members should strive to implement stabilization policies aimed at achieving nominal as well as real convergence with core EU members.

The fourth part studies the dynamics of volatility transmission between CEE currencies and the euro/dollar foreign exchange using model-free estimates of daily exchange rate volatility based on intraday data. A multivariate GARCH specification is used to model the daily realized volatility of a given exchange rate depends both on its own lags as well as on the lagged realized volatilities of the other exchange rates. For accurate measurement of the overall magnitude and evolution of volatility transmission over time, a dynamic version of the Diebold-Yilmaz volatility spillover index is constructed. The results show ample evidence of statistically significant intra-regional volatility spillovers among the CEE foreign exchange markets. With the exception of the Czech and, prior to the turbulent economic events related to the crisis in 2007, Polish currencies, no significant spillovers are found running from the euro/dollar exchange to the CEE foreign exchange markets. It is also shown that volatility spillovers tend to increase in periods characterized by market uncertainty. From a medium-term perspective, volatility increases for those countries with troubled financial sector development. A generally observed difference in the pre- and post-crisis patterns is an increase in the strength of short-term links, a sign of generally faster reaction of the markets to volatility dynamics.

The fifth, and last, part introduces a new approach how to quantify asymmetries in volatility spillovers that emerge due to bad and good volatility. The new method is based on computing the Diebold-Yilmaz volatility spillover index when negative and positive changes in returns are considered separately via realized semivariances. As a result, a volatility spillover index robust to ordering in VAR is computed so that it captures asymmetries in volatility spillovers. The new method is applied on stocks and commodity markets data. There is ample evidence of the asymmetric connectedness of the most liquid U.S. stocks in seven sectors at the disaggregate level. Moreover, the spillovers of bad and good volatility are transmitted at different magnitudes that sizably change over time in different sectors. While negative spillovers are often of substantial magnitudes, they do not strictly dominate positive spillovers. It is found that the overall intra-market connectedness of U.S. stocks increased substantially during the 2007–2008 financial crisis. Further, asymmetries in the volatility spillovers of petroleum commodities are evidenced. The increase in volatility spillovers after 2001 correlates with the progressive financialization of the commodities. Increasing spillovers from volatility among petroleum commodities substantially change their pattern after 2008 (the financial crisis and advent of tight oil production): asymmetries in spillovers markedly declined in terms of total as well as directional spillovers. For petroleum commodities, asymmetries in spillovers due to negative (price) returns materialize to a greater degree than volatility spillovers due to positive returns. An analysis of directional spillovers reveals that no petroleum commodity dominates other commodities in terms of general spillover transmission.

1. Volatility Spillovers among Stock Markets

Outline

Egert and Kočenda (2007) analyze volatility spillovers among stock markets in Central and Eastern Europe (CEE) that underwent some remarkable developments both in terms of market capitalization and daily trade volume from the very beginning of the economic transformation. Although the financial systems of these countries largely remain bank-dominated, the stock exchanges appear to be well integrated with global financial markets following the lifting of restrictions on portfolio capital movements. However, given that these markets are small compared to the stock exchanges of the largest OECD countries, they may be sensitive to shifts in regional and worldwide portfolio adjustments of large investment funds and other market participants, even though the amount of capital involved in such moves are not necessarily very large by global standards. Consequently, these markets may be more volatile than well-established stock markets.

A number of earlier papers investigated the short- and long-term linkages among the CEE stock exchanges both in terms of stock returns and stock market volatility (Gilmore and McManus (2002, 2003); Voronkova (2004); Syriopoulos (2004); Bohl and Henke (2003); Scheicher (2001); Tse, Wu, and Young (2003); Serwa and Bohl (2005)). The evidence in the earlier literature is mostly based on data with daily or even lower frequencies, since historical intraday series from the CEE stock markets were usually unavailable; the only exception at that time was Černý and Koblas (2005). Yet, developments in volatility and contagion effects that materialize during the trading day represent a finer picture that often cannot be extracted from daily observations. Another big advantage of using intraday data is that the estimates are more robust to structural breaks (Terzi, 2003) given the relatively short time horizon studied (about 2 years) as compared to studies employing daily data (up to 10 years).

Against the general lack of empirical evidence for intraday stock market interlinkages between Eastern and Western European stock markets, Egert and Kočenda (2007) fill this gap in the literature by investigating the links and possible spillover effects for stock returns and stock volatilities among markets in Budapest, Prague, and Warsaw from June 2003 to February 2005, including their interactions with selected major developed markets in the EU (Frankfurt, London, and Paris—Western markets) on the basis of intraday data recorded in five-minute intervals. Given that this period does not cover any major crisis, the focus is on interdependence rather than on contagion. No robust cointegration relationship is identified for any of the stock index pairs but short-term spillover effects are found both in terms of stock returns and stock price volatility.

Methodological contribution to analyzing stock volatility

In order to investigate volatility spillovers among markets, Granger causality tests are applied to stock volatility. In this context, one may use either volatility measures based on the implied volatility of option prices or volatility derived using econometric techniques, such as the GARCH framework.

The second avenue is followed mainly because of the general lack of data on stock options in the countries under study, especially data at an intraday frequency. In our endeavor, we estimate the component GARCH (CGARCH) model of Engle and Lee (1999), where equation (1) is the mean equation and equation (2) is the conditional variance equation:

$$\Delta s_t = \phi_1 + \sum_{i=1}^{m} \phi_{5,i} \Delta s_{t-i} + \varepsilon_t \tag{1}$$

$$\sigma_t^2 - q_t = \overline{\omega} + \alpha \cdot (\varepsilon_{t-1}^2 - \overline{\omega}) + \beta \cdot (\sigma_{t-1}^2 - \overline{\omega}) . \tag{2}$$

The optimal lag length of the mean equation is selected based on the Schwarz information criterion. The CGARCH model distinguishes between short-term (transitory) and long-term (permanent) conditional volatility. Contrary to constant conditional volatility in a standard GARCH model, long-term volatility (q_t) is allowed to vary over time, to which the short-term volatility or the transitory component of long-term volatility $(\sigma_t^2 - q_t)$ mean-reverts as shown in (3):

$$q_t = \omega + \rho \cdot (q_{t-1} - \omega) + \delta \cdot (\varepsilon_{t-1}^2 - \sigma_{t-1}^2) . \tag{3}$$

CGARCH makes it possible to separately model the effect of spillovers on stock volatility in the short- and long-run. Consequently, Granger causality tests are applied to the stock volatility derived from the CGARCH model.

The paper was the first contribution that applied the above framework with intra-day high-frequency data on stock markets in CEE countries along with developed European counterparts.

Empirical contribution to analyzing stock volatility

The estimation results indicated that for a common daily window adjusted for the observed U-shaped pattern running from mid-2003 to early 2005 there existed short-term spillover effects both in terms of stock returns and stock price volatility. We were able to identify volatility spillover effects among CEE markets, among Western markets and from Western markets to CEE markets. Specifically, an important result was the identification of volatility spillovers running from stock exchanges in Budapest and Warsaw to exchanges in Frankfurt and London, respectively. This casted some doubt on the well-established position that only dominant markets can influence volatility on other markets. Our findings also indicated a peculiar pattern in CEE: the Prague and Warsaw stock exchanges seemed to interact both in terms of returns and volatility with the Budapest stock exchange, but not with each other. As a result, short-term spillovers from Prague to Warsaw and vice versa were mostly likely to transit via Budapest.

The above result was the first of its kind published in the literature and bears an important implication. First, it was shown that even smaller markets may impact dominant markets in terms of volatility spillovers. Second, by this token, the CEE markets could be considered by hedge funds and institutional investors as a separate “asset class” as compared to stocks in Western markets.

2. Exchange Rate Volatility and Regime Change

Outline

Kočenda and Valachy (2006) analyze exchange rate volatility in the four Visegrad countries, i.e., the Czech Republic, Hungary, Poland, and Slovakia, during the period in which they were abandoning tight foreign exchange regimes in favor of more flexible ones. It was the first comprehensive analysis of exchange rate volatility that accounts for path dependency, asymmetric shocks, and movements in interest rates underlined by interest rate parity theory.

The overall monetary policy framework has an important impact on exchange rate volatility. After eliminating currency pegs, the Visegrad countries adopted direct inflation targeting (DIT). Therefore, nominal exchange rates are likely to exhibit increasing volatility for at least two reasons. First, switching from currency pegs to flexible exchange rates and adopting DIT policies, at least for Poland and to a lesser degree for the Czech Republic, is accompanied by a benign neglect of exchange rate stability, as Orlowski (2005) discusses. Second, during periods of faster money growth, the pressure on domestic inflation rises and contributes to exchange rate volatility, as evidenced in Hungary and Poland. Clearly, a converging economy should give priority to the objective of lowering inflation over exchange rate stability because price stability is a prerequisite for exchange rate stability, as shown empirically by Orlowski (2004). Other sources of exchange rate volatility are the increasing openness of the economy and instabilities related to the balance of payments. Still, the key sources of exchange rate volatility and their development can be attributed to tighter versus looser exchange regimes. Kočenda and Valachy (2006) hypothesize that volatility effects will differ depending on the specific regime and comprehensively assess the regimes.

Methodological contribution to analyzing changes in volatility under different exchange rate regimes and subject to interest rate parity

Many early empirical studies use standard deviation as a proxy for exchange rate volatility, e.g., Hallett and Anthony (1997), Andersen and Bollerslev (1998), Jorion (1995), and Scott and Tucker (1988). This approach assumes constant average daily returns, which is directly opposed to the interest rate parity condition. Hence, neglecting movements in interest rates leads to unreliable results. Therefore, in the spirit of the excess volatility debate, we consider whether and to what extent the volatility of exchange rates exceeds the volatility of interest rates. To approximate an otherwise unobservable volatility, we follow an approach suggested by Andersen, Bollerslev, Diebold, and Labys (2001). Specifically, we fit a parametric econometric model of the autoregressive conditional heteroskedasticity (ARCH) type, attributed to Engle (1982), augmented by appropriate parameters to account for the effect of interest rate differentials on the volatility of exchange rates.

To augment our ARCH-type model, we use the concept of uncovered interest rate parity (UIP), which connects movements in exchange rates and interest rates and allows us also to distinguish the effect of interest rates on exchange rate volatility (Golinelli and Rovelli, 2002; Svensson, 2000); empirical support for the UIP in the Visegrad countries was presented by Golinelli and Rovelli (2005) and Chinn (2006).

The conventional notion of interest rate parity can be expressed as:

$$s_{t+1} - s_t = i_t - i_t^*, \tag{1}$$

where s_t denotes the natural logarithm of an exchange rate at time t and i_t and i_t^* are the domestic and foreign interest rates of equal maturity, respectively. For UIP, s_{t+1} indicates an expected exchange rate one period ahead. Under the UIP condition, the exchange rate should adjust in every period so that the change is equal to the size of the interest rate differential. In contrast to this theoretical equality, the exchange rate is likely to show short-run deviations from UIP and in practice such deviations may be related to the size of the interest rate differential. Hence, such deviations may affect exchange rate volatility and corresponding movements in interest rates are also likely to affect the volatility of exchange rates.

Although the effect of movements in interest rates is ambiguous, Bilson (1999) shows that the volatility of exchange rates is related to the difference between the interest rates of the two currencies. To account for nonlinearity, an ARCH-type model should be augmented by the squared interest rate differential, i.e., $(i_t - i_t^*)^2$. However, this variable may not be sufficient because it captures only the contemporaneous effect of the differential and not its dynamics. Hence, we include the change in the interest rate differential squared, i.e., $(\Delta(i_t - i_t^*))^2$, as a second variable to account for intertemporal change.

To test empirically for exchange rate volatility, we employ the augmented generalized autoregressive conditional heteroskedasticity (GARCH) model from Bollerslev (1986). In this extension of the GARCH model, volatility, i.e., conditional variance σ_t^2, is modeled not only as a function of past squared innovations and its own past variance, but also as a function of additional parameters. First, the mean extension includes a conditional variance in the mean equation so that we can analyze the process with a path-dependent rather than the zero-conditional mean. Second, the threshold extension accounts for asymmetric information: in essence, good news and bad news do not have the same effect. Inclusion of a threshold dummy, d_t, enables us to make a distinction between positive and negative shocks to volatility or to allow innovations to have an asymmetric effect on conditional volatility. Third, we augment the variance specification by two parameters, i.e., the interest rate differential and its intertemporal change, to isolate the effect of movements in interest rates on exchange rate volatility.

We use the following specification of the augmented threshold GARCH-in-mean (TGARCH-M) model:

$$\begin{aligned} \Delta s_t &= a_0 + \sum_{i=1}^{k} a_i \Delta s_{t-i} + b \ln \sigma_t^2 + \lambda \cdot SD_t + \varepsilon_t;\ \varepsilon_t \sim N(0, \sigma_t^2) \\ \sigma_t^2 &= \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 + \xi d_{t-1} \varepsilon_{t-1}^2 + \delta_1 (i_t - i_t^*)^2 + \delta_2 (\Delta(i_t - i_t^*))^2 \end{aligned} \quad , \qquad (2)$$

where Δs_t is the difference of the log of the exchange rate between time t and t-1, i.e., the change in the exchange rate over two consecutive trading days and k, p, and q are the numbers of lags chosen by the Schwarz-Bayesian lag selection criterion. The log of the conditional variance in the mean equation, i.e., $\ln \sigma_t^2$, allows for an exponential rather than quadratic effect of observed volatility. The threshold dummy variable d_{t-1} is equal to 1 if $\varepsilon_{t-1} < 0$, i.e., a negative shock or good news, and 0 otherwise, i.e., a positive shock or bad news. The variables ($i_t - i_t^*$) and ($\Delta(i_t - i_t^*)$) are the annualized interest rate differential and the change in the interest rate differential, respectively. The shock dummy, i.e., SD_t, in the mean equation accounts for a few infrequent outliers: appreciation and depreciation movements of the currencies.

Empirical contribution to analyzing exchange rate volatility under different regimes

In this paper, we analyze exchange rate volatility in the four Visegrad countries, i.e., the Czech Republic, Hungary, Poland, and Slovakia, during the period in which they were abandoning tight regimes in favor of more flexible ones. In analyzing exchange rate volatility, we account for path dependency, asymmetric shocks, and movements in interest rates. We find that the introduction of floating regimes tends to increase exchange rate volatility in general, which conforms to conventional wisdom. Moreover, the degree of persistence in exchange rate volatility differs with respect to the currency but remains at a similar level under the floating regime. Furthermore, the effect of asymmetric news tends to decrease volatility under the float. Finally, the interest rate influences exchange rate volatility in somewhat non-obvious ways in that, under both regimes, the contemporaneous effect of interest differentials impacts exchange rate volatility but the coefficients measuring the intertemporal effect of interest differentials are insignificant.

Our estimates of conditional volatility indicate that volatility tends to increase after the switch to a more flexible regime. This finding is consistent with the stylized fact that exchange rate volatility is greater under a float than under a fixed regime. In general, our findings indicate that the width of the fluctuation band, be it narrow or broad, does not have an unambiguous influence on exchange rate fluctuation. Nonetheless, the type of regime is likely to be the strongest factor affecting exchange rate volatility because of the role played by the interest rate. Furthermore, we find that the impact of external shocks, i.e., news or surprises, on exchange rate volatility differs across countries. Hence, we conclude that volatility has been driven primarily by country-specific effects.

Finally, we conclude that exchange rate volatility is not a completely exogenous process. Budgetary imbalances are the most critical issue for the Visegrad countries because they affect not only exchange rate volatility but also the entire process of conversion to the EMU, as Kočenda, Kutan, and Yigit (2005) discuss. Uncertainty about fiscal discipline is a common exogenous factor behind exchange rate volatility for these countries. Hence, the coordination of monetary and fiscal policies would help to reduce exchange rate volatility in these four countries, but this is a considerable task for policymakers currently.

3. Macroeconomic Sources of Foreign Exchange Risk

Outline

Kočenda and Poghosyan (2009) was the first analysis of the role of macroeconomic factors as systemic determinants of currency risk in the new member states of the European Union (EU). Since currency stability has been an important part of the macroeconomic policies in these countries on their way to becoming part of the EU and adopting the Euro, the impact of macroeconomic factors appears to play a crucial role in explaining currency risk premia in these countries. The analysis of the impact of macroeconomic factors for the currency risk premium in new EU states was largely disregarded in the previous literature. However, its proper assessment can expand our understanding of the importance of theoretically motivated macroeconomic fundamentals as foreign exchange risk premium drivers.

Research on explaining the currency risk premium using the uncovered interest rate parity condition is widespread and the literature has been growing since the earliest work of Hansen and Hodrick (1980) and Fama (1984); Lustig, Roussanov, and Verdelhan (2008) review the most recent additions to the literature and empirically show that risk premia in currency markets are large and time-varying. Arguably, time-variation in the currency risk premia is closely related to the fundamental factors driving the risk appetite of investors. However, most of the existing literature either focuses on the time-series properties of the risk premium without considering its relationship with fundamental macroeconomic factors (e.g. Cheung, 1993) or derives an implausibly large impact of macroeconomic factors on the risk premium using data on developed economies (e.g., Kaminsky and Peruga, 1990; Smith and Wickens, 2002a), in which many other aspects (e.g., carry-trading) make the identification of the impact of macroeconomic factors difficult.

In terms of the new EU countries, Kočenda and Valachy (2006) show that foreign exchange risk is pronounced in new EU members. The sources of the persistency in the foreign exchange risk premium in these countries are different due to underlying systemic differences among them, but there exists a common source of foreign exchange risk propagation, which is the questionable perspective of their macroeconomic policies (Kočenda, Kutan, and Yigit, 2008). However, the question of to what extent nominal and real macroeconomic factors are significant in terms of explaining currency risk in new EU members was not addressed in the earlier literature. Hence, the empirical analysis of the macroeconomic sources of foreign exchange risk is performed on four new EU member countries: the Czech Republic, Hungary, Poland, and Slovakia over the period 1999–2008.

Methodological contribution to analyzing volatility-related foreign exchange risk

One of our methodological contributions was that we derive our results in a multivariate framework, which had been largely neglected in the literature. The main advantage of the semi-structural modeling approach employed is that it provides a broader scope for an economic interpretation of factors driving the currency risk premium. The empirical implementation is based on a multivariate GARCH model with conditional covariances in the mean of the excess returns. This methodological framework allowed us to impose a no-arbitrage condition on the estimations, a feature that is absent in the univariate models used in most previous studies.

The foreign exchange risk premium has been empirically analyzed using various approaches. Its modeling is closely associated with observed deviations from uncovered interest rate parity (UIRP): on international currency markets the domestic currency tends to appreciate when domestic interest rates exceed foreign rates (Engel, 1996). These deviations from UIRP are interpreted as a risk premium from investing in a foreign currency by a rational and risk-averse investor. Apart from the negative correlation with the subsequent depreciation of the foreign currency, another well-documented property of these deviations includes extremely high volatility.

One branch of the empirical literature analyzing the foreign exchange risk premium is based on econometric models with strong theoretical restrictions coming from two-country asset pricing models. However, pricing theory to date was not successful in producing reliable risk premium estimates (see Backus, Foresi, and Telmer, 2001). Another part of the literature pursued a pure time-series approach that imposes minimal structure on the data. These studies were more successful in capturing empirical regularities observed in the excess return series but the lack of a theoretical framework made it difficult to interpret the predictable components of the excess return as a measure of the risk premium (see Engel, 1996). Given the above disadvantages the literature to date favored a semi-structural modeling approach. The stochastic discount factor (SDF) methodology is a convenient vehicle because it imposes a reasonable amount of structure on the data sufficient for identifying a foreign exchange risk premium, but otherwise leaves the model largely unconstrained. In our analysis we followed the SDF approach with observable and theoretically motivated factors to explain the variability of the foreign exchange risk.

Modeling framework

We denote R_t and R^*_t to be nominal gross returns on risk free assets (T-Bills) between time t and t+1 in the domestic and foreign country, respectively. Further, S_t is the domestic price of the foreign currency unit at time t (an increase in S_t implies domestic currency depreciation). The excess return to a domestic investor at time t+1 from investing in a foreign financial instrument at time t is $ER_{t+1} = \frac{R_t^*}{R_t}\frac{S_{t+1}}{S_t}$, which can be expressed in logarithmic form as:

$$er_{t+1} = r_t^* - r_t + \Delta s_{t+1}, \tag{1}$$

where the lowercase letters denote the logarithmic values of the appropriate variables. In the absence of arbitrage opportunities, excess return should be equal to zero if agents are risk neutral, and to a time-varying element ϕ_t if agents are risk averse. The term ϕ_t is given the interpretation of a foreign exchange risk premium required at time t for making an investment through period t+1.

The stochastic discount factor (SDF) model is based on a generalized asset pricing equation, which states that in the absence of arbitrage opportunities there exists a positive stochastic discount factor M_{t+1}, such that for any asset denominated in domestic currency the following relationship holds:

$$1 = E_t[M_{t+1}R_t], \tag{2}$$

where E_t is an expectations operator with respect to the investor's information set at time t. In the consumption-based CAPM models, equation (2) is an outcome of the consumer's utility maximization problem and the stochastic discount factor is given the interpretation of the intertemporal marginal rate of substitution (see Smith and Wickens, 2002).

The above asset pricing relation can be extended to an international context by considering domestic currency returns on a foreign investment $R_t^* \frac{S_{t+1}}{S_t}$, which can be substituted into equation (2) to yield:

$$1 = E_t[M_{t+1} R_t^* \frac{S_{t+1}}{S_t}]. \quad (3)$$

The no-arbitrage condition between the two currencies' financial markets implies that the risk-weighted yields on domestic and foreign currency investments should be identical, e.g. $E_t[M_{t+1}R_t] = E_t[M_{t+1}R_t^* \frac{S_{t+1}}{S_t}]$. Furthermore, if returns and the discount factor are jointly log-normally distributed, then equations (2) and (3) can be expressed in logarithmic form as:

$$0 = \log E_t[M_{t+1}] + r_t = E_t[m_{t+1}] + \frac{1}{2} Var_t[m_{t+1}] + r_t \quad (4)$$

and

$$\begin{aligned} 0 &= \log E_t[M_{t+1} \frac{S_{t+1}}{S_t}] + r_t^* = \\ &= E_t[m_{t+1} + \Delta s_{t+1}] + \frac{1}{2} Var_t[m_{t+1}] + \frac{1}{2} Var_t[\Delta s_{t+1}] + Cov_t[m_{t+1}; \Delta s_{t+1}] + r_t^* \end{aligned} . \quad (5)$$

Subtracting equation (5) from (4) and using (1) yields a relationship from which risk premium can be conveniently identified:

$$E_t[er_{t+1}] + \frac{1}{2} Var_t[er_{t+1}] = -Cov_t[m_{t+1}; er_{t+1}]. \quad (6)$$

Based on equation (6), the risk premium ϕ_t is expressed as $\phi = -Cov_t[m_{t+1}; er_{t+1}]$. This implies that the excess return is a function of its time-varying covariance with the discount factor. The previous literature mainly focused on the relationship between the variance of the return and its mean and disregarded the covariance term, which is instrumental for the no-arbitrage condition to be held in equilibrium (Smith, Soresen, and Wickens, 2003).

Equation (6) suggests that uncertainty about the future exchange rate influences the expected excess returns and serves as a source for the risk premium. The economic interpretation of the required risk premium is straightforward: the larger the predicted covariance between the future excess returns and the discount factor, the lower the risk premium, since the larger future excess returns are expected to be discounted more heavily. In other words, the gain is smaller in economies where money is considered relatively more valuable.

Following the above exposition, we formally derive and present the non-arbitrage specification for the excess return as a function of its own variance plus its dynamic covariance with macroeconomic factors (the formal derivation is not presented here for the sake of space limitation but it is fully described in the paper). The derived specification takes the form:

$$E_t[er_{t+1}] = \beta_1 Var_t[er_{t+1}] + \sum_{i=2}^{K+1} \beta_i Cov_t[z_{i,t+1}; er_{t+1}], \quad (7)$$

where the β_is (i =1,2,...K+1) are the coefficients of interest to be estimated.

In terms of macroeconomic factors (z_i), the foreign exchange risk premium is modeled to be influenced by the fundamental factors of the home country and not the foreign countries. This is due to the fact that we consider the four CE countries as small open economies that are acting as price takers in international financial markets and that take the foreign interest rate as given. This means that when there is a deviation from uncovered interest parity relationship, it is the exchange rate and interest rate of the small CE country that adjusts to the international level (for example Germany), rather than vice versa.

Econometric framework

We model the distribution of the excess return in the foreign exchange market jointly with the macroeconomic factors in such a way that the conditional mean of the excess return in period t+1 given the information available at time t satisfies the no-arbitrage condition given by equation (7). We employ the multivariate GARCH-in-mean model (see Smith, Soresen, and Wickens, 2003) that allows for a time-varying variance-covariance matrix. This is because the conditional mean of the excess return depends on time-varying second moments of the joint distribution. The multivariate GARCH model with mean effects is specified in a general form as:

$$\begin{aligned} \mathbf{y_{t+1}} &= \mu + \mathbf{\Phi vech\{H_t\}} + \boldsymbol{\varepsilon}_{\mathbf{t+1}} \\ \boldsymbol{\varepsilon}_{\mathbf{t+1}} \,|\, \mathbf{I_t} &\sim \mathrm{N}[\mathbf{0}, \mathbf{H_{t+1}}] \\ \mathbf{H_{t+1}} &= \mathbf{C'C} + \mathbf{A'H_tA} + \mathbf{B'}\boldsymbol{\varepsilon}_{\mathbf{t}}\boldsymbol{\varepsilon}'_{\mathbf{t}}\mathbf{B} \end{aligned} \quad , \qquad (8)$$

where $\mathbf{y_{t+1}} = \{ER_{t+1}, z_{1,t+1}, \ldots, z_{K,t+1}\}'$ is a vector of excess returns and K (observable) macroeconomic factors used in the estimations, $\mathbf{H_{t+1}}$ is a conditional variance-covariance matrix, $\mathbf{I_t}$ is the information space at time t, and **vech{.}** is a mathematical operator that converts the lower triangular component of a matrix into a vector.

The first equation of the model is restricted to satisfy the no-arbitrage condition (7), which restricts the first row of matrix Φ to a vector of β_is. Since there is no theoretical reason for the conditional means of macroeconomic variables $z_{i,t}$ to be affected by the conditional second moments, the other rows in matrix Φ are restricted to zero.

In our estimations we employ a sandwich estimator that is robust to the distributional assumptions of variables (Huber, 1967; White, 1982). Our specification of the variance-covariance process in (8) is the so-called BEKK formulation proposed by Engle and Kroner (1995). The BEKK specification guarantees the positive definiteness of the variance-covariance matrix and still remains quite general in the sense that it does not impose too many restrictions.

For estimating our model we employ two macroeconomic factors derived from the C-CAPM model: inflation rate (π) and consumption growth (Δc). Together with the excess return, the vector of variables in the system, corresponding to specification (8), becomes $\mathbf{y_{t+1}} = \{ER_{t+1}, \pi_{t+1}, \Delta c_{t+1}\}'$. The pricing kernel thus depends on both real and nominal factors and the shocks are allowed to arrive from both sides of an economy.

Empirical contribution to the analysis of volatility-related foreign exchange risk

In this paper we presented evidence of the impact of both real and nominal macroeconomic factors derived from the stochastic discount factor model on currency risk. We also provided the first evidence of the impact of macroeconomic factors on explaining the foreign exchange risk premium in selected new EU member countries. The generalized SDF model is used to ensure the derivation of theoretically grounded factors and model specification in a multivariate estimation framework. The previous attempts to explain foreign exchange risks in new EU economies were based on univariate models, which disregard the conditional covariance terms and allow for arbitrage possibilities. A multivariate approach was adopted to overcome these weaknesses and to provide reliable empirical results.

The estimation results suggested that the real factor (consumption) plays a role in explaining the variability in foreign exchange returns. This finding was in line with the evidence coming from more developed economies (Hollifield and Yaron, 2001; Lustig and Verdelhan, 2007). The impact of the real factor was quite leveled across the countries since they were well integrated among themselves as well as with respect to the Eurozone. On other hand, the impact of consumption was much smaller than that of inflation. Inflation, as a nominal factor, was found to be a significant factor for the risk premium in all countries. The results also suggested that there are some differences across the new EU markets, as the impact of each of the Eurozone factors differs across the countries. Our findings on the nominal factor seemed to be sensitive to the differences in inflationary history experienced by each country and the monetary policy regimes adopted in the examined countries. This finding supported the idea of the optimality of monetary policies based on inflation targeting for the nominal convergence process of the new EU members towards the Eurozone (see Orlowski 2005, 2008).

Our findings had both theoretical as well as empirical applications. In general, our empirical results implied that a monetary general equilibrium model employed to study excess returns should have both real and nominal risk components. To contribute to the further stability of the domestic currency, the new EU members should strive to implement stabilization policies aimed at achieving nominal as well as real convergence with the core EU members, since both real and nominal factors play important roles in explaining the variability of the foreign exchange risk premium.

In this paper we augmented the discussion and filled a gap in the literature by sharpening a quantitative assessment of the critical real and nominal macroeconomic factors that drive currency risk. These factors are grounded in the theoretical stochastic discount factor model. Our main contribution to the financial knowledge was in strengthening the limited evidence at that time that both nominal and real factors play a role in explaining the foreign exchange risk premium. This finding was in accordance with theoretical models of currency pricing.

4. Volatility Transmission in Foreign Exchange Markets

Outline

Motivated by the impact of the 2007–2008 financial crisis, Bubák, Kočenda, and Žikeš (2011) analyze the dynamics of volatility transmission to, from, and among Central European (CE) foreign exchange markets. In particular, we analyzed volatility spillovers among the Czech, Hungarian and Polish currencies together with the U.S. dollar during the period 2003–2009, and the extent to which shocks to foreign exchange volatility in one market transmit to current and future volatility in other currencies. It was the first analysis of dynamic volatility spillovers on forex markets in Central Europe.

Despite their growing integration with developed markets, in terms of volatility transmission, European emerging markets had been under-researched. The joint behavior of the volatility of CE currencies was of key importance for international investors contemplating the diversification benefits of allocating part of their portfolio to CE assets (Jotikasthira et al. (2010), de Zwart et al. (2009)). Further, there were even more fundamental reasons to be interested in analyzing volatility transmission in European emerging markets. The new EU members committed themselves to adopting the euro upon satisfying the set of Maastricht convergence criteria, one of which was exchange rate stability. Foreign exchange volatility is a measure of currency stability. This precondition was to some extent in contrast with historical evidence that foreign exchange risk is pronounced in new EU members (Kočenda and Valachy, 2006); Kočenda and Poghosyan (2009). Soriano and Climent (2006) review the relevant volatility transmission literature: studies that aim at foreign exchange volatility transmission are less frequent than those covering equity markets. Studies of volatility transmission analyzing forex data were chiefly based on low-frequency data. A limited number of previous studies make use of intraday or high-frequency data, hoping to address these and related issues (Baillie and Bollerslev (1991) Engle et al. (2009) Wongswan (2006)). The studies that make use of high-frequency data to construct realized measures of integrated variance as means of analyzing volatility spillovers in foreign exchange markets were rare (Melvin and Melvin, 2003; Cai et al., 2008)

The contribution of our paper to the existing literature was a thorough study of volatility transmission among CE exchange rates and the U.S. dollar using high-frequency data. By relying on model-free non-parametric measures of ex-post volatility, our analysis was in sharp contrast to the existing empirical literature on CE exchange rates that employs almost exclusively a GARCH framework to study the dynamics of exchange rate volatility. We proposed a simple and flexible multivariate time-series specification for the series of realized volatilities of the four exchange rates, allowing explicitly for the time-varying nature of the volatility of realized volatility itself. The model was essentially a multivariate generalization of the HAR-GARCH model of Corsi et al. (2008). Within the model we formally tested for volatility spillovers by running simple pairwise Granger causality tests. As a more advanced approach we constructed a dynamic version of the Diebold and Yilmaz (2009) spillover index in order to properly assess the overall magnitude and dynamics of the volatility spillovers.

Methodological contribution to analyzing forex volatility spillovers

Following the approach of Andersen et al. (2007), we assume that the vector of the logarithmic spot exchange rate, $\boldsymbol{x}_t$, belongs to the class of jump-diffusions

$$\boldsymbol{x}_t = \boldsymbol{x}_0 + \int_0^t \boldsymbol{\mu}_u \mathrm{d}u + \int_0^t \boldsymbol{\Theta}_u \mathrm{d}\boldsymbol{w}_u + \boldsymbol{l}_t,$$

where $\boldsymbol{\mu}_t$ denotes a vector drift process, $\boldsymbol{\Theta}_t$ is the spot co-volatility process, $\boldsymbol{w}_t$ is a standard vector Brownian motion, and $\boldsymbol{l}_t$ a vector pure-jump process of finite activity (i.e. the associated Levy density is bounded in the neighbourhood of zero). We make no parametric assumptions regarding the respective laws of motion (Andersen et al., 2003).

A natural measure of variability in this model is the well-known quadratic variation given by

$$\boldsymbol{QV}_t = \int_0^t \boldsymbol{\Theta}'_u \boldsymbol{\Theta}_u \mathrm{d}u + \sum_{s \in [0,t]} \Delta \boldsymbol{l}'_s \Delta \boldsymbol{l}_s,$$

where the first component captures the contribution of the diffusion, while the second component is due to jumps. To measure the daily quadratic variation of the individual components of $\boldsymbol{x}_t$ using intraday data we employ the realized variance (*RV*) defined as

$$RV_{i,t,M} = \sum_{i=1}^{M} \Delta_i x_{j,t}^2, \qquad (1)$$

where $\Delta_i x_{j,t}$ denotes the *i*-th intraday return of the *j*-th components of $\boldsymbol{x}_t$ on day *t*. When we construct the realized variance estimator we have to account for the presence of market microstructure noise that renders the realized variance estimator in equation (1) biased and inconsistent. To this end, we employ the moving-average based estimator of Hansen et al. (2008).

Given the time series of realized volatilities, we employ a multivariate version of the heterogeneous autoregressive (HAR) model of Corsi (2009) to model their joint behavior. To formally define the multivariate HAR model, we stack the logarithmic realized variances of a set of assets into a vector $\boldsymbol{v}_t$. Working with logarithmic realized variance instead of realized variance itself has two advantages. First, the method requires no parameter restrictions to ensure the non-negativity of the realized variance and second, the distribution of the logarithmic realized variance is much closer to normality, which is attractive from a statistical point of view. The vector HAR (VHAR) specification is given by

$$\boldsymbol{v}_t = \boldsymbol{\beta}_0 + \boldsymbol{\beta}_1 \boldsymbol{v}_{t-1} + \boldsymbol{\beta}_5 \boldsymbol{v}_{t-1|t-5} + \boldsymbol{\beta}_{22} \boldsymbol{v}_{t-1|t-22} + \boldsymbol{\gamma} \boldsymbol{z}_t + \boldsymbol{\varepsilon}_t,$$

where the $\boldsymbol{\beta}$s are square matrices of coefficients, $\boldsymbol{z}_t$ is a vector of (exogenous) regressors, $\boldsymbol{\varepsilon}_t$ is a vector innovation term, and the lagged vector of realized variances is

$$\boldsymbol{v}_{t-1|t-k} = \frac{1}{k} \sum_{j=1}^{k} \boldsymbol{v}_{t-j.}$$

The ability of the HAR model to describe the interaction(s) of volatility across time makes it an attractive tool for studying the volatility dynamics both within and across the exchange rates. Specifically, the HAR model allows analyzing how the long-term volatility affects the expectations about the future market trends and risk. Indeed, given the multivariate framework, we can study both the qualitative and quantitative implications of short-term and/or long-term volatility components characterizing one foreign exchange market on the evolution of another. Despite its simplicity, the HAR model performs remarkably well in reproducing the widely documented presence of the volatility of financial products.

In our analysis, we further generalize the multivariate HAR model by allowing the vector innovation term ($\boldsymbol{\varepsilon}_t$) to follow a multivariate GARCH process (VHAR-MGARCH). By extending the model in this manner, we are able to capture the volatility-of-volatility effect, i.e., an empirical observation that the volatility of volatility tends to increase (decrease) whenever volatility itself increases (decreases). While the idea is not new (Corsi et al., 2008), recent findings that a univariate HAR-GARCH model fits very well the realized variances of the CE exchange rates (Bubák and Žikeš, 2009) drives our motivation for generalizing the model with an MGARCH structure.

To model the dynamics of the conditional variance of the innovation process $\boldsymbol{\varepsilon}_t$, we employ the DCC model from Engle (2002). In this model, the variance covariance matrix evolves according to

$$\boldsymbol{H}_t = \boldsymbol{D}_t \boldsymbol{R}_t \boldsymbol{D}_t,$$

where $\boldsymbol{D}_t = diag\left(h_{11,t}^{1/2}, \dots, h_{KK,t}^{1/2}\right)$ and $h_{ii,t}$ represents any univariate (G)ARCH(*p*,*q*) process, $i = 1, \dots, k$. The particular version of the dynamic conditional correlation model that we use is from Engle and Sheppard (2001) and Engle (2002). In this model, the correlation matrix is given by the transformation

$$\boldsymbol{R}_t = diag\left(q_{11,t}^{-1/2}, \dots, q_{KK,t}^{-1/2}\right) \boldsymbol{Q}_t diag\left(q_{11t}^{-1/2}, \dots, q_{KK,t}^{-1/2}\right),$$

where $\boldsymbol{Q}_t = \left(q_{ij,t}\right)$ in turn follows

$$\boldsymbol{Q}_t = (1 - \alpha - \beta)\overline{\boldsymbol{Q}} + \alpha \eta_{t-1} \eta'_{t-1} + \beta \boldsymbol{Q}_{t-1},$$

where $\eta_t = \varepsilon_{i,t} / \sqrt{h_{ii,t}}$ are standardized residuals, $\overline{\boldsymbol{Q}} = T^{-1} \sum_{t=1}^{T} \eta_t \eta'_t$ is a *k x k* unconditional variance matrix of η_t, and α and β are non-negative scalars satisfying the condition that $\alpha + \beta < 1$. Recall that it is an ARMA representation of the conditional correlations matrix that guarantees the positive definiteness of $\boldsymbol{Q}_t$ and hence of $\boldsymbol{R}_t$.

To estimate the DCC-MGARCH model, we proceed as follows. First, we find a suitable specification of the volatility transmission where all variables are significant. The DCC model is then fitted to the series of residuals, where the estimation is performed by optimizing the likelihood function using the Feasible Sequential Quadratic Programming (FSQP) algorithm of Lawrence and Tits (2001). We estimate the model efficiently in one step to obtain valid standard errors for the DCC estimates.

It is possible to write the VHAR model with determined number of lagged responses as a VAR(22) with restricted parameters. We can therefore employ the dynamic version of the Diebold and Yilmaz (2009) index to quantify the overall magnitude and evolution of volatility spillovers among the four foreign exchange markets. The Diebold-Yilmaz index is constructed as follows. Let $\boldsymbol{v}_t$ denote a *k*-dimensional random vector following a VAR(*p*) process with conditionally heteroskedastic innovations:

$$\boldsymbol{v}_t = \boldsymbol{c} + \boldsymbol{\Phi}_1 \boldsymbol{v}_{t-1} + \boldsymbol{\Phi}_1 \boldsymbol{v}_{t-1} + \cdots + \boldsymbol{\Phi}_p \boldsymbol{v}_{t-p} + \boldsymbol{\varepsilon}_t,$$

$$\boldsymbol{\varepsilon}_t = \boldsymbol{H}_t^{1/2} \boldsymbol{u}_t, \;\; \boldsymbol{u}_t \sim \mathrm{D}(\boldsymbol{0}, \boldsymbol{I}),$$

where $\boldsymbol{H}_t$ is a $\boldsymbol{F}_{t-1}$ measurable conditional covariance matrix. Provided that the VAR process is stationary, the moving-average representation exists and we can write

$$\boldsymbol{v}_t = \boldsymbol{\mu} + \boldsymbol{\varepsilon}_t + \boldsymbol{\Psi}_1 \boldsymbol{\varepsilon}_{t-1} + \boldsymbol{\Psi}_2 \boldsymbol{\varepsilon}_{t-2} + \cdots.$$

The optimal *h*-step-ahead forecast is given by

$$\mathrm{E}_t(\boldsymbol{v}_{t+h}) = \boldsymbol{\mu} + \boldsymbol{\Psi}_h \boldsymbol{\varepsilon}_t + \boldsymbol{\Psi}_{h+1} \boldsymbol{\varepsilon}_{t-1} + \cdots,$$

and the forecast error vector, $\boldsymbol{e}_{t+h|t}$, is written as

$$\boldsymbol{e}_{t+h|t} \equiv \boldsymbol{v}_{t+h} - \mathrm{E}_t(\boldsymbol{v}_{t+h}) = \boldsymbol{\varepsilon}_{t+h} + \boldsymbol{\Psi}_1 \boldsymbol{\varepsilon}_{t+h-1} + \boldsymbol{\Psi}_2 \boldsymbol{\varepsilon}_{t+h-2} + \cdots + \boldsymbol{\Psi}_{h-1} \boldsymbol{\varepsilon}_{t+1}.$$

The corresponding conditional mean-square error matrix, $\boldsymbol{\Sigma}_{t+h|t}$, is given by

$$\boldsymbol{\Sigma}_{t+h|t} \equiv \mathrm{E}_t(\boldsymbol{e}_{t+h|t} \boldsymbol{e}'_{t+h|t}) = \mathrm{E}_t(\boldsymbol{H}_{t+h}) + \boldsymbol{\Psi}_1 \mathrm{E}_t(\boldsymbol{H}_{t+h-1}) \boldsymbol{\Psi}'_1 + \cdots + \boldsymbol{\Psi}_{\mathrm{h}-1} \boldsymbol{H}_{t+1} \boldsymbol{\Psi}'_{\mathrm{h}-1}.$$

Now define $\mathbf{Q}_{t+h|t}$ to be the unique lower triangular Choleski factor of $\mathrm{E}_t(\boldsymbol{H}_{t+h})$, and let

$$\mathbf{A}_{t+h|t}^{(i)} \equiv \boldsymbol{\Psi}_i \mathbf{Q}_{t+h-i|t}, \quad i = 0, \ldots, h-1,$$

so we can write

$$\boldsymbol{\Sigma}_{t+h|t} = \mathbf{A}_{t+h|t}^{(0)} \mathbf{A}_{t+h|t}^{(0)\prime} + \mathbf{A}_{t+h|t}^{(1)} \mathbf{A}_{t+h|t}^{(1)\prime} + \cdots + \mathbf{A}_{t+h|t}^{(h-1)} \mathbf{A}_{t+h|t}^{(h-1)\prime}.$$

The time-varying Diebold-Yilmaz spillover index ($\mathbf{S}_{t+h|t}$) based on *h*-step-ahead forecasts is then defined as

$$\mathbf{S}_{t+h|t} = \frac{\sum_{l=0}^{h-1} \sum_{\substack{i,j=1 \\ i \neq j}}^{k} (a_{t+h|t}^{(l)}(i,j))^2}{\sum_{l=0}^{h-1} \mathrm{tr}(\mathbf{A}_{t+h|t}^{(l)} \mathbf{A}_{t+h|t}^{(l)\prime})}.$$

In the above definition $a_{t+h|t}^{(l)}(i,j)$ is a typical element of $\mathbf{A}_{t+h|t}^{(l)}$. If $\boldsymbol{H}_t$ follows a stationary MGARCH process, the forecasts $\mathrm{E}_t(\boldsymbol{H}_{t+h})$ can be obtained recursively.

The Diebold-Yilmaz index measures the proportion of the *h*-step-ahead forecast error of its own volatility that can be attributed to shocks emanating from other markets. In other words, the larger the fraction of *h*-step-ahead forecast error variance in forecasting the volatility of market *i* that is due to shocks to market *j* relative to the total forecast error variation, the larger the value of the spillover index and hence the degree of volatility spillovers. In the case when there are no spillovers, the index is equal to zero.

Empirical contribution to analyzing volatility spillovers on Central European forex markets

Our empirical results documented the existence of volatility spillovers between CE foreign exchange markets on an intraday basis. We found that each CE currency has a different volatility transmission pattern. During the pre-2008 period, the histories of the Czech and Polish currencies and both the short- and long-term volatility components of the Hungarian currency as well as the long-term volatility component of the EUR/USD exchange rate affected the volatilities of the Czech and Polish currencies. In contrast, the Hungarian forint seemed generally irresponsive to any foreign component. Our finding that volatility spillovers had a greater effect on the volatility of the Czech and Polish currencies correlates with the fact that both currencies exhibited very similar and small deviations from a random walk. This contrasted with the managed regime of the Hungarian currency and its volatility being irresponsive to spillovers. During the post-2008 period our results showed that volatility increased in general but the volatilities of all currencies reflect chiefly their own history. This lack of effect from neighboring markets might have been a sign of isolationist sentiment on the forex markets during the global crisis. Further, using a dynamic version of the Diebold-Yilmaz spillover index we found that the magnitude of the volatility spillovers increases significantly during periods of market uncertainty. From a medium-term perspective, volatility increased for those countries with troubled financial sector development (e.g. Hungary). Finally, a general difference in the pre- and post-crisis patterns was an increase in the strength of the short-term relation, which seemed to indicate a generally faster reaction of the market to volatility dynamics, especially in the case of the Czech koruna, Polish zloty, and the US dollar.

Our results on volatility transmission augmented the literature on developed foreign exchange markets and filled a gap in the literature on emerging markets in Europe. The uncovered differences in volatility patterns and their drivers lent new insights into the trading strategies assessed by de Zwart et al. (2009). Further, the synthesis of our findings was also relevant from the perspective of research on investment strategies, as Jotikasthira et al. (2010) show that all of the three countries under research are attractive investment destinations.

5. Asymmetries in Volatility Spillovers

Outline

Baruník, Kočenda, and Vácha (2016, 2015) extended the spillover index methodology of Dieboled and Yilmaz (2009, 2012) by employing the concept of realized semivariances from Barndorff-Nielsen et al. (2010). This new approach enables accounting for asymmetries in volatility spillovers; to date this phenomenon has not been measured and quantified dynamically.

The presence of asymmetric volatility in financial markets has long been recognized in the literature (Black, 1976; Christie, 1982; Pindyck, 1984; French et al., 1987). On the other hand, asymmetries in volatility spillovers have not yet received the same attention, despite the fact that the proper quantification of such asymmetries is highly relevant to risk valuation and portfolio diversification strategies (Garcia and Tsafack, 2011). One of the stylized facts associated with financial markets reveals that the interdependence of markets exhibits asymmetries as large negative returns are more correlated than large positive returns (Longin and Solnik, 2001; Ang and Chen, 2002). When contemporaneous returns and their conditional volatility exhibit negative correlation, then a stronger reaction to negative news results in asymmetric volatility of the assets (Wu, 2001). The causal link often leads to volatility spillovers, which tend to increase the idiosyncratic risk that diminishes gains from portfolio diversification (Kanas, 2001). In addition, Amonlirdviman and Carvalho (2010) explicitly show that the asymmetry in the correlations of returns decreases the gains from portfolio diversification.

Asymmetry in volatility on financial markets implies that past returns are negatively correlated with present volatility (Bekaert and Wu, 2000). Since volatility is transferred across markets via spillovers, it is worth assuming that volatility spillovers exhibit asymmetries as well and such asymmetries might stem from qualitative differences due to bad and good uncertainty (Segal et al., 2015). In this regard we hypothesized that volatility spillovers might substantially differ, e.g. exhibit asymmetries, depending on the qualitative nature of the preceding shock(s).

Our contribution was twofold. First, in terms of methodology, we suggested a way to quantify asymmetries in volatility spillovers due to bad and good volatility that is defined in the same way as in Segal et al. (2015). Second, we provided new empirical evidence of asymmetries in volatility spillovers among U.S. stocks as well as petroleum-based commodities over distinctively different periods before, during, and after the recent financial crisis.

Methodological contribution to analyzing asymmetries in volatility spillovers

In order to better illustrate the methodological contribution, the two previously existing concepts are first introduced. Then we describe a simple way to combine them in order to capture asymmetric volatility spillovers using high-frequency measures.

Realized variance and semivariance

The first concept we introduce describes measures of volatility. Consider a continuous-time stochastic process for log-prices, p_t, evolving over a time horizon $[0 \leq t \leq T]$, which consists of a continuous component and a pure jump component

$$p_t = \int_0^t \mu_s ds + \int_0^t \sigma_s dW_s + J_t, \quad (1)$$

where μ is a locally bounded predictable drift process and σ is a strictly positive volatility process and everything is adapted to some common filtration $\mathcal{F}$. The quadratic variation of the log-prices p_t is

$$[p_t, p_t] = \int_0^t \sigma_s^2 \, ds + \sum_{0 < s \leq t} (\Delta p_s)^2, \quad (2)$$

where $\Delta p_s = p_s - p_{s-}$ are jumps, if present. A natural measure for quadratic variation has been formalized by Andersen, Bollerslev, Diebold, and Labys (2001) and Barndorff-Nielsen (2002), who propose estimating quadratic variation as the sum of squared returns and coined the term "realized variance" (*RV*). Formally, let us suppose that the intraday returns $r_i = p_i - p_{i-1}$, defined as a difference between intraday log prices $p_0, \dots, p_n$, are equally spaced on the interval $[0, t]$, then

$$RV = \sum_{i=1}^{n} r_i^2 \quad (3)$$

converges in probability to $[p_t, p_t]$ with $n \to \infty$.

Barndorff-Nielsen, Kinnebrock, and Shepard (2010) decomposed the realized variance into estimators of realized semivariance (*RS*) that capture the variation due to negative or positive movements in a specific variable (e.g. bad and good volatility). The technique was adopted by Feunou, Jahan-Parvar, and Tédongap (2013), Patton and Shepard (2014), and Segal, Shaliastovich, and Yaron (2015). We employ the realized semivariance in a very similar manner. The negative and positive realized semivariances ($RS^-$and RS^+) are defined as follows:

$$RS^- = \sum_{i=1}^{n} \mathbb{I}(r_i < 0) r_i^2 \quad (4)$$

$$RS^+ = \sum_{i=1}^{n} \mathbb{I}(r_i \geq 0) r_i^2 \quad (5)$$

Realized semivariance provides a complete decomposition of the realized variance, as $RV = RS^- + RS^+$, and can serve as a measure of downside and upside risk. The decomposition holds exactly for any *n*. Barndorff-Nielsen, Kinnebrock, and Shepard (2010) show the limiting behavior of realized semivariance, which converges to $1/2 \int_0^t \sigma_s^2 \, ds$ and the sum of the jumps due to negative and positive returns.

Consequently, the negative and positive semivariance provides information about variation associated with movements in the tails of the underlying variable. For example negative semivariance corresponds to the bad state of the underlying variable and we use the measure as the empirical proxy for bad volatility as in Segal, Shaliastovich, and Yaron (2015). Similarly, positive semivariance corresponds to the good state of the underlying variable and serves as a proxy for good volatility. Below, we hypothesize that the two states may spill over differently across markets, creating asymmetries in volatility spillovers.

Measuring volatility spillovers

The second concept we introduce describes how to measure volatility spillovers. Diebold and Yilmaz (2009) introduce a volatility spillover measure based on forecast error variance decompositions from vector auto regressions (VARs). Variance decompositions record how much of the H-step-ahead forecast error variance of some variable i is due to innovations in another variable j, and hence provide a simple, intuitive way of measuring volatility spillovers. Later, Diebold and Yilmaz (2012) improved their early concept and use a generalized vector autoregressive framework in which forecast error variance decompositions are invariant to the variable ordering and that explicitly includes the possibility to measure directional volatility spillovers.

Further, and most important to us, Diebold and Yilmaz (2009, 2012) use the daily or weekly range-based volatility of Garman and Klass (1980) to compute spillovers. Whereas range-based estimators provide an efficient way of estimating volatility, high-frequency data can further improve the understanding of the transmission mechanism. Due to the work of Barndorff-Nielsen, Kinnebrock, and Shepard (2010) we can conveniently decompose daily volatility into negative (and positive) semivariance, providing a proxy for downside (and upside) risk. Replacing the total volatility, which enters the computation by the measures of downside (upside) risk, will allow us to measure the spillovers from bad and good volatility, and test if they are transmitted in the same magnitude. Thus, we consider $\mathbf{RV_t} = (RV_{1t}, \dots, RV_{nt})'$ to measure total volatility spillovers and $\mathbf{RS_t^-} = (RS_{1t}^-, \dots, RS_{nt}^-)'$ and $\mathbf{RS_t^+} = (RS_{1t}^+, \dots, RS_{nt}^+)'$ to measure volatility spillovers due to negative and positive returns, respectively.

To measure spillovers we use the Diebold and Yilmaz (2012) directional spillover measure, which follows directly from the variance decomposition associated with an N-variable vector autoregression fitted to volatility (in our case semivariances). To set the stage, consider an

N-dimensional vector $\mathbf{RV_t} = (RV_{1t}, \dots, RV_{nt})'$ holding the realized variance of N assets, which is modeled by a covariance stationary vector autoregression VAR(*p*) as

$$\mathbf{RV_t} = \sum_{i=1}^{p} \mathbf{\Phi_i}\, \mathbf{RV_{t-i}} + \boldsymbol{\epsilon_t} \qquad (6)$$

with $\boldsymbol{\epsilon_t} \sim \mathrm{N}(0, \mathbf{\Sigma_\epsilon})$ being a vector of independently and identically distributed disturbances and $\mathbf{\Phi_i}$ for $i = 1, \dots, p$ coefficient matrices. Provided that the VAR process is invertible, it has the moving average representation

$$\mathbf{RV_t} = \sum_{i=0}^{\infty} \mathbf{\Psi}_{\mathrm{i}}\, \boldsymbol{\epsilon_{t-i}}, \qquad (7)$$

where the $N \times N$ matrices holding coefficients $\mathbf{\Psi_i}$ can be obtained from the recursion $\mathbf{\Psi}_i = \sum_{j=1}^{p} \mathbf{\Phi}_\mathrm{j} \mathbf{\Psi_{i-j}}$ with $\mathbf{\Psi_0}$ being the identity matrix; $\mathbf{\Psi}_0 = \mathbf{I}_N$ and $\mathbf{\Psi}_\mathrm{i} = 0$ for $i < 0$. The moving average representation is key for understanding the dynamics of the system as it allows the computation of variance decompositions. These in turn allow the decomposition of the forecast error variances of each variable in the system into parts, which are attributable to various system shocks. Diebold and Yilmaz (2012) build the spillover index on the idea of assessing the fraction of the H-step-ahead error variance in forecasting the ith variable that is due to shocks to the jth variable for $j \neq i$, for each i. In order to obtain variance decompositions, which are invariant to variable ordering in the VAR system, Diebold and Yilmaz (2012) use the framework of the generalized VAR of Koop, Pesaren, and Potter (1996) and Pesaran and Shin (1998). The framework allows for correlated shocks but accounts for them by using the observed distribution of the errors, under a normality assumption. In this way, the shocks to each variable are not orthogonalized. Hence, the resulting sum of the contributions to the variance of the forecast error may not necessarily equal one.

(i) Total spillovers

To define the total spillover index, Diebold and Yilmaz (2012) consider: (i) the assets' own variance shares as the fractions of the H-step-ahead error variances in forecasting the ith variable that are due to assets' own shocks to i for $i = 1, \ldots, n$ and (ii) cross variance shares, or spillovers, as the fractions of the H-step-ahead error variances in forecasting the ith variable that are due to shocks to the jth variable, for $i, j = 1, \ldots, N$, such that $i \neq j$. The H-step-ahead generalized forecast error variance decomposition matrix $\boldsymbol{\Omega}$ has the following elements for $H = 1,2, \ldots$:

$$\omega_{ij}^{H} = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (\mathbf{e}_\mathrm{i}' \mathbf{\Psi}_\mathrm{h} \mathbf{\Sigma}_\epsilon \mathbf{e}_\mathrm{j})^2}{\sum_{h=0}^{H-1} (\mathbf{e}_\mathrm{i}' \mathbf{\Psi}_\mathrm{h} \mathbf{\Sigma}_\epsilon \mathbf{\Psi}_\mathrm{h}' \mathbf{e}_\mathrm{i})}, \tag{8}$$

where $\mathbf{\Sigma}_\epsilon$ is the variance matrix for the error vector, ϵ_t, σ_{jj} is the standard deviation of the error term for the jth equation, $\mathbf{e}_\mathrm{i}$ is the selection vector, with one as the ith element and zero otherwise, and $\mathbf{\Psi}_\mathrm{h}$ are moving average coefficients from the forecast at time t. The sum of the elements in each row of the variance decomposition table is not equal to one, $\sum_{j=1}^{N} \omega_{ij}^{H} \neq 1$, as the shocks are not necessarily orthogonal in this framework. Hence, we need to normalize each element by the row sum as:

$$\widetilde{\omega}_{ij}^{H} = \frac{\omega_{ij}^{H}}{\sum_{j=1}^{N} \omega_{ij}^{H}}. \tag{9}$$

Using the contributions from the variance decomposition, Diebold and Yilmaz (2012) then define the total spillover index, which measures the contribution of spillovers from volatility shocks across variables in the system to the total forecast error variance as

$$S^{H} = 100 \times \frac{1}{N} \sum_{\substack{i,j=1 \\ i \neq j}}^{N} \widetilde{\omega}_{ij}^{H}. \tag{10}$$

Note that by construction, $\sum_{j=1}^{N} \widetilde{\omega}_{ij}^{H} = 1$ and $\sum_{i,j=1}^{N} \widetilde{\omega}_{ij}^{H} = N$, thus the contributions of spillovers from volatility shocks are normalized by the total forecast error variance.

(ii) Directional spillovers

The total spillover index as defined by equation (10) helps us understand how much of the shocks to volatility spills over across the studied assets. However, the main advantage of the generalized VAR framework is its ability to identify directional spillovers using the normalized elements of the generalized variance decomposition matrix. Directional spillovers allow us to further uncover the transmission mechanism, as we can decompose the total spillovers to those coming from, or to, a particular asset in the system.

Diebold and Yilmaz (2012) propose to measure the directional spillovers received by asset i from all other assets j as:

$$S_{i\leftarrow\bullet}^{H} = 100 \times \frac{1}{N} \sum_{\substack{i,j=1 \\ i\neq j}}^{N} \widetilde{\omega}_{ij}^{H}. \tag{11}$$

In a similar fashion, the directional spillovers transmitted by asset i to all other assets j can be measured as:

$$S_{i\rightarrow\bullet}^{H} = 100 \times \frac{1}{N} \sum_{\substack{i,j=1 \\ i\neq j}}^{N} \widetilde{\omega}_{ji}^{H}. \tag{12}$$

(iii) Net spillovers and net pairwise spillovers

Directional spillovers can also be used to obtain the net volatility spillover from asset i to all other assets j. The directional spillover is then defined as the simple difference between gross volatility shocks transmitted to and received from all other assets:

$$S_{ij}^{H} = S_{i\rightarrow\bullet}^{H} - S_{i\leftarrow\bullet}^{H}. \tag{13}$$

The net volatility spillover tells us how much each asset contributes to the volatility in other assets in net terms.

Finally, the pairwise volatility spillover between asset i and j can be simply defined as the difference between the gross shocks transmitted from asset i to asset j and those transmitted from j to i:

$$S_{ij}^{H} = 100 \times \frac{1}{N} \sum_{\substack{i,j=1 \\ i\neq j}}^{N} (\widetilde{\omega}_{ji}^{H} - \widetilde{\omega}_{ij}^{H}) \tag{14}$$

Measuring asymmetric spillovers

We now describe how to capture and measure asymmetries in volatility spillovers. Specifically, we are able to account for spillovers from volatility due to negative returns (S^{-}) and positive returns (S^{+}) as well as directional spillovers from volatility due to negative returns ($S_{i\leftarrow\bullet}^{-}, S_{i\rightarrow\bullet}^{-}$) and positive returns ($S_{i\leftarrow\bullet}^{+}, S_{i\rightarrow\bullet}^{+}$). Based on the previous exposition, to isolate asymmetric volatility spillovers we need to replace the vector of volatilities $\mathbf{RV_t} = (RV_{1t}, \dots, RV_{nt})'$ defined in equation (6) with the vector of negative semivariances $\mathbf{RS}_t^{-} = (RS_{1t}^{-}, \dots, RS_{nt}^{-})'$ or the vector of positive semivariances $\mathbf{RS}_t^{+} =$

$(RS_{1t}^{+}, \dots, RS_{nt}^{+})'$. Note that in the above definitions we dropped the H index to ease the notational burden, but it remains a valid parameter for the estimation of spillover indices.

For ease of exposition we might also call the spillovers from bad and good volatility as negative and positive spillovers. Their quantification now enables testing several hypotheses. A comparison of the spillover values introduces the following possibilities. If the contributions of RS^- and RS^+ are equal, the spillovers are symmetric, and we expect the spillovers to be of the same magnitude as spillovers from RV. On the other hand, the differences in the realized semivariances result in asymmetric spillovers. These properties enable us to test the following hypotheses.

$\mathcal{H}_0^1$: $S^- = S^+$ against $\mathcal{H}_A^1$: $S^- \neq S^+$.

$\mathcal{H}_0^2$: $S_{i\leftarrow\bullet}^- = S_{i\leftarrow\bullet}^+$ against $\mathcal{H}_A^2$: $S_{i\leftarrow\bullet}^- \neq S_{i\leftarrow\bullet}^+$.

$\mathcal{H}_0^3$: $S_{i\rightarrow\bullet}^- = S_{i\rightarrow\bullet}^+$ against $\mathcal{H}_A^3$: $S_{i\rightarrow\bullet}^- \neq S_{i\rightarrow\bullet}^+$.

Rejecting a null hypothesis means that bad and good volatility does matter for spillover transmission in terms of magnitude as well as direction. Moreover, we assume that the values of the volatility spillover indices differ over time. To capture the time-varying nature, the indices are computed using a 200-day moving window that runs from point $t - 199$ to point t; more details are provided in Baruník, Kočenda, and Vácha (2016).

(i) Spillover asymmetry measure

In order to better quantify the extent of volatility spillovers, we introduce a spillover asymmetry measure. In case the negative and positive realized semivariance contribute to the total variation of returns in the same magnitudes, the spillovers from volatility due to negative returns (S^-) and positive returns (S^+) will be equal to the spillovers from RV, and the null hypothesis $\mathcal{H}_0^1$: $S^- = S^+$ would not be rejected. This motivates a definition of the spillover asymmetry measure (SAM) simply as the difference between negative and positive spillovers:

$$SAM = S^+ - S^- \tag{15}$$

where S^+ and S^- are volatility spillover indices due to negative and positive semivariances, RS^+ and RS^-, respectively, with an H-step-ahead forecast at time t. SAM defines and illustrates the extent of asymmetry in spillovers due to RS^- and RS^+, When SAM takes the value of zero, spillovers coming from RS^- and RS^+ are equal. When SAM is positive, spillovers coming from RS^+ are larger than those from RS^- and the opposite is true when SAM is negative.

(ii) Directional Spillover Asymmetry Measure

While the spillover asymmetry measure SAM defined by equation (15) measures to what extent the spillovers from volatility are asymmetric, we can decompose this measure and study the source of asymmetry among the studied assets. We define the asymmetry measure for directional spillovers received by asset i from all other assets j as

$$SAM_{i\leftarrow\bullet} = S^{+}_{i\leftarrow\bullet} - S^{-}_{i\leftarrow\bullet}. \qquad (16)$$

In a similar fashion, we can measure the degree of asymmetry in directional spillovers transmitted by asset i to all other assets j:

$$SAM_{i\rightarrow\bullet} = S^{+}_{i\rightarrow\bullet} - S^{-}_{i\rightarrow\bullet}. \qquad (17)$$

$SAM_{i\leftarrow\bullet}$ and $SAM_{i\rightarrow\bullet}$ allow us to identify the extent to which volatility from (or to) the ith asset spills over to (or from) other assets symmetrically. For example, if bad volatility spillover from one asset in the system is larger than a positive spillover, then $SAM_{i\rightarrow\bullet}$ will be different from zero, and we expect it to be negative. The original Diebold and Yilmaz (2012) framework is not able to capture asymmetries in volatility spillovers while our methodology contribution does so for the total as well as directional volatility spillovers.

Empirical contribution to identifying and measuring asymmetries in volatility spillovers

Based on two recent advances in the literature, we outlined a way to capture volatility spillovers that are due to bad and good volatility (proxied by negative and positive returns). Specifically, we suggested computing the volatility spillover index from Diebold and Yilmaz (2012) when negative and positive changes in returns are considered separately via the realized semivariances from Barndorff-Nielsen, Kinnebrock, and Shepard (2010). As a result, we computed volatility spillover indices robust to ordering in VAR that captured asymmetries in volatility spillovers.

We empirically showed the versatility of the above set-up by applying it on daily data covering 21 U.S. stocks divided into seven sectors defined in accordance with the Global Industry Specification Standard. We provided ample evidence showing the asymmetric connectedness of markets at the disaggregate sectoral level, which is in contrast to the symmetric volatility transmission mechanism at the aggregate level. The result can be attributed to large sector-level heterogeneity. While there was no clear pattern that would hold for all seven sectors, we were able to reject symmetric connectedness in all of them. Further, we found that negative and positive spillovers transmitted at different magnitudes in all sectors: the consumer, telecommunications, and health sectors exhibited visibly larger asymmetries in spillovers than the financial, information technology, and energy sectors. Finally, we also provided detailed results how asymmetries in spillovers propagated between specific assets and within sectoral portfolios.

Asymmetries in volatility spillovers have been conclusively detected across the U.S. stock market. While negative asymmetries in spillovers are often of substantial magnitude, they are not strictly dominant. Spillovers due to good volatility materialize quite frequently and their magnitudes are only rarely dwarfed by negative ones. Hence, in terms of volatility spillovers, market perception is not attuned to negative signals only. Thus, among many detailed inferences, we showed that the stock market might be a less dismal place than generally believed.

Further, we detected and quantified asymmetries in the volatility spillovers of petroleum commodities: crude oil, gasoline, and heating oil. The increase in volatility spillovers after 2001 correlated with the progressive financialization of the commodities. Further, the increasing spillovers from volatility among petroleum commodities substantially changed their pattern after 2008 (the financial crisis and the advent of tight oil production). After 2008, asymmetries in spillovers markedly declined in terms of total as well as directional spillovers and the decline in asymmetries in volatility spillovers after 2008 correlated with the ongoing financialization of commodities and the advent of tight oil exploration and production in the U.S. Also, our findings defied a common belief that the financial crisis should prompt spillovers to be more volatile. We provided evidence of just the opposite: spillovers from price developments in 2008 and later are less volatile than before the 2007–2008 financial crisis. In terms of asymmetries, we also showed that overall volatility spillovers due to negative (price) returns materialize to a greater degree than volatility spillovers due to positive returns. The occurrence of negative volatility spillovers correlate with low levels of crude oil inventories in the U.S. and often with world events that hamper crude oil supply. Negative spillovers frequently indicate the extent of real or potential crude oil unavailability. An analysis of directional spillovers reveals that no petroleum commodity dominates other commodities in terms of general spillover transmission.

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