UNIVERSIDAD COMPLUTENSE DE MADRID
FACULTAD DE CIENCIAS ECONOMICAS Y EMPRESARIALES
Departamento de Fundamentos del Análisis Económico II
(Economía Cuantitativa)

TESIS DOCTORAL

Estrategias de cobertura de carteras e índices de renta variable: el mercado español

MEMORIA PARA OPTAR AL GRADO DE DOCTOR

PRESENTADA POR

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Madrid, 2016

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MADRID, 2015

COMPLUTENSE UNIVERSITY OF MADRID

FACULTY OF ECONOMICS AND BUSINESS

Foundations of Economic Analysis II: Quantitative Analysis

DOCTORAL DISSERTATION

HEDGING STRATEGIES OF STOCK INDEXES AND PORTFOLIOS: SPANISH MARKET

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MADRID, 2015

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ESTRATEGIAS DE COBERTURA DE CARTERAS E INDICES DE RENTA VARIABLE: EL MERCADO ESPAÑOL

RESUMEN

En línea con la creciente importancia de la cobertura de riesgos, la eficacia de las diferentes estrategias y las posibilidades de mejorar a través de diferentes modelos estocásticos han sido analizados en un gran número de estudios académicos en diferentes campos, activos financieros, energía, petróleo, etc. La controversia en la literatura sobre estrategias de cobertura se concentra en torno a tres aspectos principals.

En primer lugar, una cuestión clave es la elección de la medida de eficacia que va a determinar la función de optimizar. Entre las diferentes medidas propuestas, la reducción de la varianza es el enfoque más simple y común. Muchos autores consideran que otros criterios, como diferentes especificaciones de funciones de utilidad, el riesgo de pérdidas o la variación de la rentabilidad ,se deben tomar en cuenta con el fin de medir la efectividad de cobertura. Estos criterios derivan en diferentes medidas de efectividad de cobertura como el equivalente cierto (CE), Valor en Riesgo (VaR), Valor en Riesgo Condicional (CVaR) o Pérdida Esperada (ES), Momentos parciales inferiores (LPM), semi-varianza, etc. . Un examen de las principales aportaciones de la literatura muestra la falta de uniformidad o resultados concluyentes en favor de una u otra estrategia.

En segundo lugar, otro tema importante es la evolución temporal de la relación de cobertura. Hay una controversia en la literatura en cuanto a si la cobertura dinámica, utilizando relaciones que incorporan la nueva información que llega al mercado, es superior a relaciones estáticas, como la cobertura unitaria o la de mínimos cuadrados.

En tercer lugar, cuando se trata de estimar los ratios de cobertura, se emplean muchas técnicas diferentes, que van desde los modelos más simples a enfoques dinámicos muy complejos. Sin embargo, no está claro que estos modelos complejos mejoren la eficacia global y en nuestra opinión, no resuelven favorablemente el compromiso entre complejidad y efectividad.

Objetivos e hipótesis

Investigamos la eficacia de la cobertura con futuros sobre índices en diferentes activos y períodos con el fin de entender cómo mejorar la eficacia de las distintas y poder hacer recomendaciones que pueden ayudar a los gestores de carteras. Estudiamos tres tipos de activos a cubrir, índices, acciones individuales y carteras, con características muy diferentes en términos de eficacia de cobertura.

En particular, se espera que las estrategias dinámicas tengan un mejor desempeño en términos de reducción de la varianza de las estrategias estáticas y se espera una mayor eficacia cuando la correlación entre la posición de contado y el activo subyacente del contrato de futuro es mayor. En términos del modelo de Lafuente y Novales (2003), una baja liquidez y las coberturas cruzadas hacen el ruido específico mayor en comparación con el ruido común. Si el ruido específico tiene una estructura de volatilidad y se modeliza correctamente, entonces la cobertura puede mejorar estrategias estáticas.

Creemos que esto es importante para generalizar cobertura condicional en la práctica sin necesidad de procesos de estimación muy complejos.

Metodología

Llevamos a cabo nuestra investigación con una visión práctica en mente. Nos centramos en el enfoque mínima varianza y complementamos este enfoque con la aplicación práctica de criterios de decisión basados en una función de utilidad, así como la CE, VaR, ES y medidas LPM para estudiar las características de la distribución de los rendimientos de las posiciones cubiertas. Basado en el trabajo previo de diferentes autores, esperamos que las estrategias dinámicas de mínima varianza también funcionarán razonablemente bien bajo otros criterios de efectividad.

Con respecto al modelo econométrico para la estimación de los momentos condicionales, utilizamos el modelo GARCH bivariante DCC propuesto por Engle (2002). Introducimos un término de corrección de error que es consistente con la cointegración entre series financieras, incorporamos la posibilidad de efectos asimétricos en la volatilidad, conocidos como apalancamiento, y usamos diferentes distribuciones de probabilidad para las innovaciones.

Con el fin de probar las capacidades de predicción de nuestro marco simulamos estrategias fuera de la cobertura de la muestra que se aplican una ratio de cobertura calculado a partir de la especificación econométrica estimada. Después de la estimación inicial incorporamos nueva información en ventanas de 10 días de observaciones fuera de la muestra y reestimamos el modelo.

Por último, se compara la eficacia de las estrategias de cobertura dinámicas con la eficacia obtenida con el ratio unitario en coberturas de índices y con la obtenida con estrategias estáticas de mínimos cuadrados ordinarios (MCO). Incorporamos el efecto de los costes de transacción con el fin de simular decisiones reales de mercado.

Análisis y resultados

En el primer capítulo se examina si la ventaja del ratio de cobertura GARCH encontrada por Lafuente y Novales (2003) se mantiene en el tiempo y está presente en los mercados maduros. Hemos utilizado los datos de 1997 a 2005 para la estimación inicial, y 2006 para las estimaciones de fuera de la muestra.

En el segundo capítulo se evalúa la eficacia de la cobertura de las acciones españolas con sus futuros individuales, SSF, y la cobertura cruzada de tales acciones con el futuro sobre el IBEX 35. Analizamos el impacto de la cobertura cruzada sobre el riesgo de pérdidas y rentabilidad a través de medidas de VaR, ES, LPM, y CE. Hemos utilizado datos de 2009 a 2013 para la estimación inicial, y 2014 para las estimaciones fuera de la muestra.

Por último, con el fin de verificar si cruzada de cobertura en un mercado maduro se beneficia de una estrategia dinámica, en el tercer capítulo estudiamos la eficacia de las coberturas cruzadas en carteras de acciones españolas de distinta liquidez con el futuro sobre el IBEX 35. Utilizamos los datos de 2001-2011 para la estimación del modelo inicial y 2007-2008 y 2012-2013 los períodos de simulaciones fuera de muestra.

Conclusiones

Los resultados obtenidos sugieren:

1. Indices, acciones individuales y carteras tienen características de riesgo muy diferentes que afectan de manera significativa la efectividad de cobertura, alcanzando reducciones de varianza de hasta un 80%, 50% y 70% respectivamente. Existe una fuerte relación entre el riesgo idiosincrático y la eficacia. El riesgo idiosincrásico reduce la eficacia de la cobertura pero aumenta la ventaja de la cobertura GARCH sobre estrategias estáticas.

2. Las estrategias GARCH mínima varianza alcanzaban una eficacia de cobertura superior en coberturas perfectas entre el IBEX 35 y su futuro, cuando el mercado de futuros no estaba lo suficientemente maduro.

3. Cuando se utilizan los contratos de futuros sobre índices de un mercado de futuros maduro en operaciones de cobertura cruzada de acciones individuales o carteras, la estrategia GARCH logra un rendimiento superior en comparación con las estrategias estáticas. Estos resultados sugieren que la ventaja GARCH no está relacionado exclusivamente a la madurez del mercado de futuros.

4. La cobertura mejora, en relación con la posición descubierta, no sólo en términos de reducción de varianza, sino también en CE, VaR, ES y medidas LPM. Es importante tener en cuenta el perfil de riesgo individual de cada inversor con el fin de tomar la decisión de cobertura.

5. Estrategias GARCH de mínima varianza también logran una eficacia de cobertura superior a la estrategia MCO estática bajo los indicadores de efectividad alternativos que hemos analizado. Nos parece un resultado importante porque el enfoque GARCH de mínima varianza es asequible en términos de complejidad y muestra un buen rendimiento bajo otras medidas de efectividad.

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HEDGING STRATEGIES FOR STOCK INDEXES AND PORTFOLIOS: THE SPANISH MARKET

SHORT SUMMARY

In line with the growing importance of hedging, the effectiveness of different hedging strategies and the possibilities of improving them through different stochastic models have been analysed in a large number of academic studies across different fields, like the analysis of risks in financial assets, and risk analysis in energy, oil and markets for other commodities. The controversy in the literature regarding hedging strategies concentrates around three main aspects that we introduce in the following paragraphs.[1]

In first place, a key issue related to the hedging effectiveness is the election of the effectiveness measure that will determine the function to optimize and the optimum hedge ratio. Among the different proposed measures, the variance reduction is the simplest and most common approach. Many authors consider that other criteria, like different utility specifications or the downside risk, with its focus on one tail of the return distribution, should be taken into consideration in order to measure hedging effectiveness. Those criteria derive in different hedging effectiveness measures like the Certainty Equivalent (CE), Value at Risk (VaR), Conditional Value at Risk (CVaR) or Expected Shortfall (ES), Lower Partial Moments (LPM), semi-variance, etc.. An examination of the main contributions in the literature shows the lack of uniformity or conclusive results in favour of one or other strategy.

In second place, another important issue is the time evolution of the hedge ratio. There is a controversy in the literature as to whether dynamic hedging, using ratios that incorporate the new information that arrives to the market, is superior to static ratios, like the unitary ratio or those that are estimated with the available data and then applied unchanged to out-of-sample simulations.

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[1] In Section 2 of chapter 2 we comment some conclusions from the related academic research.

In third place, when it comes to estimating the hedge ratios, many different techniques are employed, ranging from the simplest static approaches to very complex dynamic approaches. However, it is unclear that this complex models improve overall dynamic effectiveness, and in our opinion, they do not solve favourably the trade-off between complexity and effectiveness.

Objectives and hypothesis

We investigate hedging effectiveness of different assets and periods with stock indexes futures in order to understand how to improve hedging strategies effectiveness and to make recommendations that may help portfolio managers. We study three types of assets to be hedged, indexes, individual stocks and portfolios that imply very different hedging effectiveness characteristics.

In particular, we expect dynamic strategies to perform better in terms of variance reduction than static strategies, either unitary or OLS strategies, and we expect a greater effectiveness when the correlation between the spot asset and the underlying futures contract asset is higher. In terms of the Lafuente and Novales (2003) model, low liquidity and cross-hedging make the specific noise bigger in comparison to the common noise. If the specific noise has a volatility structure and it is properly modelled, then the hedge can be improved upon static strategies.

We believe this is important to generalize conditional hedging in practise without the need of very complex estimation processes.

Methodology

We conduct our research with a practical implementation view in mind. We focus on the minimum variance approach and we complement this approach with the practical implementation of decision criteria based on a utility function, as well as the CE, VaR, ES and LPM measures to study the characteristics of the distribution of hedged returns. Based on previous work by a number of authors, we expect that minimum variance dynamic strategies will also perform reasonably well under other criteria.

With regard to the econometric model for the estimation of conditional moments, we use the bivariate GARCH DCC model proposed in Engle (2002). We introduce an error correction term that is consistent with cointegration between financial series, we incorporate the possibility of asymmetric effects in volatility, known as leverage, and we use different probability distributions other than Normal for the innovations. This model is a compromise between an affordable and versatile model well tested in the academic literature.

In order to test the prediction capabilities of our framework we simulate out-of-sample hedging strategies that apply a hedge ratio calculated from the estimated econometric specification. After the initial estimation we incorporate new information in 10-day windows of out-of-sample observations, estimating again the econometric model for each new window.

Finally, we compare the effectiveness of dynamic hedging strategies with the effectiveness obtained with the unit hedge ratio in index hedges, usually known as a naive strategy, and with the static ordinary least squares (OLS) ratio in individual stocks and portfolios cross-hedges. We incorporate the effect of transaction costs in our utility based decision criteria in order to simulate real market decisions.

Analysis and results

In the first chapter we examine whether the advantage of the GARCH hedge ratio found by Lafuente and Novales (2003) is maintained over time and it is also present in mature markets. We have used data from 1997 to 2005 for the initial estimation, and 2006 for out-of-sample estimations.

In the second chapter we evaluate the effectiveness of the hedge of Spanish stocks with their individual futures, SSF, and the cross-hedge of such stocks with the IBEX 35 future contract. To the best of our knowledge there is no significant research on SSF hedges in the academic literature. We also examine the ability of the IBEX 35 futures to cover positions on individual stocks. We analyze the impact of the cross-hedge on the risk of losses and profitability through VaR, ES, LPM, and CE measures. We have used data from 2009 to 2013 for the initial estimation, and 2014 for out-of-sample estimations.

Finally, in order to verify if cross-hedging in a mature market benefits from a dynamic strategy, we study in the third chapter the effectiveness of cross-hedges of different liquidity portfolios of Spanish equities with the IBEX 35 future contract. We use 2001-2011 data for the estimation of the initial model and 2007-2008 and 2012-2013 periods for out-of-sample simulations.

Conclusions

Our findings across all the assets and hedging operations we have analyzed suggest that:

1. Indexes, individual stocks and portfolios have very different risk characteristics that significantly affect the hedging effectiveness achieving up to 80%, 50% and 70% variance reduction respectively. There is a strong relationship between idiosyncratic risk and effectiveness. Idiosyncratic risk reduces hedging effectiveness and increases GARCH hedging advantage over static strategies.
2. Minimum variance GARCH strategies achieve superior hedging effectiveness in perfect hedges between IBEX 35 and its futures when the futures market was not mature enough.
3. When index futures contracts from a mature futures market are used in cross-hedging operations of individual stocks or stocks portfolios, GARCH strategies achieve a superior performance in comparison to static strategies. These results suggest that the GARCH advantage is not exclusively related to futures market maturity.
4. Hedging improves, relative to the unhedged position, not only in terms of variance reduction but also under the CE, VaR, ES and LPM measures. CE criterion shows a systematic improvement from hedging during high volatility periods. It is important to take into consideration each investor individual risk profile in order to decide to hedge.
5. Minimum variance GARCH strategies also achieve superior hedging effectiveness under the alternative effectiveness indicators we have analyzed as compared to applying a static OLS ratio. We find this to be an important result because our minimum variance GARCH approach is cost-effective in terms of complexity and shows a good performance under other effectiveness measures.

HEDGING STRATEGIES FOR STOCK INDEXES AND PORTFOLIOS: THE SPANISH MARKET

INTRODUCTION

World stock markets traded volume keep**s** growing at fast pace despite the severe crises that have taken place along the past two decades. During the 2003-2014[2] period, equity markets have seen an annual 9% growth reaching their historical peak in 2014.

The need to manage the financial risks associated with equities has led to a tremendous growth of hedging instruments such as futures and options on stocks and indexes. Since the introduction of financial futures and index options in the US during the 80s and 90s, this market has experienced a very important development worldwide. World traded volume[2] in stock index options and futures has evolved from 2,815 billion in 1994 to 227,774 billion in 2014, an annual increase of 23% during 22 years. Equity derivatives market has grown during the same period, 1994-2014, from 21 billion to 5.966 billion, an equally high annual growth of 31%, although it only accounts for 2.7% of the total volume traded in index futures in 2014. The implementation of the single stock futures (SSF) market has been slower. In the US it was not created until the 2000s and in Spain, after 15 years since its inception, SSF market only reaches 3.35% of the traded volume in IBEX 35 futures.

Background

In line with the growing importance of hedging, the effectiveness of different hedging strategies and the possibilities of improving them through different stochastic models have been analysed in a large number of academic studies across different fields, like the analysis of risks in financial assets, and risk analysis in energy, oil and markets for other commodities. Since Ederington (1979) introduced the minimum variance (MV) hedging effectiveness measure, the controversy in the literature regarding hedging strategies concentrates around three main aspects that we introduce in the following

[2] Source: World Federation of Exchanges (WFE).

paragraphs.[3] Chen et al.(2013) makes an exhaustive review of different optimization criteria used to determine the optimal hedge ratio.

In first place, a key issue related to the hedging effectiveness is the election of the effectiveness measure. The chosen measure will determine the function to optimize and the optimum hedge ratio. Among the different proposed measures, the variance reduction is the simplest and most common approach. Many authors consider that other criteria, like different utility specifications or the downside risk, with its focus on one tail of the return distribution, should be taken into consideration in order to measure hedging effectiveness. Those criteria derive in different hedging effectiveness measures like the Certainty Equivalent (CE), Value at Risk (VaR), Conditional Value at Risk (CVaR) or Expected Shortfall (ES), Lower Partial Moments (LPM), semi-variance, etc. One important limitation we have found is that hedging effectiveness is often compared for different strategies and for very complex models under measures of effectiveness measures different from the one that was used as criterion for the choice of the hedge leading, in our opinion, to potentially biased conclusions. We believe that these comparisons among different strategies should be first evaluated under the measurement for which they have been optimized, and only then under other additional measures, always taking into consideration that they have been designed with a different goal in mind. When ratios are optimized for a particular effectiveness measure, another important limitation is the number of restrictive hypothesis that need to be made, that may result in different ratios for the same strategy or effectiveness measure: the specification of the utility function, the numerical values of risk aversion parameters, minimum return and maximum loss thresholds, confidence intervals, etc. In essence, hedging effectiveness is the extent to which changes of the hedge instrument offset changes in the hedged assets in terms of value or cash flows and that should be independent of utility or considerations on the tails of the returns distribution. In summary, with regard to the effectiveness measure, an examination of the main contributions in the literature shows the lack of uniformity or conclusive results in favour of one or other strategy.

In second place, another important issue is the time evolution of the hedge ratio. There is a controversy in the literature as to whether dynamic hedging, using ratios that

[3] In Section 2 of chapter 2 we comment some conclusions from the related academic research.

incorporate the new information that arrives to the market, is superior to static ratios, like the unitary ratio or those that are estimated with the available data and then applied unchanged to out-of-sample simulations. Several authors (Myers (1991); Kroner and Sultan (1993); Park and Switzer (1995); Lafuente and Novales (2003); Cotter and Hanly (2012)) show the superiority of dynamic ratios while other or even the same authors (Lien & Tse (2002); Cotter and Hanly (2006); Park and Jei (2010)) conclude in the opposite direction. Comparisons in many cases are not straightforward.

In third place, when it comes to estimating the hedge ratios, many different techniques are employed, ranging from the simplest static approaches to very complex dynamic approaches. For example, some studies use ordinary least squares (OLS) (e.g., see Ederington, 1979; Malliaris and Urrutia, 1991; Benet, 1992). Others use more complex methods like ARCH or GARCH (e.g., see Cecchetti et al., 1988; Baillie and Myers, 1991; Sephton, 1993a), the random coefficient method (e.g., see Grammatikos and Saunders, 1983), the cointegration method (e.g., see Ghosh, 1993; Lien and Luo, 1993b; Chou et al., 1996), or the cointegration-heteroscedastic method (e.g., see Kroner and Sultan, 1993). Lien and Shrestha (2007) suggested the use of wavelet analysis to match the data frequency and the hedging horizon. Lien and Shrestha (2010) suggest the use of multivariate skew-normal distribution in the estimation of the MV hedge ratio. Several authors (Salvador and Aragó, 2013; Hsu et al., 2008) implement regime switching GARCH estimation models; Sukcharoen and Choi (2015) implement copula models of tailored distributions. Regime switching and copula based models take into consideration different return distributions and changes in the market dynamics that may lead dynamic strategies to fail in high volatility periods when investors care more about risk. However, it is unclear that this complex models improve overall dynamic effectiveness, and in our opinion, they do not solve favourably the trade-off between complexity and effectiveness.

Objectives and hypothesis

Lafuente and Novales (2003) introduced a theoretical model in order to analyse the hedging effectiveness of a MV GARCH ratio and compared its effectiveness with the unitary ratio hedge. These authors found that the GARCH strategy outperformed the naive strategy in the period 1993-1996 for hedges of IBEX 35 index and its futures contract. They consider the existence of a specific noise in the futures price process that produces a component of fluctuations that is not present in the asset to be hedged, causing futures prices to deviate from the "cost of carry" model. We apply their model to other futures markets, assets and periods in order to understand how to improve hedging strategies effectiveness and to make recommendations that may help portfolio managers.

In particular, we expect dynamic strategies to perform better in terms of variance reduction than static strategies, either unitary or OLS strategies, and we expect a greater effectiveness when the correlation between the spot asset and the underlying futures contract asset is higher. In terms of the Lafuente and Novales model, low liquidity and cross-hedging make the specific noise bigger in comparison to the common noise. If the specific noise has a volatility structure and it is properly modelled, then the hedge can be improved upon static strategies.

We conduct our research with a practical implementation view in mind. We divide our analysis of hedging effectiveness in three types of assets with very different econometric characteristics, stock indexes, individual stocks and portfolios. We complete our analysis with additional criteria that explain the impact of the hedge in the risk of losses or on the profitability of the hedged position. Based on previous work by a number of authors, we expect that minimum variance dynamic strategies will also perform reasonably well under other criteria. We believe this is important to generalize conditional hedging in practise without the need of very complex estimation processes. We also expect that, based on Spanish low SSF volume and consequent pricing system, SSF might not benefit from either a GARCH strategy or an OLS dynamic strategy.

Methodology

In our opinion, the controversy in the literature regarding the effectiveness measures and optimization criteria does not reach sufficiently conclusive results. This, together with the important complexity that some optimization criteria add in terms of models and the not so trivial assumptions they incorporate,[4] takes us to focus on the minimum variance approach. Furthermore, we complement this approach with the practical implementation of decision criteria based on a utility function, as well as the CE, VaR, ES and LPM measures to study the characteristics of the distribution of hedged returns. Even though the definition of the MV hedge ratio remains the same in the model

[4] Or assuming the purpose of the hedge that is different for different hedgers, something that should be taking into account when choosing a hedge strategy.

we adopt, it admits a nice interpretation in terms of the variance ratio of the noise common to spot and futures and the noise specific to the futures market, and the conditional correlation between the spot and futures assets.

With regard to the econometric model for the estimation of conditional moments, multivariate GARCH models are usually applied to the study of the relations between the volatilities and covariances (Kearney and Patton, 2000). Another advantage of multivariate GARCH models is the computation of time-varying hedge ratios (Lien and Tse, 2002). The constant conditional correlation GARCH (CCC–GARCH) model introduced by Bollerslev (1990) is one of the most popular models because of its ease of estimation. However, a constant correlation seems too restrictive. In order to estimate the conditional variance-covariance matrix of spot and market returns and to capture the correlation between the common and specific innovations we use the bivariate GARCH DCC model proposed in Engle (2002). We introduce an error correction term that is consistent with cointegration between financial series, we incorporate the possibility of asymmetric effects in volatility, known as leverage, and we use different probability distributions other than Normal for the innovations. This model is a compromise between an affordable and versatile model well tested in the academic literature. It accounts for error correction in a multivariate specification, conditional dynamic correlation, and the possibility to simulate the disturbances under different probability distributions. Other models that are complex enough to take into account regime switches and copulas of tailored distributions do not seem to show a clear advantage.

In order to test the prediction capabilities of our framework we simulate out-of-sample hedging strategies that apply a hedge ratio calculated from the estimated econometric specification. After the initial estimation we incorporate new information in 10-day windows of out-of-sample observations, estimating again the econometric model for each new window.

Finally, we compare the effectiveness of dynamic hedging strategies with the effectiveness obtained with the unit hedge ratio in index hedges, usually known as a naive strategy, and with the static ordinary least squares (OLS) ratio in individual stocks and portfolios cross-hedges. The OLS ratio is the minimum variance ratio estimate through the slope of the OLS regression between the spot and futures returns. Among the dynamic strategies we also include an OLS ratio that varies with the arrival of new information.

We incorporate the effect of transaction costs in our utility based decision criteria in order to simulate real market decisions.

Analysis and results

In the first chapter we examine whether the advantage of the GARCH hedge ratio found by Lafuente and Novales (2003) is maintained over time and it is also present in mature markets, we analyse the effectiveness of the hedge using an extended period, and we extend the analysis to the main international indexes and their corresponding futures contracts, including also the Spanish market. In this first analysis we evaluate out-of-sample effectiveness. We have used data from 1997 to 2005 for the initial estimation, and 2006 for out-of-sample estimations.

In the second chapter we evaluate the effectiveness of the hedge of Spanish stocks with their individual futures, SSF, and the cross-hedge of such stocks with the IBEX 35 future contract. To the best of our knowledge there is no significant research on SSF hedges in the academic literature. We consider interesting to examine to what extent these instruments may serve to hedge individual stocks and whether it benefits from a dynamic strategy. We also examine the ability of the IBEX 35 futures to cover positions on individual stocks. Individual stocks have a wider range of idiosyncratic risk compared to indexes hedges or portfolio cross hedges, and this has an important impact on hedging effectiveness and the advantage of dynamic GARCH strategies over static strategies. Due to the higher basis risk of cross-hedges, we analyze the impact of the cross-hedge on the risk of losses and profitability through VaR, ES, LPM, and CE measures. We have used data from 2009 to 2013 for the initial estimation, and 2014 for out-of-sample estimations.

Finally, in order to verify if cross-hedging in a mature market benefits from a dynamic strategy, we study in the third chapter the effectiveness of cross-hedges of different liquidity portfolios of Spanish equities with the IBEX 35 future contract. We also evaluate the impact of the cross-hedge on the additional measures we mentioned in the previous paragraph. In this third analysis we use 2001-2011 data for the estimation of the initial model and 2007-2008 and 2012-2013 periods for out-of-sample simulations.

Our results show a strong relationship between idiosyncratic risk and hedging effectiveness across all the considered assets. Those assets with higher correlation with the futures contract underlying asset and lower idiosyncratic risk achieve better hedges.

In the case of portfolios, the liquidity and weighting method of the individual stocks in the portfolio significantly affect its idiosyncratic risk and the cross-hedging effectiveness. In cross hedges, although the volatility reduction is very significant, the risk profile of the investor becomes more important in order to decide to hedge or to remain unhedged, since there is a trade-off between risk and profitability that changes depending on the period and asset to be hedged.

Our results show that the advantage of GARCH ratio in the case of index hedging tends to fade as these futures markets mature, a trend that could be observed in the work of Lafuente and Novales (2003). In the period 2006 we find that this advantage of the GARCH strategies over the unitary strategy no longer existed to cover positions in IBEX 35. However, in our analysis of cross-hedges between equity portfolios, individual stocks and IBEX 35 futures we observe that there is an advantage of GARCH ratios over other strategies. We believe that these two results confirm the hypothesis that the advantage of GARCH ratio is related to the maturity and liquidity of the futures market and its speed of adjustment to equilibrium. Thus, in mature markets and under a perfect hedge, arbitrage opportunities are corrected quickly, eliminating the advantage of GARCH ratio. Nonetheless, market maturity does not seem to be a factor on determining the advantage of GARCH hedge ratios in cross-hedge situations. GARCH models provide a better hedge for portfolios. GARCH model also achieves an advantage in the case of cross-hedges of individual stocks with IBEX 35 futures over the unitary ratio, the static OLS ratio, and the dynamic OLS ratio. With regard to the SSF hedge operations, we have not been able to properly analyze its hedging effectiveness due to issues regarding the nature of data on volume and price.

CHAPTER 1: Liquidity and hedging effectiveness under futures mispricing: international evidence[5]

ABSTRACT: We analyze the hedging effectiveness of positions that replicate stock indexes using corresponding futures contracts through the application of a dynamic, stochastic hedging strategy proposed by Lafuente and Novales (2003). Conclusive gains do not emerge in any of the markets analyzed over the period considered, relative to the use of a constant unit hedge ratio. These findings are consistent with the trend observed in the IBEX 35 futures market study of Lafuente and Novales (2003). Our empirical evidence suggests that, contrary to what happens in less liquid markets, the discrepancy between theoretical and quoted prices in index futures contracts in fully developed markets does not represent a noise factor that can be successfully exploited for hedging.

Key words: futures mispricing, hedging effectiveness,

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[5] Andani, Lafuente and Novales, 2009, "Liquidity and hedging effectiveness under futures mispricing: international evidence", *Journal of Futures Markets*, 29.

1. INTRODUCTION

Financial futures are frequently used in hedging operations, in which the determination of the hedge ratio is the main issue. Several theoretical approaches have been proposed in the literature to design an optimal hedge with futures contracts (see Chen et al., 2003, for an excellent review that considers minimum variance, mean-variance, expected utility, mean extended-Gini coefficient, and semivariance approaches). The usual approach takes into account not only the dynamic nature of market risk, but also the fact that the key idea of hedging is to combine spot and futures trading to form a portfolio with negligible fluctuations in its market value. Under that view, the decision is to choose the number of futures contracts that minimizes the conditional variance of the return on the hedged portfolio. The resulting optimal hedge ratio is then obtained as the ratio between the conditional covariance of spot and futures returns and the conditional variance of futures returns. These conditional moments have usually been estimated from a particular specification of the GARCH family of models (see, for example, Lee and Yoder, 2007, Ku et al., 2007, Choudhry, 2003 and 2004, Park and Switzer, 1995 among many others).

This study reviews the use of futures contracts on a specific stock market index as hedging instrument for a portfolio that replicates the market index. After showing that the empirical evidence is consistent with the absence of a common ARCH feature between the returns from spot and futures markets, we adopt the theoretical ratio proposed by Lafuente and Novales (2003), which is consistent with the existence of a noise specific to the future market in addition to a noise common to spot and futures market returns. A bivariate model with heteroskedastic disturbances is used to represent the dynamics of returns in both markets in order to estimate the minimum variance hedge ratio.

After estimating with data for 1997-2005, empirical evidence obtained from out-of-sample simulations over 2006 for the Nikkei 225, S&P500, FTSE-100, DAX and IBEX 35 futures markets shows no systematic improvement in hedging effectiveness relative to using a constant unit hedging ratio, contrary to results in Lafuente and Novales (2003) for the IBEX 35 index for 1993-1996. We explore whether this result is consistent with the trend pointed out by Lafuente and Novales (2003) in their stochastic optimal hedge ratio towards one over the 1993-1996 period, with a decreasing gain in hedging efficiency relative to a unitary ratio, which the authors justified on the basis of increased maturity of a still underdeveloped and illiquid market. Our goal is to analyze whether that trend continued after 1996, as the Spanish market increased liquidity, as well as to examine the robustness of our empirical results by examining similar evidence in fully developed markets in the US, Japan and Germany.

If confirmed, such a finding would suggest that in mature index futures markets with high trading volume, the time-varying noise that characterizes basis risk cannot be exploited to improve upon the hedging efficiency provided by a systematic unit ratio. Our results are fully in line with Roll et al. (2007), who present empirical evidence suggesting that liquidity enhances the efficiency of the futures-cash pricing system.

The rest of the paper is organized as follows. Section 2 describes the data used in the analysis and the results of testing for the presence of a common ARCH feature in the spot and futures markets returns. Section 3 presents the model used to determine the optimal hedge ratio and describes the estimation of the relevant conditional moments. Section 4 presents the empirical evidence on the evolution of conditional moments over the analyzed period. A simulation of hedging trading is performed to test the potential implementation of the model, and section 5 summarizes and makes concluding remarks.

2. STATISTICAL CHARACTERISTICS OF RETURNS

We used daily closing data for the IBEX 35, FTSE 100, NIKKEI 225, DAX and S&P 500 indexes. We select the trading day for the rollover of contracts according to the evolution of the depth of futures market. Figure 1 shows the average relative trading volume between the nearest to maturity contract and the next to maturity contract. With the exception of the S&P 500 futures market, the other derivatives markets considered exhibit greater trading volume for the next to maturity contract all the way to expiration. In the American market, volumes traded reverse around five days before expiration.

The time period we consider, January 1997 to December 2006, is interesting because of the occurrence of several events: a) the financial crisis of 1998 that significantly affected the United States financial system; b) the technology bubble burst in 2000; c) the subsequent deep generalized recession that spread across markets and lasted until the beginning of 2003, and d) a subsequent period of systematic market stability, with the exception of isolated crises due to geo-political tensions and inflationary fears. The latter part of this period was characterized by abundant liquidity in capital markets, with low interest rates.

Table 1 presents the main statistics for the return series, computed as the first differences of the logs of closing prices between successive trading days. The sample mean daily return is negligible, as expected from a systematically long and short trading strategy on consecutive trading days. Likewise, as is usually the case with daily time series, stock return distributions show excess kurtosis and some skewness, characteristics generally associated with conditional heteroskedasticity. To assess the existence of ARCH effects in stock returns, we perform Engle's Lagrange multiplier test. Empirical values of the test, not reported in the paper, systematically reject the null, pointing to the convenience of using some parameterization for second order moments of stock market returns in the family of GARCH models.

In order to empirically justify the use of our proposed model, which assumes the existence of a noise common to spot and futures returns, together with a noise specific to the yield of the derivative instrument, we follow the approach of Engle and Kozicki (1993) to test the null hypothesis that there is a linear combination of the returns from the two markets which is homoskedastic, i.e., that the ARCH feature is common to both return series. The empirical values of the test statistic are presented in Table 2, systematically leading to rejection of the hypothesis of a common ARCH feature. This pattern is consistent with the proposed theoretical model.

3. OPTIMAL DYNAMIC HEDGING

3.1. The optimal hedge ratio

In accordance with the empirical evidence above, we follow Lafuente and Novales (2003) consider that the hedging problem can be specified:

$$\begin{aligned}
&\underset{\{h_t\}}{Min} \quad Var_t\left(b_t \frac{dS_t}{S_t dt} - h_t \frac{dF_{t,T}}{F_{t,T} dt}\right) \\
&s.t. \\
&dS_t = \mu_{S,t} S_t dt + \sigma_{S,t} S_t dz_{1,t} \\
&dF_{t,T} = \mu_{f,t} F_{t,T} dt + \sigma_{S,t} F_{t,T} dz_{1,t} + \sigma_{N,t} F_{t,T} dz_{2,t}
\end{aligned}$$

where b_t denotes the spot position we want to hedge, and h_t is the hedging futures position, while S_t and F_t represent spot and futures market prices, respectively. We denote the correlation between the two Brownian processes: $\rho_{12,t} = Corr(dz_{1t}, dz_{2t})$. $\sigma_{S,t}$ denotes the size of the common noise shared by the two markets. The discrepancy between the price quoted in the futures market and the theoretical price according to the cost-of-carry valuation model arises from a basis risk of size $\sigma_{N,t}$, that we specifically attribute to the futures market. As shown in Lafuente and Novales (2003), the theoretical expression for the minimum variance (optimal) hedge ratio solving the problem above is:

$$\frac{h_t^*}{b_t} = \frac{\sigma_{s,t}^2 + \rho_{12,t}\sigma_{s,t}\sigma_{N,t}}{\sigma_{s,t}^2 + \sigma_{N,t}^2 + 2\rho_{12,t}\sigma_{s,t}\sigma_{N,t}} = \frac{1 + \rho_{12,t}\delta_t}{1 + \delta_t^2 + 2\rho_{12,t}\delta_t}$$

where $\delta_t = \frac{\sigma_{N,t}}{\sigma_{S,t}}$ represents the relative importance of the specific noise as compared to the common noise. Under the proposed model, the optimal hedge ratio remains below one provided that spot and futures market returns do not share a single common noise. The optimal ratio is positive (implying a short futures position) when both disturbances are positively correlated. In contrast, if the correlation between the two noises was negative, the optimal hedge ratio could lie either above or below 1.0.

3.2. Estimating time-varying variances for the theoretical noises

Given the conclusive empirical evidence in the literature on the existence of a cointegration relationship between the logarithms of spot market and futures market prices, our specification of the conditional mean for both series of returns incorporates an error correction term. Lien (1996) shows that disregarding the cointegrating relationship could lead to a smaller than optimal futures position and a relatively poor hedging performance. There is also abundant empirical evidence [see Lien and Yang (2006), among many others] supporting the hypothesis that the cointegration vector is (1, -1) which, in turn, implies that the empirical basis is stationary. Estimated cointegration vectors for the pair: [log(futures price) log(spot price)] by Johansen's procedure, after normalizing the first entry to unity are: S&P 500: [1.000, -1.005], Nikkei 225: [1.000, -1.015], FTSE100: [1.000, -1.006], DAX: [1.000, -1,001], IBEX 35: [1, -0,999]. In all cases, the null hypothesis of the cointegration vector being [1.000, -1.000] is not rejected at conventional significant levels. Hence, we define the error correction term as the "spread" between the logarithm of the spot price and the future price.

To capture the correlations between the return innovations and estimate the conditional variance-covariance matrix of spot and futures markets returns, we use the bivariate dynamic conditional correlation (DCC) GARCH model proposed in Engle (2002). Monte Carlo experiments reveal not only that the bivariate version of the DDC-MV-GARCH model provides a very good approximation to a variety of time-varying correlation processes, but also that this model often compares favourably with the simple multivariate GARCH. The (DCC) GARCH specification combines the flexibility of univariate GARCH models with a parsimonious parametric specification for the conditional correlation. Furthermore, bearing in mind the objectives of the present study, Ku et al. (2007) compare the DCC-GARCH model proposed in Engle (2002) with the constant correlation specification, to find evidence of greater hedging effectiveness from the model with time-varying correlation.

Hence, we represent the dynamics of spot and futures markets returns, $r_{s,t}$ and $r_{f,t}$, through the error correction model:

$$\begin{pmatrix} r_{s,t} \\ r_{f,t} \end{pmatrix} = \sum_{i=1}^{n} \begin{pmatrix} \alpha(i)_{11} & \alpha(i)_{12} \\ \alpha(i)_{21} & \alpha(i)_{22} \end{pmatrix} \begin{pmatrix} r_{s,t-i} \\ r_{f,t-i} \end{pmatrix} + \begin{pmatrix} \gamma_s \\ \gamma_f \end{pmatrix} \left(\ln S_{t-1} - \ln F_{t-1} \right) + \begin{pmatrix} \varepsilon_{s,t} \\ \varepsilon_{f,t} \end{pmatrix}$$

with $\left(\varepsilon_{s,t}\ \varepsilon_{f,t}\right)' / \Omega_{t-1} \sim N(0, \Sigma_t)$, where Ω_{t-1} is the information set available at time t-1 and Σ_t is the conditional variance-covariance matrix of market return innovations[6] .

We represent the time evolution of the elements in the conditional variance-covariance matrix by a GARCH (p,q) specification with possible asymmetric effects:

$$\begin{pmatrix} \sigma^2_{s,t} \\ \sigma^2_{f,t} \end{pmatrix} = \begin{pmatrix} \omega_s \\ \omega_f \end{pmatrix} + \sum_{i=1}^{p} \begin{pmatrix} A(i)_{11} & A(i)_{12} \\ A(i)_{21} & A(i)_{22} \end{pmatrix} \begin{pmatrix} \varepsilon^2{}_{s,t-i} \\ \varepsilon^2{}_{f,t-i} \end{pmatrix} + \sum_{j=1}^{q} \begin{pmatrix} B(j)_{11} & B(j)_{12} \\ B(j)_{21} & B(j)_{22} \end{pmatrix} \begin{pmatrix} \sigma^2_{s,t-1} \\ \sigma^2_{f,t-1} \end{pmatrix}$$

$$+ \begin{pmatrix} D_{11} & D_{12} \\ D_{21} & D_{22} \end{pmatrix} \begin{pmatrix} \varepsilon^2{}_{s,t-1} I_{s,t-1} \\ \varepsilon^2{}_{f,t-1} I_{f,t-1} \end{pmatrix}, \qquad I_{k,t-1} = \begin{Bmatrix} 1, if\ \varepsilon_{k,t-1} < 0,\ k = s,f \\ 0, if\ \varepsilon_{k,t-1} < 0,\ k = s,f \end{Bmatrix}$$

[6] When the Normality assumption was rejected for the residuals, we estimated the model using a t-Student conditional distribution for the innovations when evaluating the log-likelihood function.

With regard to the conditional correlation, the dynamics of the DCC model is:

$$\rho_{sf,t} = (1-\kappa_1-\kappa_2)\overline{\rho} + \kappa_1 \rho_{sf,t-1} + \kappa_2 \Psi_{t-1}$$

where:

$$\Psi_{t-1} = \frac{\sum_{h=1}^{m} \eta_{s,t-h}\eta_{f,t-h}}{\sqrt{\left(\sum_{h=1}^{m} \eta^2_{s,t-h}\right)\left(\sum_{h=1}^{m} \eta^2_{f,t-h}\right)}}, \; \eta_{k,t} = \frac{\varepsilon_{k,t}}{\sigma_{k,t}}, k = s, f$$

Once the conditional moments have been estimated, the conditional variance for futures market returns, as well as their conditional covariance and correlation with spot market returns can be recovered using the expressions in Lafuente and Novales (2003):

$$\hat{\sigma}^2_{f,t} = \hat{\sigma}^2_{s,t} + \hat{\sigma}^2_{N,t} + 2\hat{\sigma}_{s,t}\hat{\sigma}_{N,t}\hat{\rho}_{12,t}$$

$$\hat{\sigma}_{sf,t} = \hat{\sigma}^2_{s,t} + \hat{\sigma}_{s,t}\hat{\sigma}_{N,t}\hat{\rho}_{12,t}$$

$$\hat{\rho}_{12,t} = \frac{\hat{\sigma}_{sf,t} - \sigma^2_{s,t}}{\hat{\sigma}_{s,t}\sqrt{\hat{\sigma}^2_{s,t} + \hat{\sigma}^2_{f,t} - 2\hat{\sigma}_{sf,t}}}$$

where $\hat{\sigma}^2_{f,t}$, $\hat{\sigma}^2_{s,t}$ and $\hat{\sigma}_{s,f,t}$ denote the conditional variances of futures and spot market returns and their conditional covariance, as estimated from the DCC-GARCH model.

4. EMPIRICAL EVIDENCE

The sample information was divided into two sub-periods. The first period runs from January 1997 to December 2005, which was used for initial estimation and specification testing. The second sub-period, from January 2006 to December 2006, was left as an out-of-sample window to test the effectiveness of simulated hedging operations.

4.1. The bivariate GARCH model

Table 3 shows the parameters obtained in the estimation of the DCC-GARCH model. In all cases, we sought for the most parsimonious specification possible[7]. In the case of the S&P 500 and FTSE-100, a *t*-Student conditional distribution was considered, while the Normal distribution was used for IBEX 35, DAX and NIKKEI 225. In general, the estimates show significant coefficients for ARCH and GARCH effects, suggesting volatility clustering in both market returns. Similarly, the parameters that represent the cross effects in mean and variance also reveal significant cross-market interactions. The speed of adjustment to short-run price deviations from their long-run equilibrium is also significant, thus evidencing that the markets are arbitraged in such a way that the empirical basis has a restricted evolution over time. Finally, the presence of significant asymmetric effects should be noted for the S&P 500 as well as the NIKKEI 225. Figures 2a, 2b and 2c (see Appendix 2) show the evolution over time of the relative importance of the noise specific to the futures market, as compared to the common noise, $\hat{\sigma}_{N,t} / \hat{\sigma}_{s,t}$, in each of the stock markets considered.

4.2. Hedging simulations

Having estimated the model for the period 1997-2005, we incorporated data for the out-of-sample 2005-2006 period in 10-day windows. This is a compromise between maintaining a constant hedge ratio and changing the hedge too often, which would imply unbearable transaction costs. The model was re-estimated every 10 days, obtaining at each point a hedge ratio, before incorporating additional data on a 10-day period for a new estimation. Once the entire series of hedge ratios had been obtained for 2006, we implemented two different hedging strategies by applying to each 10-day trading window (the time interval [*t*+1, *t*+10]), either the hedge ratio estimated the last day in each rolling sample (at time t) or the average hedge ratio computed over the last five trading days in each sample (from *t*-4 to *t*). Thus, the 250 market days in the year allowed for performing 25 10-day hedging operations with each strategy, except in the case of the NIKKEI, for which only 24 were carried out.[8] The volatility of the series of returns on the portfolio hedged with the GARCH ratio was then obtained under each of these two hedging

[7] To assess the ability of the estimated model to capture the main statistical characteristics of market returns, a battery of standard specification tests was employed, including the Ljung-Box Q-statistics on the standardized residual and their squared values. All series of residuals were found to be free of serial correlation at the 5% significance level.
[8] Due to the availability of a shorter number of market days.

strategies, computing the reduction in volatility relative to the spot position. The volatility of the portfolio hedged with the unitary ratio was obtained similarly, and the implied reduction in volatility was also calculated. Finally, we compared the reduction in volatility obtained by application of each of the two strategies based on a GARCH ratio and the strategy based on imposing a constant unit ratio:

$$Hedging\ effectiveness = 100x\left(\frac{Volatility(hedged\ \ position) - Volatility(Unhedged\ \ position)}{Volatility(Unhedged\ \ position)}\right)$$

where volatility is measured by the standard deviation of returns over the period chosen for comparison.

We present results obtained throughout the out-of-sample period, as well as over each quarter. Tables 4 and 5 present the results of applying the two hedging strategies described in the previous paragraph. The results obtained do not exhibit a systematic advantage over the unit ratio, which suggests that the incorporation of transaction costs would make the application of a dynamic hedging strategy with the GARCH ratio even less interesting.

Finally, we now consider the gain or loss in terms of utility, taking into account the transaction costs from adjusting the position in the derivatives market. To this end, we consider a specification of the expected utility function: $E_t U(x) = E_t(x) - \gamma\sigma_t^2(x)$ [as in Kroner and Sultan (1993), Lee et al. (2006) and Kofman and McGlenchy (2005), among others], where γ denotes the degree of risk aversion, with the level of risk being measured by the conditional variance of returns. Denoting transaction costs by τ and assuming a zero expected return, an investor would have an expected utility of $-\tau - \gamma\sigma_t^2(x^{**})$ if the hedge ratio is updated from h_t^* / b_t to h_t^{**} / b_t, as against an expected utility equal to $-\gamma\sigma_t^2(x^*)$ if the hedge ratio remains unchanged. Thus, an investor whose utility is given by the specification considered will adjust the hedging position if and only if:

$$\tau - \gamma(\sigma_{s,t}^2 - 2\sigma_{sf,t}(h_t^{**}/b_t) + \sigma_{f,t}^2(h_t^{**}/b_t)^2) > -\gamma(\sigma_{s,t}^2 - 2\sigma_{sf,t}(h_t^*/b_t) + \sigma_{f,t}^2(h_t^*/b_t)^2)$$

where (h_t^{**}/b_t) denotes the hedge ratio applied as the result of the last revision of the futures position.

To implement this strategy, we consider a risk aversion coefficient of 4 and average costs of 0.0011%[9], and the optimal ratio obtained in the last trading day in each rolling sample, t, is applied to the following 10 trading days (from t+1 to t+10). Thus, over the out-of-sample period, we use the utility comparison rule every 10 trading days to decide on whether to maintain the same hedge ratio that was applied previously, or to change it to the variance-minimizing ratio calculated in the immediately preceding period. The results obtained for each market are presented in Table 6 in terms of aggregate utility for 2006, as well as in terms of the utility gain relative to the non-hedged market position. Managing the hedge ratio according to the utility comparison rule often provides the highest utility gain, but it is very similar to the one obtained under the constant unit ratio, as well as to the one emerging from applying the GARCH ratio from the previous period.

5. CONCLUSIONS

This paper analyzes the use of index futures as a hedging instrument for a portfolio that replicates the underlying asset for the futures contract. To this end, we have used the theoretical model proposed by Lafuente and Novales (2003), which includes a specific noise in the futures price in addition to the common noise that it is assumed to share with the spot market price, according to the cost-of-carry valuation model.

We have analyzed daily closing data on futures and spot markets for the NIKKEI 225, S&P 500, FTSE 100, DAX and IBEX 35 indexes over the 1997-2005 period. The null hypothesis on the existence of a common ARCH feature [Engle and Kozicki (1993)] underlying the heteroskedastic behavior detected in spot and futures markets returns is rejected, validating the existence of a noise specific to the futures market, as included in our econometric model. We estimate an asymmetric bivariate error-correction model with a DCC-GARCH structure to represent the conditional mean, variance and covariance of

9 This corresponds to the MEFF Spanish commission of 1.3 Euros for the regular futures contract and the 2006 average value of the IBEX 35. As to the transaction costs associated to the bid-ask spread, we use the mean spread for the short-term index futures contracts on FTSE-100 (1,4 £), as reported in Fahlenbrach and Sandas (2003). We applied the same commission to all indexes. Since the position does not change often, our results are robust to transaction costs inside a (.0020% , .0060%) range.

future and spot market returns, and we simulate out-of-sample hedging strategies that apply a hedge ratio calculated from the estimated econometric specification.

The results show that GARCH dynamic strategies do not lead to a systematic improvement in hedging effectiveness, as compared to the improvement that would be obtained by applying a constant unit ratio.

These results are in sharp contrast with those obtained using intraday data for the period 1993-1996 by Lafuente and Novales (2003) for the Spanish market. One reason might be that the present study uses daily data, which implies a loss of information on price fluctuations that may bias upward the estimation of co-movement between spot and futures prices, moving optimal hedge ratios closer to 1.

But we believe that what is really central to explain the different results is the fact that the Spanish market was in 2006 a significantly more mature market, with a sufficiently high level of activity that would quickly correct any arbitrage opportunity. Indeed, our results are consistent with the trend detected in Lafuente and Novales (2003) about the optimal hedge ratio for the Spanish market gradually coming closer to 1 towards the end of the 1993-1996 sample period, thereby limiting the potential gain in hedging effectiveness obtained from the dynamic GARCH ratio. Similar conclusions have been reached for fully developed option markets in the US, Japan and Germany, reinforcing that interpretation.

The empirical evidence for the Spanish futures market is also consistent with the recent paper of McMillan and Quiroga (2008). These authors show that the equilibrium speed of adjustment between spot and futures market prices was reduced after the introduction of the mini-futures contract in the Spanish market in November 2001, the effect being particularly pronounced after the second year, when mini-futures contracts started being more heavily traded.

Even more significantly, the result that noisy deviations from the no-arbitrage relationship in mature market prices may be of no consequence for improving the efficiency of hedging a spot portfolio with futures contracts goes along the lines of Roll et al. (2007), who have shown evidence that liquidity enhances the efficiency of the futures-cash pricing system for the S&P 500 stock index futures market.

REFERENCES

Chen, S., Lee, C. and Shrestha, K., 2003, Futures hedge ratios: a review, *The Quarterly Review of Economics and Finance,* 43, 433-465.

Choudhry, T., 2004, The hedging effectiveness of constant and time-varying hedge ratios using three Pacific Basin stock futures, *International Review of Economics & Finance,* 4, 371-385.

Choudhry, T., 2003, Short-run deviations and optimal hedge ratio: evidence from stock futures, *Journal of Multinational Financial Management,* 13, 171-192.

Engle, R.F., 2002, Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models, *Journal of Business and Economic Statistics,* 20, 339-350.

Engle,R.F. and Kozicki, S., 1993, Testing for common features, *Journal of Business and Economic Statistics,* 11, 369–380.

Fahlenbrach, R. and Sandas, P., 2003, Bid-Ask spreads and inventory risk: Evidence from the FTSE-100 Index Options Market, University of Pennsylvania.

Kofman P. and McGlenchy, P., 2005, Structurally sound dynamic index futures hedging, *Journal of Futures Markets,* 25, 1173-1202.

Koutmos, G. and Tucker, M., 1996, Temporal relationships and dynamics interactions between spot and futures stock markets, *Journal of Futures Markets,* 16, 55–69.

Kroner, K.F and Sultan, J., 1993, Time-varying distributions and dynamic hedging with foreign currency futures, *Journal of Financial and Quantitative Analysis,* 28, 535-551.

Ku, Y.H., Chen, H. and Chen, K., 2007, On the application of the dynamic conditional correlation model in estimating optimal time-varying hedge ratios, *Applied Economics Letters, 7*, 503-509.

Lafuente, J.A. and Novales, A., 2003, Optimal hedging under departures from the cost-of-carry valuation: Evidence from the Spanish stock index futures market, *Journal of Banking & Finance,* 27, 1053-1078.

Lee, H., Yoder, J., Mittelhamner, J. and McCluskey, R., 2006, A random coefficient autoregressive Markov switching model for dynamic futures hedging, *Journal of Futures Markets,* 26, 103–129.

Lee, H., Yoder, J., 2007, Optimal hedging with a regime switching time-varying correlations GARCH model, *Journal of Futures Markets,* 27, 495-516.

Lien, D., 1996, The effect of the cointegration relationship on futures hedging: A note, *The Journal of Futures Markets,* 16, 773-780.

Lien, D. and Yang, L., 2006, Spot-Futures Spread, Time-Varying Correlation, and hedging with Currency Futures, *The Journal of Futures Markets,* 26, 1019-1038.

McMillan D.G. and Quiroga R., 2008, Efficiency of the IBEX spot-futures basis: The impact of the mini-futures, *Journal of Futures Markets,* 28, 398–415.

Park, T.H., and Switzer, L.N., 1995, Bivariate GARCH estimation of the optimal hedge ratios for stock index futures: A note, *Journal of Futures Markets,* 15, 61–67.

Roll, R., Schwartz, E. and A. Subrahmanyam, 2007, Liquidity and the law of one price: The case of the futures-cash basis, *The Journal of Finance*, 52, 5, 2201-2234.

Appendix 1. Tables

Table 1. Descriptive statistics of stock market returns

	NIKKEI 225		S&P 500		FTSE 100		DAX		IBEX 35	
	Spot	Futures	Spot	Futures	Spot	Futures	Spot	Futures	Spot	Futures
Mean	-0.0001	-0.0001	0.0003	0.0003	0.0002	0.0002	0.0003	0.0003	0.0004	0.0004
Standard Dev.	0.0147	0.0152	0.0115	0.0119	0.0115	0.0120	0.0162	0.0161	0.0141	0.0148
Asymmetry	-0.0367	-0.1741	-0.0725	-0,1323	-0.1771	-0.0867	-0.2300	-0.0040	-0.1803	-0.1734
Kurtosis	1.7501	2.4852	3.0553	3,5657	2.5418	2.7153	2.6376	3.3604	2.4828	2.7844

Table 2. Testing for common ARCH features

K	1	2	3	4	5	6	7	8	9	10
Min TR^2										
NIKKEI 225	41.1	65.3	98.9	110.4	142.9	158.5	178.5	180.1	177.3	188.5
S&P 500	70.5	113.6	160.0	169.9	187.1	189.8	207.4	223.3	224.5	238.8
FTSE 100	102.4	268.1	336.8	353.0	361.2	378.7	378.9	379.2	380.4	380.5
DAX	82.2	217.7	257.4	262.9	291.1	324.7	329.0	333.0	375.9	387.5
IBEX	83.1	153.3	197.6	228.2	229.5	281.6	324.7	348.4	350.1	370.2
Critical values										
α=0.05	6.0	11.1	15.5	19.7	23.7	27.6	31.4	35.2	38.9	42.6
α=0.01	9.2	15.1	20.1	24.7	29.1	33.4	37.6	41.6	45.6	49.6

Notes: The first panel shows the minimum T*R^2 in a set of regressions of $(r_{s,t}-dr_{f,t})^2$ on k lags of $r^2_{s,t}$, $r^2_{f,t}$ and $r_{s,t}r_{f,t}$, over a grid of values for d, where T denotes the sample size. The last two rows show critical values at the α-significance level.

Table 3. Maximum Likelihood estimation of the parameters involved in the DCC-GARCH model

	NIKKEI 225		S&P 500		FTSE 100		DAX		IBEX 35	
Spot mean equation										
a_{11}	-0.037		-0.300	**	-0.184	**	-0.198	**	-0.506	**
a_{12}	0.018		0.286	**	-0.224	**	0.230	**	-0.290	**
$a(2)_{11}$					0.200	**			0.515	**
$a(2)_{12}$					0.203	**			0.275	**
g_s	-0.406	**	-0.085	**	-0.070	*	-0.473	**	-0.021	
Futures mean equation										
a_{21}	0.054		0.097	**	0.296	**	0.139	**	-0.219	
a_{22}	-0.090		-0.110	**	-0.003		-0.123	**	-0.189	
$a(2)_{21}$					-0.274	**			0.230	
$a(2)_{22}$					-0.018				0.166	
g_f	0.342	**	-0.002		0.020		-0.221	**	0.342	**
Spot Variance equation										
w_s	0.000	**	0.000		0.000		0.000	**	0.000	
A_{11}	0.024		-0.076	*	0.176	**	0.004		-0.169	**
A_{12}	0.038		0.092	**	-0.070		0.123	**	0.207	**
B_{11}	0.528		1.013	**	0.633	**	0.877	**	-1.602	*
B_{12}	0.351		-0.058		0.247	**	-0.005		2.460	**
D_{11}	0.079	**	0.049	**						
D_{12}	0.131	**	0.059	**						
Futures Variance equation										
w_f	0.000	*	0.000		0.000		0.000	**	0.000	
A_{21}	0.081		-0.056		0.170	**	0.094	**	0.010	
A_{22}	-0.047		0.066	*	-0.057		0.033		0.039	
B_{21}	0.716	*	0.031		-0.313	**	-0.111	**	-0.106	
B_{22}	0.208		0.924	**	1.184	**	0.978	**	1.049	**
D_{21}	0.962	**	-0.057	**						
D_{22}	0.361	**	0.037	**						
Correlation dynamics										
k_1	0.037	*	0.021		0.143	**	0.112	**	0.009	*
k_2	0.959	**	0.970	**	0.800	**	0.870	**	0.990	**

* Significant at the 5% level
** Significant at the 1% level

Note: In the case of the S&P 500 and the FTSE-100, the conditional distribution is a t-Student. Degrees of freedom were estimated at 7.1 and 5.7 respectively.

Table 4. Out-of-sample hedging effectiveness

	GARCH Hedge Ratio	Hedging effectiveness		Difference (%)
		GARCH	Unitary	|GARCH|-|Unit.|
NIKKEI 225				
January-March 2006	0.962	-81.34%	-82.41%	-1.07%
April-June 2006	0.942	-81.90%	-82.12%	-0.22%
July-September 2006	0.966	-76.45%	-76.77%	-0.32%
September-December 2006	0.947	-75.49%	-75.07%	0.42%
Average 2006	0.954	-79.78%	-80.22%	-0.44%
S&P 500				
January-March 2006	0.975	-74.32%	-74.73%	-0.41%
April-June 2006	0.967	-76.70%	-77.36%	-0.66%
July-September 2006	0.976	-70.04%	-70.53%	-0.49%
September-December 2006	1.001	-68.58%	-68.89%	-0.31%
Average 2006	0.980	-73.37%	-73.87%	-0.50%
FTSE 100				
January-March 2006	1.002	-80.58%	-80.54%	0.03%
April-June 2006	0.978	-88.91%	-88.71%	0.20%
July-September 2006	0.990	-80.86%	-80.86%	0.00%
September-December 2006	1.007	-79.63%	-79.91%	-0.28%
Average 2006	0.995	-83.62%	-83.59%	0.03%
DAX				
January-March 2006	0.964	-83.01%	-84.53%	-1.52%
April-June 2006	0.986	-77.66%	-77.66%	0.00%
July-September 2006	0.981	-81.76%	-82.60%	-0.85%
September-December 2006	0.955	-80.89%	-81.02%	-0.14%
Average 2006	0.971	-80.06%	-80.52%	-0.45%
IBEX 35				
January-March 2006	0.945	-79.42%	-79.90%	-0.48%
April-June 2006	0.951	-80.77%	-80.86%	-0.09%
July-September 2006	0.946	-85.57%	-87.29%	-1.72%
September-December 2006	0.966	-85.18%	-85.76%	-0.58%
Average 2006	0.952	-82.43%	-83.07%	-0.63%

Note: The hedge ratio obtained for the last day in each rolling sample is applied to the following 10 trading days.

Table 5. Out of-sample hedging effectiveness

	GARCH	Hedging effectiveness		Difference (%)
	Hedge Ratio	GARCH	Unitary	|GARCH|-|Unit.|
NIKKEI 225				
January-March 2006	0.949	-80.81%	-82.41%	-1.60%
April-June 2006	0.945	-82.12%	-82.12%	0.00%
July-September 2006	0.949	-76.09%	-76.77%	-0.68%
September-December 2006	0.942	-75.28%	-75.07%	0.20%
Average 2006	0.946	-79.56%	-80.22%	-0.66%
S&P 500				
January-March 2006	0.977	-74.32%	-74.73%	-0.40%
April-June 2006	0.965	-76.55%	-77.36%	-0.81%
July-September 2006	0.984	-70.14%	-70.53%	-0.39%
September-December 2006	1.001	-68.69%	-68.89%	-0.21%
Average 2006	0.982	-73.36%	-73.87%	-0.51%
FTSE 100				
January-March 2006	0.991	-80.34%	-80.54%	-0.20%
April-June 2006	0.982	-88.74%	-88.71%	0.03%
July-September 2006	0.991	-80.84%	-80.86%	-0.01%
September-December 2006	1.005	-79.34%	-79.91%	-0.57%
Average 2006	0.993	-83.49%	-83.59%	-0.10%
DAX				
January-March 2006	0.968	-83.33%	-84.53%	-1.20%
April-June 2006	0.988	-77.65%	-77.66%	-0.01%
July-September 2006	0.980	-82.06%	-82.60%	-0.55%
September-December 2006	0.953	-80.89%	-81.02%	-0.13%
Average 2006	0.973	-80.18%	-80.52%	-0.34%
IBEX 35				
January-March 2006	0.940	-79.36%	-79.90%	-0.55%
April-June 2006	0.952	-80.80%	-80.86%	-0.06%
July-September 2006	0.950	-85.72%	-87.29%	-1.57%
September-December 2006	0.971	-85.31%	-85.76%	-0.45%
Average 2006	0.954	-82.49%	-83.07%	-0.58%

Note: The average hedge ratio over the last five trading days in each rolling sample is applied to the following 10 trading days.

Table 6. Utility gains under different hedging strategies

	NIKKEI 225	S&P 500	FTSE 100	DAX	IBEX 35
Aggregate utility					
Spot position	-0.17320	-0.04371	-0.06721	-0.10819	-0.06527
Unitary hedge ratio	-0.00558	-0.00261	-0.00252	-0.00976	-0.00233
GARCH hedge ratio (*)	-0.00649	-0.00381	-0.00374	-0.01095	-0.00322
GARCH hedge ratio with decision criterion (**)	-0.00526	-0.00256	-0.00252	-0.01091	-0.00228
Utility gain on the spot position					
Unitary hedge ratio	96.8%	94.0%	96.2%	91.0%	96.4%
GARCH hedge ratio (*)	96.3%	91.3%	94.4%	89.9%	94.9%
GARCH hedge ratio with decision criterion (**)	97.0%	94.1%	96.3%	89.9%	96.5%

(*) The hedge ratio is changed every 10 days, applying the ratio from the last trading day in each rolling sample.
(**)The desirability of applying a new ratio was appraised every 10 days, the decision being made in accordance with the expected utility.

Appendix 2. Figures

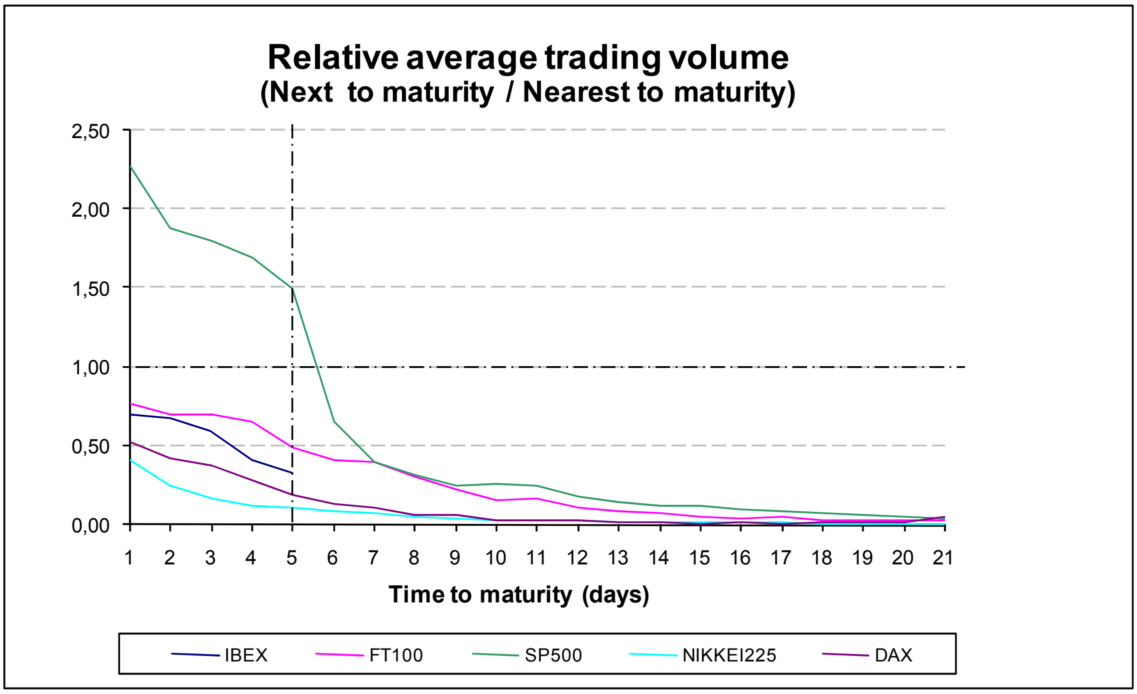
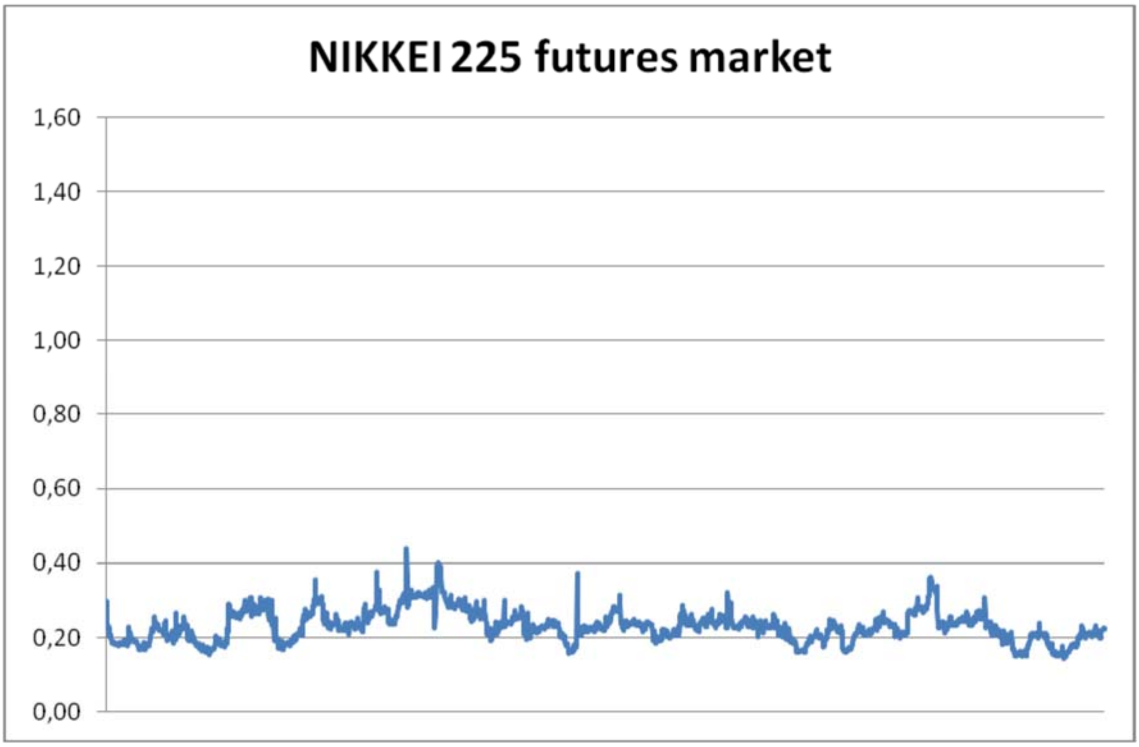


Figure 1. Relative volume traded in each stock market: number of next to maturity contracts traded over number of Nearest to maturity futures contracts traded, as a function of Time to maturity.



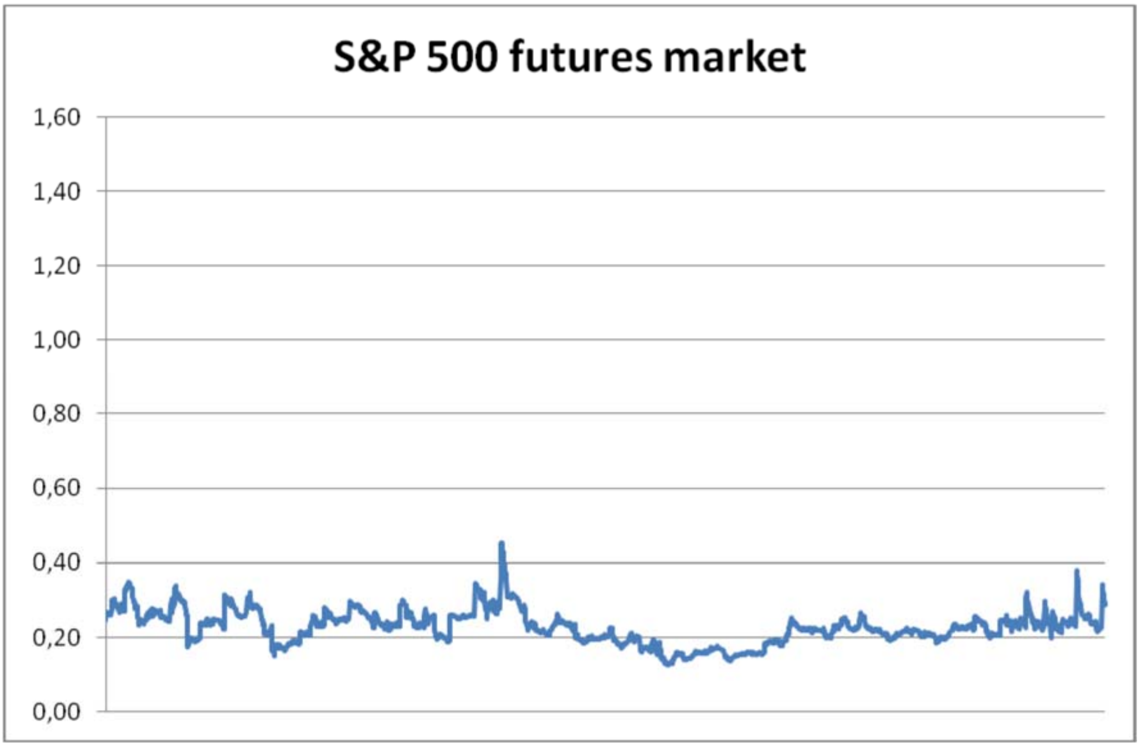
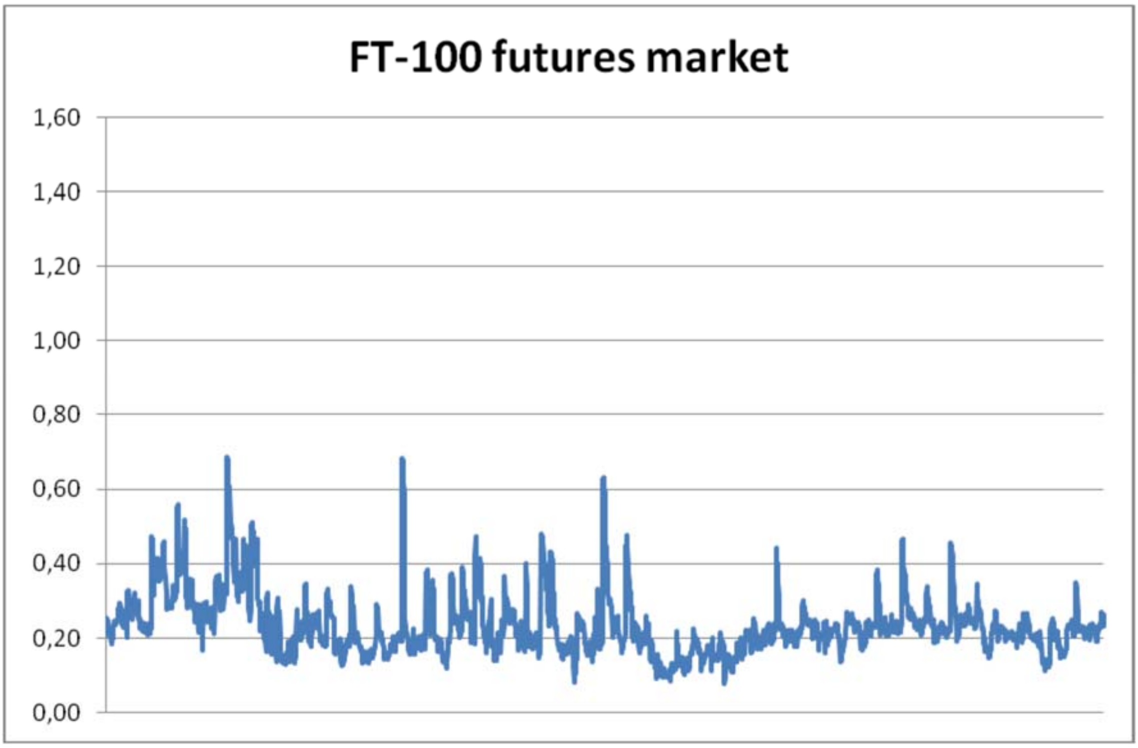


Figure 2a. Ratio of estimated variances for specific and common noise components: NIKKEI 225 and S&P500.



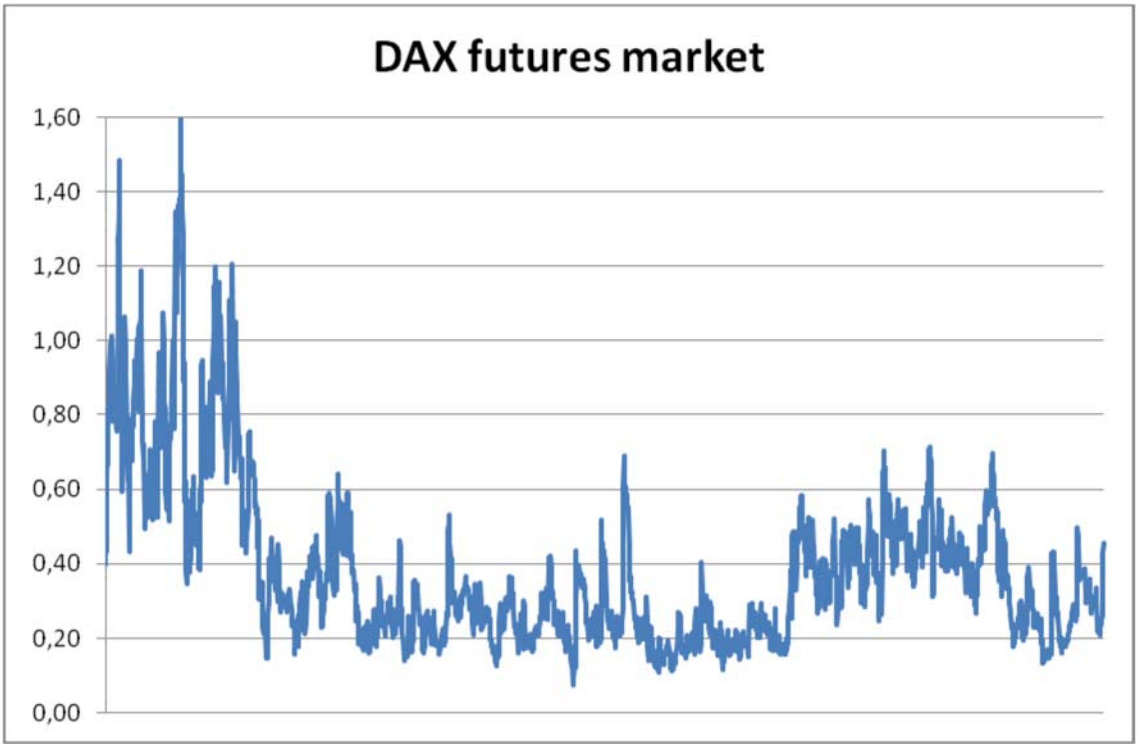


Figure 2b. Ratio of estimated variances for specific and common noise components: FTSE 100 and DAX.

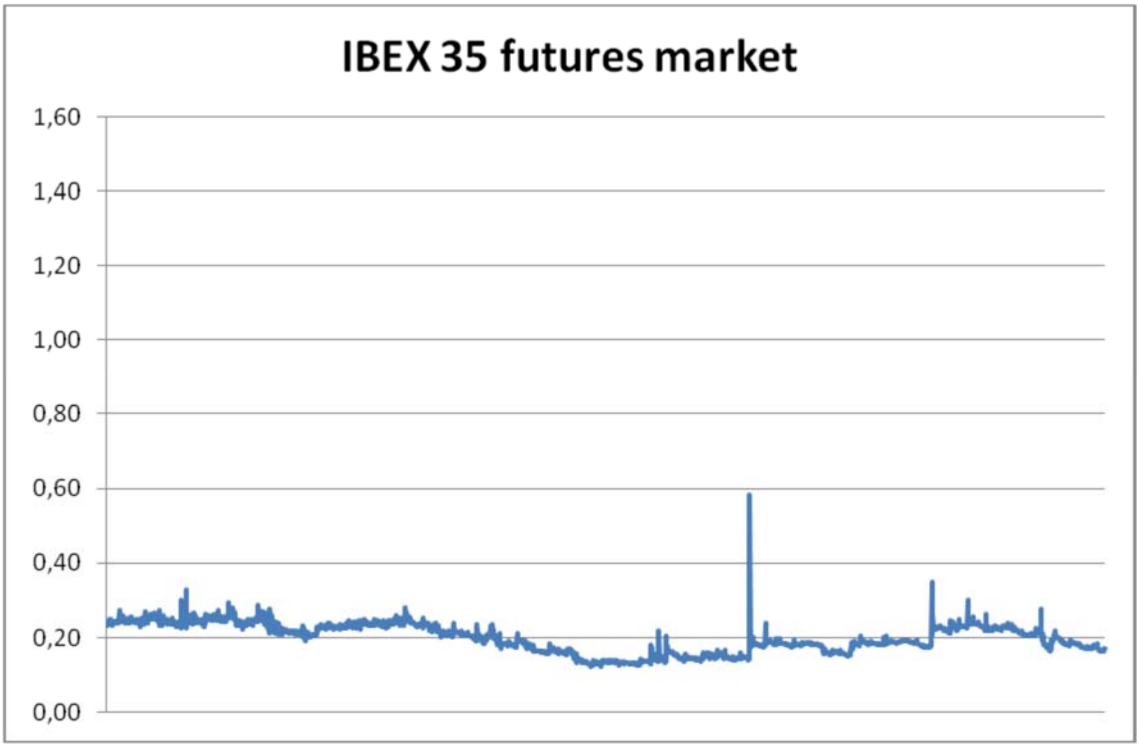


Figure 2c. Ratio of estimated variances for specific and common noise components: IBEX 35.

CHAPTER 2: Hedging and cross-hedging effectiveness of individual stocks

ABSTRACT: We analyze the effectiveness of hedging strategies for individual stocks using their own futures contracts as well as index futures contracts. First Chapter results[10] show that the dynamic hedge offered by the GARCH model for index portfolios improves upon the effectiveness of a static ratio in markets less than fully developed. Our analysis suggests that when hedging positions in individual stocks, the better behaviour of the GARCH ratio seems to arise even in fully developed index futures markets. We find that when individual stocks from the Spanish stock market are hedged with index futures, a dynamic strategy obtained from GARCH specifications achieves a more effective hedge than the static OLS ratio and the dynamic OLS ratio, exploiting the existence of a specific noise in futures prices as observed in the Third Chapter [11]. The decision to hedge would be heavily dependent on each investor preferences. Even though variance reduction or left tail risk measures suggest a recommendation for hedging, other measures that consider loss aversion may result in the opposite recommendation.

Key words: futures mispricing, cross-hedging effectiveness, GARCH models, stocks.

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[10] Andani, Lafuente and Novales, 2009, "Liquidity and hedging effectiveness under futures mispricing: international evidence", Journal of Futures Markets 29, is the first chapter of this thesis.
[11] Andani, Lafuente and Novales, 2015, "Portfolio cross-hedging effectiveness: the role of liquidity", is the third chapter of this thesis.

1. INTRODUCTION

Since the introduction of financial futures on indexes in the US in the 80's and 90's, that market has experienced a dramatic development that has not been accompanied by a similar growth of the market for individual stock futures (SSF).[12] SSF were introduced towards the end of the 90's and beginning of the 2000-2010 decade, with volumes that even today, are still well below those for index futures. The SSF nominal negotiated in Spain in the 2010-2014 period is just 3.35% of the volume negotiated in IBEX 35 futures over the same period[13]. Among the reasons for the lower development of individual stock futures in the Spanish case, is the fact that a reduced number of stocks account for a large percentage of IBEX 35, making the index future to be a good hedging instrument for liquid portfolios or for those individual stocks with higher weight in the index composition. Another reason seems to be the competition that the development of such products implies for the activity of market makers. Finally, reputational issues and the traditional uncertainty in Spain regarding dates for dividend payment also affect the characteristics of the SSF as hedging instruments. In spite of not being as developed as index futures, investing in SSF offers the investor some advantages[14] over the stocks which, once the previous limitations are solved, should lead to their final consolidation. The upcoming introduction of total return SSF is expected to help in this regard.

The goal of this paper is to analyze the effectiveness of hedging individual stock positions using the future on IBEX 35 as cross-hedging instrument for individual stocks. In particular, together with the decision of hedging, we want to examine whether dynamic hedging strategies based on conditional moments improve upon unconditional strategies. Even though the effectiveness of the cross-hedge with the index future is lower, in theory, than the one that might obtained with SSF hedges, the index futures does not have the limitations that arise from the latter. Essentially, the idea is that the hedge analysis with SSF data do not mean that the strategy could have been actually implemented, since the quoted futures price may not correspond to an actual trade. We provide SSF results as

[12] We will denote them by SSF, as an acronym for Single Stock Futures

[13] MEFF statistics bulletin.

[14] Some uses of these instruments that should be expected to favour their consolidation are: (i) leveraged investment under better financing conditions than those for stock purchases, (ii) short positions easier to implement and without many of the limitations of trading with stocks and (ii) lower regulatory constraints that limit the concentration of investments for some agents.

secondary to our analysis of IBEX 35 futures cross-hedging effectiveness. Unfortunately, to the best of our knowledge there is not literature on the efficiency of hedging single stock positions using SSF that might allow us to compare our results with those obtained for different countries and for stock markets with different degrees of development.

When analysing the effectiveness of a hedging strategy, the main question is the determination of the criterion to be used. Chen et al. (2013) make an exhaustive review of different optimization criteria that can be used to determine the optimal hedge ratio. Possibly the most popular approach consists on minimizing the variance of the hedged position, relative to the unhedged position. This is quite natural, since an essential objective of financial hedging is to minimize the size of fluctuations in the hedged position. We follow that same variance reduction approach to characterize the hedge but we add other criteria that help to assess the decision of hedging beyond volatility considerations. Nonetheless, it is worth to comment the controversy in the literature and the choices made in this paper with regard to the three main aspects in the determination of the hedge effectiveness: the measure of effectiveness to be used, the evaluation of the impact of new information on the hedge ratio and the models used to estimate the hedge ratios. We review these three issues in Section 2. To determine the hedge ratio, we follow the theoretical approach proposed by Lafuente and Novales (2003). These authors consider the existence of a specific noise in the futures contract to be used in the hedge, that produces a component of fluctuations that is not present in the portfolio to be hedged. Even though the definition of the minimum variance hedge ratio remains the same in their model, it admits a nice interpretation in terms of the variance ratio between the noise common to spot and futures and the noise specific to the futures market, and the conditional correlation between the spot and futures assets.

To estimate the conditional moments, we will use bivariate DCC GARCH specifications, with the possibility of including asymmetric effects in volatility, known as leverage, and probability distributions other than Normal for the innovations. In order to assess the decision of hedging individual stocks versus not hedging them, together with the variance reduction criteria we provide more information on the distribution of returns of the hedged position. To this end, we also consider the Certainty Equivalent (CE), Value at Risk (VaR), Conditional Value at Risk or Expected Shortfall (ES), and Lower Partial Moments (LPM) as secondary measures.

Finally, we compare the effectiveness of dynamic stochastic hedging strategies with the effectiveness obtained with the minimum variance ratio estimated through the slope of the OLS regression between the spot and futures returns. We will consider a static OLS ratio and a dynamic OLS ratio using a rolling window approach. In particular, we focus on the interest of considering a model that introduces a wedge between the stochastic processes followed by the spot portfolio and the future contract to be used in the hedge. To that end we will use a utility criterion that incorporates the effect of transaction costs in order to simulate real market decisions.

After estimating the model with data for 2010-2013, we use the obtained estimates out-of-sample along 2014. Our results show that the decision of entering into a cross-hedge is heavily influenced by the risk-profitability preferences of each investor. Under the variance reduction measure, the one used to optimize our GARCH and OLS strategies, or under left-tail risk measures, the risk reduction is important and the decision may be to hedge if the investor have strong aversion to these risks. On the contrary, measures based on aversion to the profitability reduction, asymmetry and kurtosis may result in the decision of leaving the spot position unhedged. Our results also show that, when a cross-hedge is performed between a stock and the corresponding index future, the dynamic strategy based on the conditional moments estimated from a GARCH offers advantages over static and dynamic OLS ratios in most cases. This suggest that, independently of the relationship found in the First Chapter[10] between the GARCH advantage and the immaturity of the futures market for the hedge of a stock index with its own future, the GARCH strategy also poses an advantage in cross-hedging operations even in a mature market**.** Such result is consistent with Third Chapter [11] results, hedging portfolios with the index future, and it suggests the adequacy of the dynamic GARCH strategies to design cross-hedge strategies of stocks using index futures.

The rest of the paper is organized as follows. Section 2 comments on different approaches to hedging effectiveness, Section 3 describes the data used in the analysis and the results of testing for the presence of a common ARCH feature in the spot and futures markets returns. Section 4 summarizes the model used to determine the optimal hedge ratio and the estimation of the relevant conditional moments. Section 5 presents the empirical evidence on the evolution of conditional moments over the analyzed period and a simulation of hedging trading is performed to test the potential implementation of the model. Section 6 summarizes and makes concluding remarks.

2. SOME CONSIDERATIONS ON MEASURES OF HEDGING EFFECTIVENESS, TIME VARYING HEDGING AND HEDGING MODELS

Hedging effectiveness measures

The controversy in the literature regarding hedging strategies concentrates around three main aspects. In the first place, a key issue related to hedging effectiveness is the election of the effectiveness measure itself that will determine the function to optimize in order to calculate the optimum hedge ratio. Several measures have been proposed in the literature the simplest and most common approach being Variance Reduction, from which the Minimum Variance (MV) ratio is usually obtained. Many authors consider that other aspects should be taken into account to measure effectiveness, like economic aspects of the hedge related to the mean-variance approach and different utility specifications or the downside risk that does not equally weights both tails of the returns distribution. Those criteria derive in hedging effectiveness measures like the Certainty Equivalent, (CE), Value at Risk (VaR), Conditional Value at Risk (CVaR) o Expected Shortfall (ES), Lower Partial Moments (LPM), semi variance, etc. One important limitation we have found is that studies often compare hedging effectiveness for different strategies and for very complex models under effectiveness measures different from the criterion they have used to characterize the optimal hedge ratio, leading to potentially biased conclusions. In our opinion, these comparisons among different strategies are only appropriate when evaluated under the measurement for which they have been optimized. If they are used as a secondary criteria to compare hedging strategies it should not be forgotten that the hedge ratio was chosen with a variance reduction goal in mind.

There are authors that design strategies optimized for a specific measure and then they properly compare such strategies effectiveness under that measure and add other secondary measures to characterize the distribution of returns of the hedged portfolio. Among those who optimize the strategies for specific measures and compare strategies upon such measures, Yang et al. (2009) implements optimized ratios for expected utility under a quadratic utility function. Their results comparing unitary or OLS ratios versus optimized ratios in terms of expected utility depend on markets and risk aversion parameters or the dynamic model specification. Chang (2010) considers mean-variance and VaR optimized ratios and compares their hedging effectiveness against naive and

MV ratios. He concludes that the MV ratio has the highest effectiveness in terms of variance reduction, with a reduction in VaR similar to the one from the optimum VaR ratio. Furthermore, the optimum VaR ratio barely differs in terms of VaR and variance when compared with the MV ratio. Hung et al. (2006) also derive ratios optimized for zero-VaR and mean-variance target functions and compare them with the MV ratio with better results in terms of returns but almost similar or worse results in terms of variance reduction, depending on the confidence levels and the numerical values of risk aversion parameters. Unfortunately, these authors do not explore out-of-the sample results in order to evaluate hedging performance in a practical implementation. Lien and Tse (2000) employ optimized ratios for MV and LPM. Even though the LPM hedge ratio performs slightly better than the MV ratio in some cases in terms of LPM effectiveness, both ratios are almost equal in most comparisons and LPM ratios are worse in terms of the level of variance they achieve for the hedged portfolio.

When ratios are optimized for a particular effectiveness measure another important limitation is the number of restrictive hypothesis that need to be made regarding utility function specification, risk aversion parameters, minimum returns and maximum loss thresholds, confidence intervals, etc., that result in different ratios for the same strategy or effectiveness measure. Finally, from an accounting point of view, hedge effectiveness is the extent to which changes in the hedging instrument offset changes in the hedged assets in terms of value or cash flows and that is independent of utility or considerations on the tails of the returns distribution. In summary, with regard to the effectiveness measure, an examination of these and other contributions shows the lack of uniformity or concluding significant results in favour of one or other strategy. Together with added significant complexity and the need to make less than trivial assumptions,[15] takes us to focus on the MV approach when choosing the hedge ratio and evaluating its effectiveness. Besides, we complement this approach with the practical implementation of decision criteria based on a utility function, incorporating the level of Utility, the CE, VaR, CVaR, and LPM measures to study characteristics of the distribution of hedged returns that may influence the decision of hedging the spot position. The minimum variance approach is intuitive and simple in terms of implementation, and we enrich it with the consideration of the structure of the futures prices process proposed by Lafuente

[15] Or assuming the purpose of the hedge that is different for different hedgers, something that should be taking into account when choosing a hedging strategy.

and Novales (2003) and allowing our estimation model for asymmetric effects, as we point out later. We are adopting the position of an investor that wants to minimize value or cash flow fluctuations in his spot position by means of the most effective hedge under such terms.

Static versus time varying hedging

A second core matter is the time evolution of the hedge ratio. There is a controversy in the literature as to whether dynamic hedging, using ratios that change with the new information that arrives to the market, is superior to static hedge ratios, like the unitary ratio or those that are estimated with the available data and then applied unchanged to out-of-sample simulations. Several authors (Myers (1991); Kroner and Sultan (1993); Park and Switzer (1995); Lafuente and Novales (2003); Cotter and Hanly (2012)) show the superiority of dynamic ratios while other authors (Lien & Tse (2002); Cotter and Hanly (2006); Park and Jei (2010)) conclude in the opposite direction. Comparisons in many cases are not straight.

Sim and Zurbruesgg (2001) do not find a conclusive superior performance for either static or dynamic hedge ratios. Cotter and Hanly (2012) find dynamic ratios to be superior to static ratios under different effectiveness measures for crude oil. In another work, Cotter and Hanly (2005), find that static and dynamic minimum variance strategies compare against each other quite differently under different effectiveness measures, but dynamic strategies reduce volatility for the hedged position in a variety of international financial indexes and their corresponding futures. Using a complex regime-switching approach, Salvador and Aragó (2013) conclude in favour of dynamic hedge ratios. Sukcharoen et al.(2015) analyze gasoline optimal hedging strategies with futures and ETF to find that in terms of the variance of the hedged position, static ratios perform better than dynamic ratios in high volatility crisis. However, under other metrics, dynamic ratios have an advantage, depending on the market and the time period. Another important limitation found in the literature is that either the evaluation is done only in-sample, not evaluating predictable capabilities from a practical standpoint, or it considers daily rebalances, something that is neither realistic nor economic, due to transaction costs. We believe that markets react to the new information arriving to the market and that this effect can be successfully captured by GARCH structures that would lead to dynamic strategies. To analyze the extent to which such advantage exists as well as to discuss what is the optimal rebalancing frequency for the hedged portfolio is one of the purposes of this paper.

Hedging models

In the third place, when it comes to estimating the hedge ratios, many different techniques are employed, ranging from the simplest static approaches to very complex dynamic ones. For example, some studies use such a simple method as the ordinary least squares (OLS) technique (e.g., see Ederington, 1979; Malliaris and Urrutia, 1991). However, others use more complex methods such as the conditional heteroscedastic (ARCH or GARCH) method (e.g., see Baillie and Myers, 1991), the random coefficient method (e.g., see Grammatikos and Saunders, 1983), the cointegration method (e.g., see Ghosh, 1993), or the cointegration-heteroscedastic method (e.g., see Kroner and Sultan, 1993). Lien and Shrestha (2007) has suggested the use of wavelet analysis to match the data frequency with the hedging horizon. Lien and Shrestha (2010) also suggests the use of multivariate skew-normal distribution in estimating the minimum variance hedge ratio. Several authors (Salvador and Aragó (2013); Hsu et al. (2008) implement regime-switch GARCH estimation models; Sukcharoen and Choi (2015) implement copula based models with tailored distributions.

With regard to the trade-off between complex models or simple models, Salvador and Aragó (2013) study effectiveness in hedging international indexes with their corresponding futures and find that regime-switching nonlinear GARCH models are slightly superior to OLS or BEKK in terms of MV, VaR and CVaR but depending on the specification or markets, they sometimes perform worse than OLS or BEKK. Sukcharoen and Choi (2015) study gasoline hedge strategies and find that, in terms of variance reduction, OLS ratios do better than DCC GARCH or than copula based models during crisis period with high volatility. During normal periods, the DCC GARCH is superior to both, OLS or complex copula models, although copula models perform sometimes better than DCC GARCH or OLS in terms of other measures. However, in our opinion, such improved performance is not obtained consistently. Hsu et al. (2008) study the hedging effectiveness of ratios estimated upon copula models for several international indexes and their futures and find that copula GARCH models are superior to DCC GARCH model in some markets but also find the opposite for other markets. It is clear that regime switching and copula based models allow for taking into account tailored distributions for returns and changes in the market dynamics that may prevent dynamic strategies to fail in high volatility periods, when investors care more about risk. However, it is unclear that they improve dynamic effectiveness, and in our opinion, they do not solve favourably the trade-off between complexity and effectiveness. In our analysis we will compare the minimum variance ratio estimated through a GARCH model, the GARCH ratio, with the minimum variance ratios estimated through ordinary least squares, the OLS ratios. For the latter we will use a static OLS ratio calculated with in-sample information and kept constant through the out-of-sample simulations, and a dynamic OLS ratio that is recalculated with each 10 days of new out-of-sample information. The DCC GARCH hedge ratio optimized for minimum variance that is also recalculated with new out-of-sample information but on a daily basis.

3. DATA

We have divided the data in two windows. The first window is used to estimate the model with data from 2010 to 2013. The second window covers the full 2014 year and it is used as out-of-sample data to test the effectiveness of simulated hedging operations. We have used daily closing prices on six Spanish stocks: Telefónica (TEF), Banco Santander (SAN), Banco Bilbao Vizcaya (BBVA), Repsol (REP), Iberdrola (IBE), and Banco Popular (POP). These stocks account for 60% of negotiated volume on the Spanish Stock Exchange main index IBEX-35 over 2014.

Several reasons justify considering the cross-hedging of positions on individual stocks using IBEX 35 futures contracts when there is a more natural hedge with their own SSF: (*i*) SSF volume is not comparable to that of futures on IBEX 35[16]. (*ii*) There are many days without SSF negotiation. (iii) The settlement price of a SSF is not calculated to represent the best market price, as it is the case of the price of the IBEX 35 future contract; instead it is daily adjusted to the cost of carry valuation[17]. (iv) Uncertainty on dividend payment dates in Spain discourages investors to enter in SSF contracts. We have

[16] Over the 2010-2014 period, the nominal negotiated in these contracts was about 3% of the nominal negotiated in IBEX 35 futures contracts.

[17] Given current low interest rates, the cost of carry valuation used by MEFF often results in settlement prices equal to the closing spot price. This happens in 72% of the total out-of sample observations.

used daily settlement prices for the IBEX 35 futures contract nearest to maturity, implementing the rollover of futures contracts the day of before expiration. This seems to be the appropriate date for the rollover, as shown in the First Chapter.

We have used daily settlement prices for Spanish futures SSF contracts on the selected stocks that account for 92% of 2010-2014 negotiated volume for all SSF listed in MEFF *(Mercado Español de Futuros Financieros)*, Spanish derivatives market.[18] Time series of prices for the nearest to maturity contract have been obtained by rollover of one contract to the next the day before expiration.

For spot data we have used daily closing prices. Figure 1 shows log returns for the he six selected stocks and IBEX 35 future contract. We have made the required prices adjustments for splits and counter splits. We have not adjusted the individual stocks by dividends, these are discounted from the spot price at the time of payment and therefore underestimates the true return from holding the various securities.[19]

Panel A in Table 1 presents the main statistics for the return series computed as the first differences of the logs of closing prices between successive trading days. The sample mean for daily returns is negligible, as expected. Likewise, as is usually the case with daily time series, stock return distributions show excess kurtosis and some skewness, characteristics generally associated with conditional heteroskedasticity. Banco Popular (POP) shows acute kurtosis because of several extreme values due to a heavily discounted capital increase. Panel B in Table 1 we present some descriptive data on relative volumes for spot and futures markets as well as for the selected stocks and SSF.

In order to empirically justify the use of our proposed model, which assumes the existence of a noise common to spot and futures returns, together with a noise specific to the yield of the derivative instrument, we follow the approach of Engle and Kozicki (1993) to test the null hypothesis that there is a linear combination of the returns from the two markets which is homoskedastic, i.e., that the ARCH feature is common to both return series. The empirical values of the test statistic for the stocks and IBEX 35 future

[18] MEFF and BME *(Bolsas y Mercados Españoles)* statistics bulletins and author estimations.
[19] Following Laws and Thompson (2005), excluding dividends from the returns seemed to have little effect on the performance of the hedges and this exclusion seems to be generally accepted by researchers.

returns are presented in Table 2, systematically leading to rejection of the hypothesis of a common ARCH feature. This pattern is consistent with the specific noise interpretation of the proposed theoretical model. In the case of stock returns and the corresponding SSF, the null hypothesis is only rejected in Banco Popular (POP) stock, and in Repsol (REP) stock for some lags. We believe that this result is strongly related to the settlement price calculation for SSF.

4. OPTIMAL DYNAMIC HEDGING

4.1. The optimal hedge ratio

Derivative markets often have some imperfections, making the process for spot and future prices to display significant differences. To characterize the difference between the volatility of spot and futures we adopt the model proposed by Lafuente and Novales (2003). These authors consider that the noise in the process for futures prices is the aggregate of the same noise in the process for spot prices noise and a second noise factor that captures the discrepancy between spot and future prices beyond the cost of carry. In accordance with this idea, the optimal minimum variance ratio can be restated as follows:

$$\frac{h_t^*}{b_t} = \frac{\sigma_{s,t}^2 + \rho_{12,t}\sigma_{s,t}\sigma_{N,t}}{\sigma_{s,t}^2 + \sigma_{N,t}^2 + 2\rho_{12,t}\sigma_{s,t}\sigma_{N,t}} = \frac{1 + \rho_{12,t}\delta_t}{1 + \delta_t^2 + 2\rho_{12,t}\delta_t} \tag{1}$$

where $\delta_t = \frac{\sigma_{N,t}}{\sigma_{S,t}}$ represents the relative importance of the specific noise as compared to the common noise and $\rho_{12,t}$ represents the correlation between both noises.

4.2. Estimating time-varying variances for the theoretical noises

To estimate the conditional variance-covariance matrix of spot and market returns and to capture the correlation between the common and specific innovations we use the bivariate DCC-GARCH model proposed in Engle (2002). Ku *et al.* (2007) compare the DCC-GARCH model proposed in Engle (2002) with the constant correlation specification, and find evidence of greater hedging effectiveness from the time-varying correlation model. Hsu et al. (2008) compare DCC with complex copula-based models with little or negative trade-off in terms of effectiveness and complexity.

Given the empirical evidence we mentioned in the First Chapter[10] on the existence of a cointegration relationship between the logarithms of spot market and futures market prices, our specification of the conditional mean incorporates an error correction term that we define as the "spread" between the logarithm of the spot price and the future price. If there is no cointegration relationship, the inclusion of an error term does not bias the estimation of the rest of parameters since the error term parameters are then not statistically significant. On the other hand, if cointegration relationship is disregarded and it exists, it could lead to a smaller than optimal position in the hedging instrument and a relatively poor hedging performance as shown by Lien (1996). Hence, we represent the dynamics of spot and futures markets returns, $r_{s,t}$ and $r_{f,t}$, through the following error correction model:

$$\begin{pmatrix} r_{s,t} \\ r_{f,t} \end{pmatrix} = \sum_{i=1}^{n} \begin{pmatrix} \alpha(i)_{11} & \alpha(i)_{12} \\ \alpha(i)_{21} & \alpha(i)_{22} \end{pmatrix} \begin{pmatrix} r_{s,t-i} \\ r_{f,t-i} \end{pmatrix} + \begin{pmatrix} \gamma_s \\ \gamma_f \end{pmatrix} (\ln S_{t-1} - \ln F_{t-1}) + \begin{pmatrix} \varepsilon_{s,t} \\ \varepsilon_{f,t} \end{pmatrix} \tag{2}$$

where Ω_{t-1} is the information set at time t-1 and Σ_t is the conditional variance-covariance matrix of innovations[20].

We represent the time evolution of the elements in the conditional variance-covariance matrix by a GARCH (p, q) specification with possible asymmetric effects:

$$\begin{pmatrix} \sigma^2_{s,t} \\ \sigma^2_{f,t} \end{pmatrix} = \begin{pmatrix} \omega_s \\ \omega_f \end{pmatrix} + \sum_{i=1}^{p} \begin{pmatrix} A(i)_{11} & A(i)_{12} \\ A(i)_{21} & A(i)_{22} \end{pmatrix} \begin{pmatrix} \varepsilon^2_{s,t-i} \\ \varepsilon^2_{f,t-i} \end{pmatrix} + \sum_{j=1}^{q} \begin{pmatrix} B(j)_{11} & B(j)_{12} \\ B(j)_{21} & B(j)_{22} \end{pmatrix} \begin{pmatrix} \sigma^2_{s,t-1} \\ \sigma^2_{f,t-1} \end{pmatrix}$$

$$+ \begin{pmatrix} D_{11} & 0 \\ 0 & D_{22} \end{pmatrix} \begin{pmatrix} \varepsilon^2_{s,t-1} I_{s,t-1} \\ \varepsilon^2_{f,t-1} I_{f,t-1} \end{pmatrix}, \qquad I_{k,t-1} = \begin{Bmatrix} 1, if\ \varepsilon_{k,t-1} < 0,\ k = s,f \\ 0, if\ \varepsilon_{k,t-1} \geq 0,\ k = s,f \end{Bmatrix} \tag{3}$$

[20] We estimated the model using a t-Student conditional distribution for the innovations when evaluating the log-likelihood function. We used a Normal distribution when convergence was not possible under t-Student specification. In the Third Chapter[11] we analyze hedging simulations obtained under different probability distributions without finding significant differences in hedging effectiveness.

The diagonal elements in matrices A_i capture the ARCH effects, while the diagonal elements in matrices B_j measure the own GARCH effects. The elements in matrix D measure the asymmetry effects. The off-diagonal elements capture the cross-effects in volatility and innovations spill over effects. The structure p=q=1 appears to be a valid specification to capture the volatility dynamics[21].

With regard to the conditional correlation, the dynamics of the DCC model is:

$$\rho_{sf,t} = (1-\kappa_1-\kappa_2)\overline{\rho} + \kappa_1\rho_{sf,t-1} + \kappa_2\Psi_{t-1}$$

$$\Psi_{t-1} = \frac{\sum_{h=1}^{m}\eta_{s,t-h}\eta_{f,t-h}}{\sqrt{\left(\sum_{h=1}^{m}\eta^2_{s,t-h}\right)\left(\sum_{h=1}^{m}\eta^2_{f,t-h}\right)}},\ \eta_{k,t} = \frac{\varepsilon_{k,t}}{\sigma_{k,t}}, k = s, f \tag{4}$$

When p=q=1 the variances of spot and futures markets are:

$$\sigma^2_{s,t} = \omega_s + \varepsilon^2{}_{s,t-1}(A_{11} + D_{11}I_{s,t-1}) + A_{12}\varepsilon^2{}_{f,t-1} + B_{11}\sigma^2_{s,t-1} + B_{12}\sigma^2_{f,t-1} \tag{5}$$

$$\sigma^2_{f,t} = \omega_f + A_{21}\varepsilon^2{}_{s,t-1} + \varepsilon^2{}_{f,t-1}(A_{22} + D_{22}I_{f,t-1}) + B_{21}\sigma^2_{s,t-1} + B_{22}\sigma^2_{f,t-1} \tag{6}$$

With the numerical values obtained from expressions (5) and (6) after estimation, we could use the expressions in Lafuente and Novales (2003) for the conditional variances, the conditional correlation between spot and futures markets returns and the conditional correlation between common and specific noises:

$$\hat{\sigma}^2_{f,t} = \hat{\sigma}^2_{s,t} + \hat{\sigma}^2_{N,t} + 2\hat{\sigma}_{s,t}\hat{\sigma}_{N,t}\hat{\rho}_{12,t} \tag{7}$$

$$\hat{\sigma}_{sf,t} = \hat{\sigma}^2_{s,t} + \hat{\sigma}_{s,t}\hat{\sigma}_{N,t}\hat{\rho}_{12,t} \tag{8}$$

$$\hat{\rho}_{sf,\mathrm{t}} = \frac{\hat{\sigma}^2_{s,t} + \rho_{12,t}\sigma_{s,t}\sigma_{N,t}}{\sqrt{\hat{\sigma}^2_{s,t}(\hat{\sigma}^2_{s,t} + \hat{\sigma}^2_{N,t} + 2\rho_{12,t}\sigma_{s,t}\sigma_{N,t})}}, \tag{9}$$

$$\hat{\rho}_{12,t} = \frac{\hat{\sigma}_{sf,t} - \sigma^2_{s,t}}{\hat{\sigma}_{s,t}\sqrt{\hat{\sigma}^2_{s,t} + \hat{\sigma}^2_{f,t} - 2\hat{\sigma}_{sf,t}}} \tag{10}$$

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[21] To assess the ability of the estimated model to capture the main statistical characteristics of market returns, a battery of standard specification tests was employed, including the Ljung-Box Q-statistics on the standardized residual and their squared values. All series of residuals were found to be free of serial correlation at the 5% significance level with the exception of POP spot standardized residuals that were to be free of serial correlation at the 1% significance level.

5. EMPIRICAL EVIDENCE

5.1. Spillover effects

Panel A in Table 3 shows the parameters obtained in the estimation of the DCC-GARCH model for cross-hedges of the six stocks with IBEX 35 future. A bivariate t-Student conditional distribution for the innovations and asymmetric effects were considered in all cases. We find very little coefficient estimates statistically significant in the return equations, although we do find significant cross-effects in the variance equations and significant asymmetry effects in volatility. As Figure 1 shows there is volatility clustering in spot market returns. This is confirmed by significant coefficients for the GARCH and ARCH terms in spot and also in futures variance equations. Our empirical findings also suggest not only that there is a clear volatility transmission channel between spot and futures market returns but also that the transmission occurs asymmetrically. The impact of the futures market on the spot market is stronger, with the exception of BBVA and REP where the transmission appears is the opposite way, from the spot to the futures market.

The cointegration relationship between the stock spot position and the index future in the case is rejected and is consistent with the error correction parameters that turn out not to be significant or they are close to zero.

Panel B in Table 3 shows the parameters obtained in the estimation of the DCC-GARCH model for the SSF hedge. In all cases we tried to find the most parsimonious specification possible. In the case of SAN, BBVA and REP, a bivariate t-Student conditional distribution was considered for the innovations, while a bivariate Normal distribution was used for TEF, IBE and POP[22]. Coefficients for ARCH and GARCH terms are statistically significant in both market returns. The parameters that represent the cross-effects in mean and variance also show significant cross-market interactions. The error correction term parameters that determine the speed of adjustment to short-run price deviations from their long-run equilibrium are also significant in half the stocks

[22] However, these estimates are not too satisfactory, since they suggest a t-Student with a very small number of degrees of freedom, far away from the normality assumed for the rest of the stocks.

evidencing that the markets or, in this case, the settlement calculation made by the market supervisor, limits the possible deviations between spot and future prices over time. Finally, significant asymmetric effects are present for all the stocks except TEF and REP that rejected the asymmetry term in order to achieve convergence.

5.2. Decomposing the hedge ratio

We observe in Table 4 that the average relative importance of the specific noise as compared to the common noise, $\delta_t = \dfrac{\sigma_{N,t}}{\sigma_{S,t}}$, is higher as the correlation between the spot and the futures contract decreases. In cross-hedges with IBEX 35 futures, δ_t for 2014 ranges from 0.43 of Banco Santander (SAN) to 0.74 of Banco Popular (POP). These estimates of δ_t for the hedge with IBEX 35 futures are comparable with those in the Third Chapter[11] when hedging stock portfolios. They obtain estimates of the δ_t ratio between $\delta_t = 0.24$ for the portfolio with highest correlation with IBEX 35, and $\delta_t = 0.55$ for portfolios less liquid and less correlated with IBEX 35.

On the other hand, in hedges with SSF the δ_t average for 2014 ranges from 0.08 Banco Popular (POP) to 0.33 for Telefónica (TEF). These values for δ_t, with the exception of Telefónica (TEF), are low when compared to the results found in the First Chapter[10] for hedges between several international indexes and their futures, where they obtain an average δ_t of 0.25. We believe this last result to be a consequence of price corrections towards the cost of carry valuation in the case of Spanish SSF settlement prices made by MEFF. In Figure 3 we show δ_t evolution for the different hedges. We observe that δ_t in SSF hedges is very close to zero with very abrupt punctual jumps. This is due to both, the lack of quality prices that are adjusted to the cost of carry valuation by MEFF and show a flat low δ_t, and to the uncertainty regarding dividend payments that causes jumps in futures prices and δ_t when such date is not properly anticipated by the market. We believe these jumps, responsible for the biggest part of the SSF specific noise, do not cause persistence in volatility, and therefore, SSF hedging effectiveness can hardly benefit from a GARCH modelization. We observe the same behaviour in the conditional correlation between spot and SSF returns in Figure 4. As a result of this behaviour in SSF prices, we can already anticipate that the GARCH strategy may not yield any advantage for SSF and we have serious doubts that even the OLS ratios, which seems to provide the best effectiveness under variance reduction performance measure for SSF, is a feasible strategy from a practical implementation standpoint.

Figures 4 and 5 show that conditional correlation and ratios in the case of cross-hedges with IBEX 35 do not move together among the different stocks. This is numerically confirmed, as presented in Table 10, by very low cross-correlations for this variables among the different stocks.

5.3. Cross-hedging and hedging simulations

In order to test the prediction capabilities of our framework we simulate out-of-sample hedging strategies.[23] After an initial in-sample estimation for the period 2010-2013, we incorporate new information in 10-day windows of out-of-sample observations estimating again the model for each new window. We then rebalance the hedge using the new information and we apply the rebalanced hedge to the following 10 trading days. We think that 10 days is a good compromise between changing the hedge too often with consequently higher transaction costs or to keep it constant at the cost of a potential loss in effectiveness. Once the entire series of hedge ratios had been obtained for 2014, we implemented two different hedging strategies by applying to each 10-day trading window (the time interval [*t*+1, *t*+10]) either the hedge ratio estimated the last day in each rolling sample (at time t) or the average hedge ratio computed over the last five trading days in each sample (from *t*-4 to *t*). Finally, we compared the reduction in volatility achieved by each of the two strategies based on a GARCH ratio, the strategy based on a static OLS ratio and the strategy based on a dynamic OLS:

$$Hedging\ effectiveness = 100x\left(\frac{Volatility(hedged\ \ position) - Volatility(Unhedged\ \ position)}{Volatility(Unhedged\ \ position)}\right)$$

where volatility is measured by the standard deviation of returns over the period chosen for comparison.

[23] We consider a position in IBEX 35 futures equal to the spot position value in each stock multiplied by the hedge ratio assuming that the spot position is large enough to be covered by IBEX-35 future. If needed, fine adjustments to complete the position are also made by Mini IBEX operations

We present results obtained throughout the out-of-sample period, as well as over each quarter. Table 4 presents the empirical results as if optimal ratios were rebalanced daily. Table 5 and Table 6 present the empirical results from applying the two hedging strategies described in the previous paragraph. When hedging with the IBEX 35 future we find an almost systematic advantage of the GARCH ratio over the OLS ratios. On the other hand, as expected, the results obtained in the hedge with SSF do not exhibit any advantage over the OLS ratios, which suggests that the incorporation of transaction costs would make the application of a dynamic hedging strategy with the GARCH ratio even less interesting. However, as mentioned before, even though the hedge with IBEX 35 futures is, in theory, less effective than the hedge with SSF, the lack of liquidity in the latter may take the investor to hedge with index futures. In that respect, a GARCH hedge ratio can be more appropriate than an OLS hedge ratio, which is consistent with the conclusions we will see in the Third Chapter[11].

With regard to the decision to hedge, in addition to this automatic rebalance, we have defined a decision criteria. Under this criteria, the cross-hedge with the IBEX 35 futures contract is rebalanced only if the expected utility of rebalancing exceeds the expected utility from keeping the hedge ratio from the previous 10-day window. In this utility decision criteria we have incorporated the associated transaction costs. Thus we have simulated the practical situation where a financial agent estimates the model every few days and decides to rebalance the position or to maintain the previous portfolio unchanged. To this end, we consider a specification of the expected utility function: $E_t U(x) = E_t(x) - \gamma\sigma_t^2(x)$ where x are either the spot or hedged returns. The level of risk is measured by the conditional variance of returns and γ denotes the degree of risk aversion, transaction costs are denoted by τ and assuming a zero expected return, an investor would have an expected utility of $-\tau - \gamma\sigma_t^2(x^{**})$ if the hedge ratio were rebalanced from h_t^* / b_t to h_t^{**} / b_t, as against an expected utility equal to $-\gamma\sigma_t^2(x^*)$ if the hedge ratio remains the same. Hence, an investor will adjust the hedging position if and only if:

$$\tau - \gamma(\sigma_{s,t}^2 - 2\sigma_{sf,t}(h_t^{**} / b_t) + \sigma_{f,t}^2(h_t^{**} / b_t)^2) > -\gamma(\sigma_{s,t}^2 - 2\sigma_{sf,t}(h_t^* / b_t) + \sigma_{f,t}^2(h_t^* / b_t)^2)$$

where (h_t^{**} / b_t) denotes the hedge ratio applied as the result of the last revision of the futures position.

To implement this strategy, we consider a risk aversion coefficient of 4 and average costs of 0.0031%[24] for the IBEX 35 future. The optimal ratio obtained in the last trading day in each rolling sample, *t,* is applied to the following 10 trading days (from *t*+1 to *t*+10). Thus, over the out-of-sample period, we use the utility comparison rule every 10 trading days. The results obtained for each market are presented in Table 7 in terms of aggregate utility for 2014, as well as in terms of the utility gain relative to the non-hedged market position. Cross-hedges improve the unhedged utility in all the stocks and therefore, based on this volatility-utility criteria, the decision would be to hedge all of them. The utility gain provided by the decision criteria in cross-hedges with the IBEX 35 future is very similar to the one emerging from applying the GARCH ratio from the previous period and both are significantly higher than the one obtained under both OLS ratios in REP, IBE, TEF simulations and very similar in SAN, BBVA and POP simulations.

5.4. Downside risk and profitability

Investors care about volatility but also about losses and profitability. The decision to cross-hedge based exclusively in volatility reduction and its utility may be difficult to assess without additional considerations. To this end, we consider different criteria as additional performance measures that provide information on the returns distribution of the hedged portfolio that an investor might want to take into account when taking his decision. We want to note, that the effectiveness values we analyze, are obtained by simulations of a strategy optimized for minimum variance. Hedging strategies optimized for other criteria may change the conclusions, although in the results observed in the literature, as commented in Section 2, minimum variance strategies compare also well under different measures with strategies optimized for such measures. We consider the Certainty Equivalent (CE) for an investor with exponential utility on wealth W: $U(W) = -\exp(-\gamma W)$, with $\gamma > 0$ being the coefficient of absolute risk aversion. The Certainty Equivalent that the investor would accept for not taking the risk of the uncertain return on his/her portfolio is approximately given by:

[24] This corresponds to the MEFF commission of 0.225 € for the Mini IBEX future contract and the 2014 average value of the IBEX 35 future contract, as we assume that corrections in the ratio are made by Mini IBEX operations, and to the transaction costs associated to the December 2014 mean half bid-ask spread, 2.97 € for the Mini IBEX future contract.

$$CE \approx \mu - \frac{1}{2}\gamma\sigma^2 + \frac{\tau}{6}\gamma^2\sigma^3 - \frac{\kappa - 3}{24}\gamma^3\sigma^4$$

Where μ, σ, τ and κ denote the mean, standard deviation, skewness and kurtosis of a given portfolio. Such an investor would ask for a lower Certainty Equivalent the higher the volatility and the excess kurtosis. The Certainty Equivalent would also be lower in the presence of negative skewness. Considering higher order moments should be important for any investor: A high kurtosis can indicate that the hedge can be wrong anytime, while a negative skewness indicates that the portfolio is more likely to lead to losing than to making money. We can then compare the different hedges for an investor with a specific level of risk aversion ($\lambda = 4$) on the basis of the moments of the hedged portfolio.

We also consider Lower Partial Moments (LPM) that take into account only the part of the distribution of returns below certain threshold τ. The LPM measure is attributed to Bawa (1975). We consider 0% as the adequate threshold since our purpose for the hedge would be to obtain a not lower than 0% profitability.

$$LPM_{K,\tau}(X) = \mathrm{E}\left[\left|\min(X - \tau, 0)\right|^k\right]^{1/k} = \mathrm{E}\left[\max(\tau - \mathrm{X}, 0)^k\right]^{1/k}$$

Under this threshold the first order LPM, k=1, can be interpreted as the expected average loss:

$$LPM_{1,\tau}(X) = \mathrm{E}\left(\left|\min(X - \tau, 0)\right|\right) = \mathrm{E}\left[\max(\tau - \mathrm{X}, 0)\right]$$

Table 8 displays the mean return, volatility, skewness, excess kurtosis, Certainty Equivalent, VaR, CVaR, ES and $LPM_{1,0}$ for each cross-hedge with IBEX 35 futures contract as well as for the spot position in the stock. Table 9 displays the relative change in all these measures of each strategy against the static OLS strategy. The CE measure clearly favors GARCH strategies with the exception of SAN. VaR and ES at 1% favor OLS strategies in some cases and GARCH strategy in others but VaR and ES at 5% and LPM 1 measures clearly favor GARCH strategies with the exception of SAN stock, the same than in the CE comparison. In summary, GARCH strategies outperform, under these measures, OLS static strategy and the proposed OLS dynamic strategy in 5 out of the 6 stocks analyzed.

With respect to the effects of hedging as compared to the unhedged position, hedging reduces volatility relative to the spot position in all cases. Kurtosis increases significantly with the hedge indicating the possibility of large positive and negative extreme returns. With the exception of Banco Santander (SAN), cross-hedges produce asymmetry to move toward the negative tails, suggesting the possibility of large negative returns. All cross-hedging strategies with IBEX 35, with the exception of POP, reduce the CE, suggesting that reductions in profitability offset gains in volatility reduction under the specified utility function. Increases in negative asymmetry and excess kurtosis do not change the CE performance classification of the different strategies, which depends mainly of the profitability risk trade-off. VaR and ES are reduced by the hedge in all cases[25]. $LPM_{1,0}$ is improved very significantly in all cases, in consistency with the reduction in VaR.

The results do not show a clear conclusion regarding to hedge or not to hedge, as this will depend on each investor preferences. An investor concerned just about risk, understood as the variability of the returns, or just about left tail risk or downside risk, should enter into a cross-hedge with IBEX-35 futures contracts for the six analyzed stocks. But a common situation is that investors are concerned not only about minimization of the two mentioned risks but also about maximization of profits. When we measure the average profitability of the cross-hedge and we compare it with the unhedged position profitability we find an average reduction in absolute profitability of 11.5% for the six stocks along 2014, ranging from a 9% reduction for IBE to a 14.7 % reduction for SAN. The CE measure takes into consideration profitability and risk together, and if an investor preferences were represented by this measure, the recommendation would be to leave the spot position unhedged with the exception of POP. Nonetheless, we have implemented a particular specification of the utility function from which the EC is derived and used a level of risk aversion of 4. If we raise the level of aversion to 5.2 the recommendation would be to also hedge BBVA, at level 8 to hedge TEF and SAN, at level 10 to hedge REP, and at level 16 to hedge IBE. The election among the different strategies is quite easier than the decision to hedge since GARCH strategies perform better than OLS strategies in general terms. Transaction costs associated to the more dynamic strategies are negligible, thus a daily rebalance of the

[25] with the exception of Iberdrola (IBE) at 1% confidence, for which they remain unchanged.

GARCH strategy would have implied a cost of 0.027% over 2014, the 10-day rebalance 0,010%, the decision criteria 0,005% and the dynamic OLS 0,0003%.

6. CONCLUSIONS

This paper analyzes the use of SSF and index futures as hedging and cross-hedging instruments for the underlying stock of the SSF contract. In particular we analyze the suitability of the decision of hedging and if a dynamic conditional strategy improves the effectiveness of OLS ratios hedges. To this end, we have used the theoretical model of interpretation of futures prices proposed by Lafuente and Novales (2003), which includes a specific noise in the futures price in addition to the common noise that it is assumed to share with the spot market price, according to the cost-of-carry valuation model. We have adopted the minimum variance as optimization and effectiveness criteria.

We have analyzed daily settlement data on futures markets and daily closing data on spot markets over the 2010-2014 period for six stocks: Telefónica, Banco Santander, BBVA, Repsol, Iberdrola and Banco Popular. The existence of a noise specific to the futures market, as included in our econometric model, is validated by the rejection of the existence of a common ARCH feature in stocks/IBEX 35 futures returns and for some stocks/SSF returns. We estimate a bivariate error-correction model with a DCC-GARCH structure and possible asymmetric effects to represent the conditional mean, variance and covariance of future and spot market returns. After the initial estimation we simulate out-of-sample hedging strategies.

The results shows that the decision of hedging or leaving the spot position in any of the stocks is heavily influenced by each investor particular preferences. Hedgers with an objective of minimizing the variability of returns or with an objective of minimizing the downside risk under variance reduction, VaR, ES and LPM measures should consider to hedge. On the other hand, we cannot forget the impact of the hedge in the profitability of the position, something that up to certain extent most investors will be concerned about. When we take profitability into consideration through the CE measure, the recommendation of hedging would remain in place only for one stock, Iberdrola (IBE). Nonetheless, if we gradually raise risk aversion level, the decision of hedging would extend to more stocks, and something similar may happen if we change the utility function specification.

The results also show that GARCH dynamic strategies in the case of SSF hedge do not lead to a systematic improvement in hedging effectiveness, as compared to the improvement that would be obtained by applying a minimum variance OLS strategy. On the contrary, in the case of cross-hedging operations between individual stocks and the IBEX 35 index future, GARCH dynamic strategies do lead to a systematic advantage over minimum variance OLS static and dynamic ratios in terms of variance reduction and also in terms of left tail and returns excess based performance measures.

This advantage from the GARCH ratio in the cross-hedges with IBEX 35 futures is in line with the results obtained by Lafuente and Novales (2003) for 1993-1996 and with the results in the Third Chapter. The results obtained in the First Chapter[10] for different international indexes and their nearest to maturity futures contracts for 1993-1996, did not show a significant advantage for the GARCH ratio over a static strategy, suggesting that in mature future markets the time-varying noise could not be exploited, in line with Roll et al. (2007) who presented evidence that liquidity enhances the efficiency of the futures pricing system.

We believe that the main reason to explain the GARCH advantage found in a mature market like the IBEX 35 futures is the nature of the cross-hedge itself. The higher specific noise related to the common noise allows for exploiting better volatility clusters through a GARCH dynamic ratio since the quick corrections of any arbitrage opportunity that happens when the index is hedged by its future contract do not happen, or at least do not happen so quickly, in cross-hedges even when applied to a mature market. The arbitrage opportunities, if any, are not so evident and easy to accomplish in a cross-hedge as it is also seen in the Third Chapter[11] when working with portfolios. Therefore, we believe a dynamic stochastic strategy based on the specified GARCH structure is superior to OLS strategies for cross-hedging operations with an index future contract even in a mature futures market. It would be advisable to conduct further investigation on different rebalance periods in order to assess the optimum rebalance strategy.

With regard to the effectiveness of the SSF hedge operations, this market is not mature enough yet to ensure the replication of the results obtained in our analysis for a practical implementation due to volume and price issues that make the cross-hedge with the index future a more realistic approach despite of being apparently less effective. Total return SSF are expected to incorporate to the Spanish Futures Market in the medium term and that will be an opportunity to re-evaluate the hedging effectiveness of using single stock future contracts as well as a to see whether a dynamic stochastic strategy can provide any advantage.

REFERENCES

Andani, A., Lafuente, J.A. and Novales, A., 2009, Liquidity and hedging effectiveness under futures mispricing: international evidence, *Journal of Futures Markets, 29*, 1050-1066.

Baillie, R. and Myers, R., 1991, Bivariate GARCH estimation of the optimal commodity futures hedge, *Journal of Applied Econometrics,* 6, 2, 109-124.

Chang, K., 2010, The optimal value-at-risk hedging strategy under bivariate regime switching ARCH framework, *Applied Economics,* 43:21, 2627-2640.

Chen, S., Lee, C. and Shrestha, K., 2013, Futures hedge ratios: a review, *Encyclopedia of Finance,* 871-890. Springer, New York.

Cotter, J. and Hanly, J., 2005, Re-evaluating hedging performance, *MPRA,* 3512.

Cotter, J. and Hanly, J., 2012, Hedging effectiveness under conditions of asymmetry, *European Journal of Finance*, 18-2, 135-147.

Ederington, L.H., 1979. The hedging performance of the new futures markets. *Journal of finance,* 34, 157-170.

Engle, R.F., 2002, Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models, *Journal of Business and Economic Statistics,* 20, 339-350.

Engle, R.F. and Kozicki, S., 1993, Testing for common features, *Journal of Business and Economic Statistics,* 11*,* 369–380.

Grammatikos, T. and Saunders, A., 1983, Stability and the hedging performance of foreign currency futures, *Journal of Futures Markets*, 3, 3, 295-305.

Hsu, C., Tseng, C. and Wang, Y., 2008, Dynamic hedging with futures: A copula based GARCH model, *Journal of Futures Markets,* 28, Issue II, 1095-1116.

Hung, J., Chiu, C. and Lee, M., 2006, Hedging with zero-value at risk hedge ratio, *Applied Financial Economics,* 16, 259-269.

Kroner, K.F and Sultan, J., 1993, Time-varying distributions and dynamic hedging with foreign currency futures, *Journal of Financial and Quantitative Analysis,* 28, 535-551.

Ku, Y.H., Chen, H. and Chen, K., 2007, On the application of the dynamic conditional correlation model in estimating optimal time-varying hedge ratios, *Applied Economics Letters, 7*, 503-509.

Lafuente, J.A. and Novales, A., 2003, Optimal hedging under departures from the cost-of-carry valuation: Evidence from the Spanish stock index futures market, *Journal of Banking & Finance,* 27, 1053-1078.

Laws, J. and Thompson, J., 2005, Hedging effectiveness of stock index futures, *Financial Modelling and Risk Management,* 163, 1, 177-191.

Lien, D., 1996, The effect of the cointegration relationship on futures hedging: A note, *Journal of Futures Markets,* 16, 773-780.

Lien, D. andShrestha, K., 2007, An empirical analysis of the relationship between hedge ratio and hedging horizon using wavelet analysis, *Journal of Futures Markets*, 27, 2, 127-150.

Lien, D. and Shrestha, K., 2010, Estimating optimal hedge ratio: a multivariate skew-normal distribution approach, *Applied Financial Economics,* 20, 8, 627-636.

Lien, D. and Tse, Y., 2000, Hedging downside risk with futures contracts, *Applied Financial Economics,* 10, 163-170.

Lien, D. and Tse, Y., 2002, Some recent developments in futures hedging, *Journal of Economic Surveys,* 17, 357-396.

Malliaris, A. and Urrutia, J., 1991, The impact of the lengths of estimation periods and hedging horizons on the effectiveness of a hedge: Evidence from foreign currency futures, *Journal of Futures Markets*, 11, 3, 271-289.

Myers, R., 1991. Estimating time varying hedge ratio on futures markets. *Journal of Futures Markets,* 11, 39-53.

Park, T.H. and Switzer, L.N., 1995, Bivariate GARCH estimation of the optimal hedge ratios for stock index futures: A note, *Journal of Futures Markets,* 15, 61–67.

Park, S. and Jei, Y., 2010, Estimation and hedging effectiveness of time-varying hedge ratio: Flexible bivariate GARCH approaches, *Journal of Futures Markets*, 30, 71-99.

Roll, R., Schwartz, E. and A. Subrahmanyam, 2007, Liquidity and the law of one price: The case of the futures-cash basis, *Journal of Finance*, 52, 5, 2201-2234.

Salvador, E. and Aragó, V., 2013, J*ournal of Futures Markets,* 34, 4, 374-398.

Sim, A. and Zurbruegg, R., 2001, Dynamic hedging effectiveness in South Korean index futures and the impact on the Asian financial crisis, *Asia-Pacific Financial Markets, 8, 237-258.*

Sukcharoen, K., Choi, H. and Leatham, D., 2015, Optimal gasoline hedging strategies using futures contracts and exchange-traded funds, *Applied Economics,* 47, 32, 3482-3498.

Yang, M. and Lai, Y., 2009, An out-of-sample comparative analysis of hedging performance of stock index futures: dynamic versus static hedging, *Applied Financial Economics,* 19:13, 1059-1072.

Appendix 1. - Tables

TABLE 1. Descriptive statistics on spot market returns and descriptive data on spot and futures markets.

Panel A. Descriptive statistics of daily spot market returns

Stocks	TEF	SAN	BBVA	REP	IBE	POP	
Mean	0.000	0.000	0.000	0.000	0.000	-0.001	
Standar deviation	0.016	0.022	0.023	0.019	0.018	0.026	
Skewness	-0.09	0.62	0.59	0.23	0.08	0.48	
Excess kurtosis	4.28	7.73	5.85	3.71	4.96	3.89	
Futures	TEF	SAN	BBVA	REP	IBE	POP	IBEX 35
Mean	0.000	0.000	0.000	0.000	0.000	-0.001	0.000
Standar deviation	0.016	0.022	0.023	0.019	0.018	0.026	0.016
Skewness	0.03	0.65	0.60	0.28	0.20	0.48	0.33
Kurtosis	4.04	7.58	5.93	3.67	5.37	3.82	5.77

Note: 2010-2014 data. Daily basis.

Panel B Other descriptive data on spot and futures markets

	TEF	SAN	BBVA	REP	IBE	POP	IBEX 35
Stocks							
2014 volatility	17%	17%	21%	21%	23%	23%	18%
2014 IBEX 35 correlation	0.83	0.91	0.90	0.78	0.74	0.71	1.00
2014 Volume (€ Mill) *	52,160	89,439	61,684	29,623	32,451	19,193	492,876
% s IBEX Volume	10.6%	18.1%	12.5%	6.0%	6.6%	3.9%	100.0%
% Weight in IBEX	11.6%	18.5%	10.2%	4.5%	7.3%	1.9%	
Futures contracts 2010-2014							
Days with volume	1,271	1,273	1,270	1,243	1,090	965	1,273
Days without volume	2	0	3	30	183	308	0
% days with volume	100%	100%	100%	98%	86%	76%	100%
Volume (€ Mill)**	35,621	17,741	18,692	11,222	1,758	2,932	2,847,006
% Total SSF	37%	19%	20%	12%	2%	3%	
% IBEX 35 futures	1%	1%	1%	0%	0%	0%	

* Ordinary operations. ** Estimated based on contract volume and average price

TABLE 2. Testing for common ARCH features. Stocks and IBEX 35 Future. Engle and Kozicki test.

k	1	2	3	4	5	6	7	8	9	10
Min TR^2										
TEF	4.4	16.2	25.8	37.9	40.0	42.7	49.0	51.2	52.0	53.3
SAN	4.8	15.6	20.6	22.6	27.8	34.0	35.7	37.2	48.5	51.6
BBVA	7.0	8.7	17.7	26.7	32.8	33.9	34.6	36.8	60.8	64.2
REP	8.7	11.1	11.3	24.4	33.8	39.8	39.9	42.5	43.2	43.8
IBE	3.8	7.2	14.8	17.7	18.4	30.2	31.9	35.5	40.5	45.8
POP	13.9	17.9	18.2	43.4	44.9	46.7	48.4	50.0	52.2	63.5
Critical values										
a=0.05	6.0	11.1	15.5	19.7	23.7	27.6	31.4	35.2	38.9	42.6
a=0.01	9.2	15.1	20.1	24.7	29.1	33.4	37.6	41.6	45.6	49.6

Notes: The first panel shows the minimum T*R^2 in a set of regressions of $(r_{s,t}-dr_{f,t})^2$ on k lags of $r^2_{s,t}$, $r^2_{f,t}$ and $r_{s,t}r_{f,t}$, over a grid of values for d, where T denotes the sample size. The last two rows show critical values at the α-significance level.

TABLE 3. Maximum Likelihood estimation of the parameters involved in the DCC-GARCH model. Panel A presents parameters of the IBEX 35 future and stocks bivariate model and Panel B presents parameters of the stocks and SSF bivariate model.

Panel A. IBEX 35 future cross-hedge.

	TEF	SAN	BBVA	REP	IBE	POP
Spot mean equation						
α_{11}	0.030	0.080	0.087	-0.032	0.094	0.036 *
α_{12}	0.015	-0.048	-0.033	0.074	-0.022	0.097 **
γ_s	0.069	0.072	0.044	-0.031	-0.022	0.000 **
Futures mean equation						
α_{21}	-0.038	0.055	0.043	0.012	0.106 *	-0.004
α_{22}	0.109	-0.013	-0.015	0.053	-0.040	0.047 **
γ_s	0.055 *	0.020	0.006	0.025	-0.006	0.112 **
Spot Variance equation						
ω_s ***	0.007	0.087 **	0.020	0.009 **	0.003 *	0.244 **
A_{11}	0.068	-0.014	0.004	-0.020	0.065	0.190 **
A_{12}	-0.019	0.060	0.039	0.060	-0.023 **	-0.110 **
B_{11}	0.737	-0.874 *	0.861 **	0.979 **	0.850 **	0.366 **
B_{12}	0.151	2.505 **	0.052	-0.084	0.082 **	0.329 **
D_1	0.100	0.049	0.100 *	0.070 *	0.059 **	-0.053
Futures Variance equation						
ω_f ***	0.007	0.018 **	0.008	0.006 **	0.003 **	0.002 **
A_{21}	-0.039	0.031	0.037	0.003	0.098 **	-0.012 **
A_{22}	0.037	-0.030	-0.047	0.003	-0.086 **	-0.009 *
B_{21}	0.071	-0.514 *	-0.022	0.023	-0.125 **	0.052 **
B_{22}	0.854 *	1.554 **	0.934 **	0.904 **	1.075 **	0.884 **
D_2	0.120	0.106 **	0.137 **	0.099 **	0.057 **	0.187 **
Correlation dynamics						
κ_1	0.100	0.022	0.036 *	0.021 *	0.050 **	0.014 **
κ_2	0.799 *	0.727 *	0.916 **	0.968 **	0.911 **	0.986 **
Shape	5.212 *	5.473 *	6.461 **	5.489 **	6.028 **	4.534 **

* Significant at the 5% level
** Significant at the 1% level
*** Multiplied by 1,000

TABLE 3. Maximum Likelihood estimation of the parameters involved in the DCC-GARCH model. Panel A presents parameters of the IBEX 35 future and stocks bivariate model and Panel B presents parameters of the stocks and SSF bivariate model.

Panel B. SSF hedge.

	TEF	SAN	BBVA	REP	IBE	POP
Spot mean equation						
α_{11}	0.106	-0.336 **	-0.168 **	-0.004 **	0.045 **	-0.191 **
α_{12}	-0.035	0.352 **	0.249 **	-0.002 **	0.064 **	0.274 **
γ_s ***	0.205 **	0.069	-0.050	-0.019 **	-0.003	-0.125
Futures mean equation						
α_{21}	0.103	-0.150 **	0.073 *	0.002 **	0.088 **	0.128 **
α_{22}	-0.051	0.168 **	0.008	-0.007 **	0.024 **	-0.047
γ_s ***	0.244 **	0.071	-0.051	-0.014 **	0.067 **	0.042
Spot Variance equation						
ω_s	0.010 *	0.371 **	0.195 *	0.329 **	0.018 **	0.000
A_{11}	-0.055 *	0.423 **	-0.618 *	0.199 **	0.156 **	-0.113 **
A_{12}	0.208 **	0.413 **	1.311 **	-0.008 **	0.099 **	0.095 **
B_{11}	0.392 **	0.745 **	0.687 **	0.732 **	0.533 **	1.037 **
B_{12}	0.434 *	0.157	0.200 **	-0.042 **	0.228 **	-0.063 *
D_1		2.608 **	2.584 **		-0.041 **	0.087 **
Futures Variance equation						
ω_f	0.029	0.393 **	0.187 *	0.328 **	0.026 **	0.000
A_{21}	-0.015 **	0.316 **	1.166 **	0.034 **	0.166 **	-0.092 **
A_{22}	0.140 *	0.487 **	-0.465	0.157 **	0.073 **	0.074 **
B_{21}	0.281	0.198 *	0.068 **	-0.025 **	0.017 **	0.199 **
B_{22}	0.499 **	0.706 **	0.820 **	0.714 **	0.725 **	0.778 **
D_2		2.649 **	2.547 **		-0.018 **	0.086 **
Correlation dynamics						
κ_1	0.000 *	0.657 **	0.566 **	0.250 **	0.182 **	0.128 **
κ_2	0.171 *	0.324 **	0.411 **	0.750 **	0.000	0.852 **
Shape		2.027 **	2.045 **	2.193 **		

* Significant at the 5% level
** Significant at the 1% level
*** Multiplied by 1,000

TABLE 4. Out-of-sample hedging effectiveness simulations. σ change under daily rebalance of the hedge ratio. Panel A presents simulations of cross-hedges with IBEX 35 future and Panel B presents simulations of cross-hedges with SSF contracts.

Panel A: Cross-hedge with IBEX 35 futures contract.

	GARCH ratio	σ_s	δ_t	ρ_{sf}	ρ_{sgarch}	Hedging effectiveness. Variance reduction			Garch reduction excess vs	
						GARCH	OLS Dyn	OLS	OLS Dyn	OLS
TEF										
Q1	0.836	18.4%	0.520	0.839	0.525	**-45.9%**	-44.7%	-44.5%	-1.2%	-1.4%
Q2	0.818	14.9%	0.576	0.735	0.686	**-34.6%**	-31.9%	-31.7%	-2.6%	-2.9%
Q3	0.807	13.4%	0.547	0.827	0.409	**-41.7%**	-39.1%	-38.4%	-2.6%	-3.3%
Q4	0.824	23.3%	0.526	0.867	0.531	**-50.7%**	-49.7%	-49.5%	-1.0%	-1.2%
2014	0.821	17.5%	0.543	0.824	0.542	**-44.0%**	-42.4%	-42.1%	-1.6%	-1.9%
SAN										
Q1	1.358	20.5%	0.427	0.923	-0.222	-51.0%	-54.1%	**-55.1%**	3.0%	4.0%
Q2	1.313	17.1%	0.437	0.830	0.298	-40.6%	-42.0%	**-42.3%**	1.3%	1.6%
Q3	1.227	19.6%	0.419	0.866	0.322	**-48.1%**	-47.9%	-47.8%	-0.2%	-0.3%
Q4	1.272	29.2%	0.426	0.961	-0.036	-68.9%	**-71.3%**	-71.0%	2.4%	2.1%
2014	1.291	21.5%	0.427	0.908	0.086	-54.0%	-55.6%	**-55.8%**	1.6%	1.8%
BBVA										
Q1	1.397	26.8%	0.446	0.908	0.315	**-58.3%**	-57.4%	-57.4%	-0.8%	-0.8%
Q2	1.354	19.3%	0.458	0.852	0.433	-47.0%	-47.2%	**-47.2%**	0.2%	0.2%
Q3	1.314	21.1%	0.436	0.900	0.290	**-56.0%**	-55.3%	-55.2%	-0.7%	-0.8%
Q4	1.315	29.9%	0.442	0.914	0.117	**-57.9%**	-56.0%	-55.7%	-1.9%	-2.1%
2014	1.345	24.2%	0.445	0.895	0.280	**-55.2%**	-54.5%	-54.4%	-0.7%	-0.8%
REP										
Q1	0.910	16.8%	0.608	0.876	0.248	**-49.4%**	-45.7%	-43.2%	-3.8%	-6.3%
Q2	0.787	16.6%	0.696	0.314	0.805	**3.0%**	6.8%	8.8%	-3.8%	-5.8%
Q3	0.806	15.0%	0.642	0.850	0.544	**-46.3%**	-42.6%	-41.1%	-3.8%	-5.2%
Q4	0.895	25.1%	0.539	0.894	0.537	**-54.2%**	-54.1%	-53.3%	-0.1%	-0.9%
2014	0.845	18.3%	0.626	0.775	0.550	**-35.6%**	-33.2%	-31.6%	-2.4%	-4.0%
IBE										
Q1	0.696	13.2%	0.700	0.692	0.444	**-20.9%**	1.5%	5.0%	-22.5%	-25.9%
Q2	0.657	11.7%	0.700	0.747	0.689	**-32.9%**	-23.8%	-21.4%	-9.1%	-11.5%
Q3	0.607	12.4%	0.789	0.671	0.681	**-26.0%**	-5.6%	-2.0%	-20.4%	-24.0%
Q4	0.683	16.9%	0.656	0.828	0.365	**-42.5%**	-19.1%	-13.4%	-23.4%	-29.1%
2014	0.658	13.5%	0.716	0.740	0.531	**-30.8%**	-11.6%	-7.6%	-19.2%	-23.1%
POP										
Q1	1.433	44.2%	0.783	0.633	0.796	**-22.1%**	-20.4%	-20.3%	-1.7%	-1.8%
Q2	1.486	30.7%	0.748	0.780	0.792	**-34.8%**	-31.8%	-31.2%	-3.1%	-3.7%
Q3	1.315	27.3%	0.711	0.757	0.668	**-34.2%**	-34.2%	-34.0%	0.0%	-0.2%
Q4	1.300	44.0%	0.693	0.765	0.706	**-35.2%**	-34.6%	-34.2%	-0.7%	-1.0%
2014	1.386	36.9%	0.736	0.718	0.754	**-30.0%**	-28.8%	-28.6%	-1.2%	-1.4%

Notes: σs: Spot position standard deviation; δt: Specific noise/common noise; ρsf: Correlation between spot and futures returns; ρsGARCH: Correlation between spot position and the hedged portfolio with the GARCH strategy; OLSDyn: Dynamic ordinary least squares strategy, the ratio is recalculated each 10 days with new information and applied to the following 10 days; OLS: The ordinary least squares ratio is calculated with the in-sample information and kept constant. When GARCH ratio performs better results are marked red; Best results are marked in bold.

TABLE 4. Out-of-sample hedging effectiveness simulations. σ change under daily rebalance of the hedge ratio. Panel A presents simulations of cross-hedges with IBEX 35 future and Panel B presents simulations of cross-hedges with SSF contracts.

Panel B: Hedge with SSF futures contract.

	GARCH ratio	σ_s	δ_t	ρ_{sf}	ρ_{sgarch}	Hedging effectiveness. Variance reduction			Garch reduction excess vs	
						GARCH	OLS Dyn	OLS	OLS Dyn	OLS
TEF										
Q1	0.906	18.4%	0.321	1.000	0.941	-89.9%	**-94.7%**	-94.3%	4.7%	4.4%
Q2	0.891	14.9%	0.331	1.000	0.938	-88.9%	**-94.6%**	-94.5%	5.8%	5.6%
Q3	0.887	13.4%	0.332	1.000	0.992	-88.9%	-94.0%	**-94.5%**	5.1%	5.6%
Q4	0.932	23.3%	0.317	1.000	0.896	-93.5%	-95.7%	**-95.9%**	2.2%	2.5%
2014	0.903	17.5%	0.326	1.000	0.916	-90.7%	-94.9%	**-94.9%**	4.2%	4.2%
SAN										
Q1	0.970	20.5%	0.178	0.999	0.510	-95.1%	**-95.1%**	-95.1%	0.0%	0.0%
Q2	0.957	17.1%	0.185	0.998	0.374	-91.9%	-93.5%	**-93.5%**	1.6%	1.6%
Q3	0.989	19.6%	0.121	1.000	0.213	-94.1%	-96.7%	**-96.9%**	2.6%	2.8%
Q4	0.986	29.2%	0.099	1.000	0.307	-97.1%	-97.3%	**-97.5%**	0.2%	0.4%
2014	0.976	21.5%	0.146	0.999	0.332	-94.8%	-95.8%	**-95.9%**	1.0%	1.1%
BBVA										
Q1	0.995	26.8%	0.069	1.000	0.003	**-97.1%**	-97.1%	-97.0%	0.0%	-0.1%
Q2	0.986	19.3%	0.117	0.999	0.365	-94.2%	-95.4%	**-95.4%**	1.3%	1.3%
Q3	0.991	21.1%	0.091	0.999	0.255	-96.0%	**-96.5%**	-96.5%	0.5%	0.5%
Q4	1.002	29.9%	0.016	1.000	-0.350	**-99.6%**	-99.4%	-99.3%	-0.3%	-0.3%
2014	0.993	24.2%	0.077	1.000	0.153	-96.6%	**-97.0%**	-97.0%	0.5%	0.4%
REP										
Q1	0.944	16.8%	0.169	0.997	0.427	-87.0%	**-92.3%**	-92.3%	5.3%	5.3%
Q2	0.958	16.6%	0.326	0.999	0.185	-93.2%	**-96.3%**	-96.3%	3.2%	3.1%
Q3	0.974	15.0%	0.084	0.997	0.414	-87.6%	-91.9%	**-91.9%**	4.3%	4.3%
Q4	1.000	25.1%	0.025	0.999	0.196	**-95.7%**	-95.1%	-95.1%	-0.6%	-0.5%
2014	0.967	18.3%	0.148	0.998	0.304	-90.7%	**-93.9%**	-93.9%	3.2%	3.2%
IBE										
Q1	0.896	13.2%	0.317	0.995	0.752	-78.4%	**-88.1%**	-88.1%	9.8%	9.8%
Q2	0.930	11.7%	0.275	0.996	0.678	-88.7%	**-90.7%**	-90.6%	2.0%	1.9%
Q3	0.941	12.4%	0.236	0.997	0.653	-90.0%	-91.1%	**-91.2%**	1.1%	1.2%
Q4	0.950	16.9%	0.277	0.996	0.264	-89.9%	-90.5%	**-90.5%**	0.5%	0.5%
2014	0.929	13.5%	0.272	0.996	0.565	-85.9%	-90.1%	**-90.1%**	4.1%	4.2%
POP										
Q1	0.997	44.2%	0.095	1.000	-0.028	-97.4%	**-97.8%**	-97.7%	0.4%	0.3%
Q2	0.995	30.7%	0.061	0.999	0.071	**-96.3%**	-96.2%	-96.1%	-0.1%	-0.2%
Q3	0.994	27.3%	0.080	0.999	0.027	-94.6%	**-94.7%**	-94.6%	0.0%	0.0%
Q4	0.997	44.0%	0.078	1.000	0.632	**-99.5%**	-98.5%	-98.2%	-1.1%	-1.3%
2014	0.996	36.9%	0.078	1.000	0.041	**-97.0%**	-97.0%	-96.9%	-0.1%	-0.2%

Notes: σs: Spot position standard deviation; δt: Specific noise/common noise; ρsf: Correlation between spot and futures returns; ρsGARCH: Correlation between spot position and the hedged portfolio with the GARCH strategy; OLSDyn: Dynamic ordinary least squares strategy, the ratio is recalculated each 10 days with new information and applied to the following 10 days; OLS: The ordinary least squares ratio is calculated with the in-sample information and kept constant. When GARCH ratio performs better results are marked red; Best results are marked in bold.

TABLE 5. Out-of-sample hedging effectiveness simulations. σ change. The hedge ratio obtained for the last day in each rolling sample is applied to the following 10 trading days. Panel A presents simulations of cross-hedges with IBEX 35 future and Panel B presents simulations of cross-hedges with SSF contracts.

Panel A: Cross-hedge with IBEX 35 futures contract.

	GARCH ratio	σ_s	δ_t	ρ_{sf}	ρ_{sgarch}	Hedging effectiveness. Variance reduction			Garch reduction excess vs	
						GARCH	OLS Dyn	OLS	OLS Dyn	OLS
TEF										
Q1	0.836	18.4%	0.520	0.839	0.516	-44.6%	**-44.7%**	-44.5%	0.2%	0.0%
Q2	0.870	14.9%	0.576	0.735	0.718	-29.9%	**-31.9%**	-31.7%	2.1%	1.8%
Q3	0.804	13.4%	0.547	0.827	0.369	**-42.0%**	-39.1%	-38.4%	-2.9%	-3.5%
Q4	0.822	23.3%	0.526	0.867	0.574	**-50.6%**	-49.7%	-49.5%	-0.9%	-1.2%
2014	0.833	17.5%	0.543	0.824	0.556	**-42.7%**	-42.4%	-42.1%	-0.3%	-0.6%
SAN										
Q1	1.347	20.5%	0.427	0.923	-0.221	-50.2%	-54.1%	**-55.1%**	3.9%	4.9%
Q2	1.327	17.1%	0.437	0.830	0.272	**-43.6%**	-42.0%	-42.3%	-1.7%	-1.3%
Q3	1.232	19.6%	0.419	0.866	0.311	**-49.2%**	-47.9%	-47.8%	-1.3%	-1.4%
Q4	1.299	29.2%	0.426	0.961	-0.057	-69.9%	**-71.3%**	-71.0%	1.4%	1.0%
2014	1.300	21.5%	0.427	0.908	0.065	-55.0%	-55.6%	**-55.8%**	0.6%	0.7%
BBVA										
Q1	1.412	26.8%	0.446	0.908	0.300	-57.2%	-57.4%	**-57.4%**	0.3%	0.3%
Q2	1.365	19.3%	0.458	0.852	0.446	-47.0%	-47.2%	**-47.2%**	0.3%	0.3%
Q3	1.327	21.1%	0.436	0.900	0.271	**-56.1%**	-55.3%	-55.2%	-0.8%	-0.9%
Q4	1.304	29.9%	0.442	0.914	0.188	**-57.7%**	-56.0%	-55.7%	-1.8%	-2.0%
2014	1.354	24.2%	0.445	0.895	0.291	**-55.0%**	-54.5%	-54.4%	-0.5%	-0.6%
REP										
Q1	0.931	16.8%	0.608	0.876	0.207	**-48.2%**	-45.7%	-43.2%	-2.5%	-5.0%
Q2	0.835	16.6%	0.696	0.314	0.797	**-0.2%**	6.8%	8.8%	-7.0%	-8.9%
Q3	0.803	15.0%	0.642	0.850	0.573	**-46.3%**	-42.6%	-41.1%	-3.7%	-5.1%
Q4	0.883	25.1%	0.539	0.894	0.565	-53.5%	**-54.1%**	-53.3%	0.6%	-0.1%
2014	0.860	18.3%	0.626	0.775	0.550	**-36.3%**	-33.2%	-31.6%	-3.2%	-4.7%
IBE										
Q1	0.728	13.2%	0.700	0.692	0.402	**-17.7%**	1.5%	5.0%	-19.2%	-22.7%
Q2	0.639	11.7%	0.700	0.747	0.685	**-33.2%**	-23.8%	-21.4%	-9.4%	-11.8%
Q3	0.599	12.4%	0.789	0.671	0.676	**-24.4%**	-5.6%	-2.0%	-18.8%	-22.4%
Q4	0.697	16.9%	0.656	0.828	0.321	**-40.3%**	-19.1%	-13.4%	-21.2%	-26.9%
2014	0.662	13.5%	0.716	0.740	0.501	**-29.2%**	-11.6%	-7.6%	-17.6%	-21.5%
POP										
Q1	1.452	44.2%	0.783	0.633	0.728	-18.7%	**-20.4%**	-20.3%	1.7%	1.7%
Q2	1.512	30.7%	0.748	0.780	0.806	**-34.8%**	-31.8%	-31.2%	-3.0%	-3.6%
Q3	1.323	27.3%	0.711	0.757	0.649	**-34.6%**	-34.2%	-34.0%	-0.4%	-0.6%
Q4	1.296	44.0%	0.693	0.765	0.712	**-35.7%**	-34.6%	-34.2%	-1.1%	-1.5%
2014	1.399	36.9%	0.736	0.718	0.723	-28.8%	**-28.8%**	-28.6%	0.0%	-0.2%

Notes: σs: Spot position standard deviation; δt: Specific noise/common noise; ρsf: Correlation between spot and futures returns; ρsGARCH: Correlation between spot position and the hedged portfolio with the GARCH strategy; OLSDyn: Dynamic ordinary least squares strategy, the ratio is recalculated each 10 days with new information and applied to the following 10 days; OLS: The ordinary least squares ratio is calculated with the in-sample information and kept constant. When GARCH ratio performs better results are marked red; best results are marked in bold.

TABLE 5. Out-of-sample hedging effectiveness simulations. σ change. The hedge ratio obtained for the last day in each rolling sample is applied to the following 10 trading days. Panel A presents simulations of cross-hedges with IBEX 35 future and Panel B presents simulations of cross-hedges with SSF contracts.

Panel B: Hedge with SSF futures contract.

	GARCH ratio	σ_s	δ_t	ρ_{sf}	ρ_{sgarch}	Hedging effectiveness. Variance reduction			Garch reduction excess vs	
						GARCH	OLS Dyn	OLS	OLS Dyn	OLS
TEF										
Q1	0.907	18.4%	0.321	1.000	0.934	-89.0%	**-94.7%**	-94.3%	5.7%	5.4%
Q2	0.879	14.9%	0.331	1.000	0.938	-87.5%	**-94.6%**	-94.5%	7.1%	7.0%
Q3	0.890	13.4%	0.332	1.000	0.993	-88.9%	-94.0%	**-94.5%**	5.1%	5.6%
Q4	0.924	23.3%	0.317	1.000	0.879	-94.2%	-95.7%	**-95.9%**	1.5%	1.8%
2014	0.899	17.5%	0.326	1.000	0.917	-90.2%	-94.9%	**-94.9%**	4.7%	4.7%
SAN										
Q1	0.978	20.5%	0.178	0.999	0.432	-94.9%	**-95.1%**	-95.1%	0.2%	0.2%
Q2	0.962	17.1%	0.185	0.998	0.522	-91.0%	-93.5%	**-93.5%**	2.5%	2.6%
Q3	0.999	19.6%	0.121	1.000	0.173	**-97.1%**	-96.7%	-96.9%	-0.4%	-0.2%
Q4	0.952	29.2%	0.099	1.000	0.557	-92.5%	-97.3%	**-97.5%**	4.8%	5.0%
2014	0.974	21.5%	0.146	0.999	0.446	-93.4%	-95.8%	**-95.9%**	2.4%	2.4%
BBVA										
Q1	1.001	26.8%	0.069	1.000	-0.040	**-97.1%**	-97.1%	-97.0%	0.0%	-0.1%
Q2	0.989	19.3%	0.117	0.999	0.105	**-95.5%**	-95.4%	-95.4%	-0.1%	-0.1%
Q3	0.986	21.1%	0.091	0.999	0.168	-95.7%	**-96.5%**	-96.5%	0.8%	0.8%
Q4	0.999	29.9%	0.016	1.000	0.297	**-99.7%**	-99.4%	-99.3%	-0.3%	-0.4%
2014	0.993	24.2%	0.077	1.000	0.114	-96.9%	**-97.0%**	-97.0%	0.2%	0.2%
REP										
Q1	0.951	16.8%	0.169	0.997	0.547	-82.8%	**-92.3%**	-92.3%	9.6%	9.5%
Q2	0.974	16.6%	0.326	0.999	0.455	-95.5%	**-96.3%**	-96.3%	0.8%	0.8%
Q3	0.970	15.0%	0.084	0.997	0.481	-87.9%	-91.9%	**-91.9%**	4.0%	4.0%
Q4	1.000	25.1%	0.025	0.999	0.197	**-95.7%**	-95.1%	-95.1%	-0.6%	-0.5%
2014	0.972	18.3%	0.148	0.998	0.386	-89.9%	**-93.9%**	-93.9%	4.0%	4.0%
IBE										
Q1	0.924	13.2%	0.317	0.995	0.772	-85.8%	**-88.1%**	-88.1%	2.3%	2.3%
Q2	0.929	11.7%	0.275	0.996	0.635	-89.1%	**-90.7%**	-90.6%	1.6%	1.5%
Q3	0.925	12.4%	0.236	0.997	0.734	-89.3%	-91.1%	**-91.2%**	1.8%	1.9%
Q4	0.969	16.9%	0.277	0.996	0.205	**-90.9%**	-90.5%	-90.5%	-0.4%	-0.4%
2014	0.935	13.5%	0.272	0.996	0.570	-88.8%	-90.1%	**-90.1%**	1.3%	1.3%
POP										
Q1	0.993	44.2%	0.095	1.000	0.394	-96.5%	**-97.8%**	-97.7%	1.3%	1.2%
Q2	0.995	30.7%	0.061	0.999	0.054	**-96.3%**	-96.2%	-96.1%	-0.1%	-0.2%
Q3	0.996	27.3%	0.080	0.999	0.003	**-94.7%**	-94.7%	-94.6%	-0.1%	-0.1%
Q4	0.996	44.0%	0.078	1.000	0.681	**-99.3%**	-98.5%	-98.2%	-0.8%	-1.1%
2014	0.995	36.9%	0.078	1.000	0.198	-96.7%	**-97.0%**	-96.9%	0.3%	0.2%

Notes: σs: Spot position standard deviation; δt: Specific noise/common noise; ρsf: Correlation between spot and futures returns; ρsGARCH: Correlation between spot position and the hedged portfolio with the GARCH strategy; OLSDyn: Dynamic ordinary least squares strategy, the ratio is recalculated each 10 days with new information and applied to the following 10 days; OLS: The ordinary least squares ratio is calculated with the in-sample information and kept constant. When GARCH ratio performs better results are marked red; Best results are marked in bold.

TABLE 6. Out-of-sample hedging effectiveness simulations. σ change. The average hedge ratio over the last five trading days in each rolling sample is applied to the following 10 trading days. Panel A presents simulations of cross-hedges with IBEX 35 future and Panel B presents simulations of cross-hedges with SSF contracts.

Panel A: Cross-hedge with IBEX 35 futures contract.

	GARCH ratio	σ_s	δ_t	ρ_{sf}	ρ_{sgarch}	Hedging effectiveness. Variance reduction			Garch reduction excess vs	
						GARCH	OLS Dyn	OLS	OLS Dyn	OLS
TEF										
Q1	0.872	18.4%	0.520	0.839	0.575	-43.2%	**-44.7%**	-44.5%	1.6%	1.4%
Q2	0.797	14.9%	0.576	0.735	0.606	-31.7%	**-31.9%**	-31.7%	0.3%	0.0%
Q3	0.818	13.4%	0.547	0.827	0.383	**-42.2%**	-39.1%	-38.4%	-3.1%	-3.8%
Q4	0.801	23.3%	0.526	0.867	0.548	**-49.8%**	-49.7%	-49.5%	-0.1%	-0.4%
2014	0.823	17.5%	0.543	0.824	0.541	**-42.5%**	-42.4%	-42.1%	-0.1%	-0.4%
SAN										
Q1	1.376	20.5%	0.427	0.923	-0.185	-47.8%	-54.1%	**-55.1%**	6.2%	7.2%
Q2	1.331	17.1%	0.437	0.830	0.270	**-44.2%**	-42.0%	-42.3%	-2.2%	-1.9%
Q3	1.225	19.6%	0.419	0.866	0.293	**-48.8%**	-47.9%	-47.8%	-0.9%	-1.0%
Q4	1.292	29.2%	0.426	0.961	-0.077	-69.8%	**-71.3%**	-71.0%	1.5%	1.1%
2014	1.305	21.5%	0.427	0.908	0.068	-54.4%	-55.6%	**-55.8%**	1.2%	1.4%
BBVA										
Q1	1.416	26.8%	0.446	0.908	0.309	**-57.5%**	-57.4%	-57.4%	0.0%	0.0%
Q2	1.338	19.3%	0.458	0.852	0.418	-46.9%	-47.2%	**-47.2%**	0.3%	0.3%
Q3	1.337	21.1%	0.436	0.900	0.281	**-55.5%**	-55.3%	-55.2%	-0.2%	-0.2%
Q4	1.270	29.9%	0.442	0.914	0.138	**-58.2%**	-56.0%	-55.7%	-2.3%	-2.5%
2014	1.343	24.2%	0.445	0.895	0.276	**-55.1%**	-54.5%	-54.4%	-0.6%	-0.7%
REP										
Q1	0.939	16.8%	0.608	0.876	0.220	**-47.8%**	-45.7%	-43.2%	-2.2%	-4.7%
Q2	0.807	16.6%	0.696	0.314	0.790	**-1.1%**	6.8%	8.8%	-7.9%	-9.8%
Q3	0.807	15.0%	0.642	0.850	0.569	**-45.1%**	-42.6%	-41.1%	-2.5%	-3.9%
Q4	0.881	25.1%	0.539	0.894	0.566	**-54.2%**	-54.1%	-53.3%	-0.1%	-0.9%
2014	0.856	18.3%	0.626	0.775	0.550	**-36.6%**	-33.2%	-31.6%	-3.4%	-4.9%
IBE										
Q1	0.725	13.2%	0.700	0.692	0.382	**-18.5%**	1.5%	5.0%	-20.1%	-23.5%
Q2	0.653	11.7%	0.700	0.747	0.710	**-33.2%**	-23.8%	-21.4%	-9.4%	-11.9%
Q3	0.610	12.4%	0.789	0.671	0.693	**-24.1%**	-5.6%	-2.0%	-18.5%	-22.1%
Q4	0.689	16.9%	0.656	0.828	0.323	**-42.1%**	-19.1%	-13.4%	-23.0%	-28.7%
2014	0.667	13.5%	0.716	0.740	0.503	**-29.9%**	-11.6%	-7.6%	-18.3%	-22.3%
POP										
Q1	1.527	44.2%	0.783	0.633	0.751	-18.7%	**-20.4%**	-20.3%	1.7%	1.6%
Q2	1.454	30.7%	0.748	0.780	0.783	**-34.5%**	-31.8%	-31.2%	-2.7%	-3.3%
Q3	1.348	27.3%	0.711	0.757	0.657	**-34.8%**	-34.2%	-34.0%	-0.6%	-0.8%
Q4	1.304	44.0%	0.693	0.765	0.721	**-35.9%**	-34.6%	-34.2%	-1.3%	-1.6%
2014	1.412	36.9%	0.736	0.718	0.733	**-28.9%**	-28.8%	-28.6%	-0.1%	-0.3%

Notes: σs: Spot position standard deviation; δt: Specific noise/common noise; ρsf: Correlation between spot and futures returns; ρsGARCH: Correlation between spot position and the hedged portfolio with the GARCH strategy; OLSDyn: Dynamic ordinary least squares strategy, the ratio is recalculated each 10 days with new information and applied to the following 10 days; OLS: The ordinary least squares ratio is calculated with the in-sample information and kept constant. When GARCH ratio performs better results are marked red; Best results are marked in bold.

TABLE 6. Out-of-sample hedging effectiveness simulations. σ change. The average hedge ratio over the last five trading days in each rolling sample is applied to the following 10 trading days. Panel A presents simulations of cross-hedges with IBEX 35 future and Panel B presents simulations of cross-hedges with SSF contracts.

Panel B: Hedge with SSF futures contract.

	GARCH ratio	σ_s	δ_t	ρ_{sf}	ρ_{sgarch}	Hedging effectiveness. Variance reduction			Garch reduction excess vs	
						GARCH	OLS Dyn	OLS	OLS Dyn	OLS
TEF										
Q1	0.909	18.4%	0.321	1.000	0.915	-89.7%	**-94.7%**	-94.3%	5.0%	4.7%
Q2	0.898	14.9%	0.331	1.000	0.952	-90.4%	**-94.6%**	-94.5%	4.3%	4.1%
Q3	0.890	13.4%	0.332	1.000	0.986	-88.9%	-94.0%	**-94.5%**	5.1%	5.7%
Q4	0.913	23.3%	0.317	1.000	0.925	-92.7%	-95.7%	**-95.9%**	3.0%	3.2%
2014	0.902	17.5%	0.326	1.000	0.901	-90.7%	-94.9%	**-94.9%**	4.2%	4.3%
SAN										
Q1	0.981	20.5%	0.178	0.999	0.467	-94.8%	**-95.1%**	-95.1%	0.3%	0.3%
Q2	0.955	17.1%	0.185	0.998	0.361	-91.2%	-93.5%	**-93.5%**	2.3%	2.3%
Q3	0.994	19.6%	0.121	1.000	-0.070	**-96.9%**	-96.7%	-96.9%	-0.3%	-0.1%
Q4	0.964	29.2%	0.099	1.000	0.522	-94.9%	-97.3%	**-97.5%**	2.4%	2.6%
2014	0.974	21.5%	0.146	0.999	0.389	-94.4%	-95.8%	**-95.9%**	1.4%	1.5%
BBVA										
Q1	1.001	26.8%	0.069	1.000	-0.035	**-97.1%**	-97.1%	-97.0%	0.0%	0.0%
Q2	0.985	19.3%	0.117	0.999	-0.006	-94.7%	-95.4%	**-95.4%**	0.7%	0.7%
Q3	0.996	21.1%	0.091	0.999	0.324	-96.5%	**-96.5%**	-96.5%	0.0%	0.0%
Q4	0.989	29.9%	0.016	1.000	0.145	-97.8%	**-99.4%**	-99.3%	1.5%	1.5%
2014	0.993	24.2%	0.077	1.000	0.085	-96.6%	**-97.0%**	-97.0%	0.4%	0.4%
REP										
Q1	0.951	16.8%	0.169	0.997	0.547	-82.8%	**-92.3%**	-92.3%	9.6%	9.5%
Q2	0.961	16.6%	0.326	0.999	0.204	-94.3%	**-96.3%**	-96.3%	2.0%	2.0%
Q3	0.968	15.0%	0.084	0.997	0.472	-86.9%	-91.9%	**-91.9%**	5.0%	5.0%
Q4	1.000	25.1%	0.025	0.999	0.192	**-95.7%**	-95.1%	-95.1%	-0.6%	-0.5%
2014	0.968	18.3%	0.148	0.998	0.353	-89.5%	**-93.9%**	-93.9%	4.4%	4.4%
IBE										
Q1	0.879	13.2%	0.317	0.995	0.742	-79.6%	**-88.1%**	-88.1%	8.5%	8.5%
Q2	0.927	11.7%	0.275	0.996	0.637	-89.5%	**-90.7%**	-90.6%	1.2%	1.1%
Q3	0.932	12.4%	0.236	0.997	0.740	-89.7%	-91.1%	**-91.2%**	1.4%	1.5%
Q4	0.957	16.9%	0.277	0.996	0.135	**-90.8%**	-90.5%	-90.5%	-0.3%	-0.3%
2014	0.922	13.5%	0.272	0.996	0.553	-86.8%	-90.1%	**-90.1%**	3.3%	3.3%
POP										
Q1	0.993	44.2%	0.095	1.000	0.434	-96.9%	**-97.8%**	-97.7%	0.9%	0.9%
Q2	0.994	30.7%	0.061	0.999	0.035	**-96.3%**	-96.2%	-96.1%	-0.1%	-0.2%
Q3	0.996	27.3%	0.080	0.999	0.007	**-94.7%**	-94.7%	-94.6%	-0.1%	-0.1%
Q4	0.995	44.0%	0.078	1.000	0.543	**-99.3%**	-98.5%	-98.2%	-0.8%	-1.1%
2014	0.995	36.9%	0.078	1.000	0.213	-96.8%	**-97.0%**	-96.9%	0.2%	0.1%

Notes: σs: Spot position standard deviation; δt: Specific noise/common noise; ρsf: Correlation between spot and futures returns; ρsGARCH: Correlation between spot position and the hedged portfolio with the GARCH strategy; OLSDyn: Dynamic ordinary least squares strategy, the ratio is recalculated each 10 days with new information and applied to the following 10 days; OLS: The ordinary least squares ratio is calculated with the in-sample information and kept constant. When GARCH ratio performs better results are marked red; Best results are marked in bold.

TABLE 7. Out-of-sample simulations of utility gains under different hedging strategies. Cross-hedge with the IBEX 35 future.

	TEF	SAN	BBVA	REP	IBE	POP
Aggregate utility						
Spot position	-0.152	-0.275	-0.332	-0.176	-0.098	-0.630
Unitary hedge ratio	-0.044	-0.051	-0.066	-0.067	-0.048	-0.351
OLS ratio	-0.041	-0.040	-0.049	-0.071	-0.054	-0.337
OLS dynamic ratio (*)	-0.041	-0.040	-0.050	-0.069	-0.049	-0.336
GARCH hedge ratio (**)	-0.041	-0.041	-0.049	-0.064	-0.031	-0.338
GARCH hedge ratio with decision criterion (***)	-0.039	-0.042	-0.050	-0.064	-0.033	-0.332
Utility gain on the spot position						
Unitary hedge ratio	70.9%	**81.6%**	80.1%	62.1%	51.2%	44.3%
OLS ratio	73.0%	**85.6%**	85.3%	59.6%	45.1%	46.5%
OLS dynamic ratio (*)	73.0%	85.4%	85.1%	60.9%	49.8%	46.6%
GARCH hedge ratio (**)	72.9%	85.1%	**85.3%**	63.6%	**68.5%**	46.4%
GARCH hedge ratio with decision criterion (***)	**74.4%**	84.6%	85.0%	**63.6%**	66.6%	**47.2%**

Notes: Best results are marked in bold. (*) The ratio is recalculated each 10 days with new information and applied to the following 10 days. (**) The hedge ratio is changed every 10 days, applying the ratio from the last trading day in each rolling sample. (***) The desirability of applying a new ratio was appraised every 10 days, the decision being made in accordance with the expected utility.

TABLE 8. Out-of-sample simulations. Hedging effectiveness measures under different cross-hedging strategies with IBEX 35 futures contract.

		GARCH 1	GARCH 2	GARCH 3	Utility decision	OLS D	OLS	Unhedged
TEF	Profitability *	5.62%	4.63%	3.91%	4.43%	3.26%	3.20%	13.35%
	Standard Deviation *	**9.78%**	10.04%	10.00%	9.90%	10.06%	10.11%	17.46%
	Skewness	-0.7	-0.6	-0.6	-0.7	-0.6	-0.5	**-0.5**
	Excess Kurtosis	3.1	3.0	2.9	2.9	2.6	2.6	**1.6**
	Certainty Equivalent *	3.70%	2.60%	1.90%	2.46%	1.23%	1.14%	**7.21%**
	VAR 1%	-1.90%	-1.96%	-1.94%	-1.97%	-1.85%	**-1.83%**	-3.10%
	VAR 5%	**-0.89%**	-0.94%	-0.92%	-0.92%	-0.98%	-1.01%	-1.86%
	Expected Shortfall 1%	-2.54%	-2.55%	-2.54%	-2.54%	-2.48%	**-2.47%**	-3.67%
	Expected Shortfall 5%	**-1.45%**	-1.51%	-1.48%	-1.51%	-1.49%	-1.50%	-2.54%
	LPM1	**0.22%**	0.23%	0.23%	0.23%	0.23%	0.24%	0.41%
SAN	Profitability *	0.5%	-2.1%	-2.6%	-2.0%	-0.4%	-0.5%	**13.5%**
	Transaction costs *	0.040%	0.011%	0.011%	0.007%	0.000%	0.000%	0.000%
	Standard Deviation *	9.90%	9.80%	9.67%	10.12%	9.54%	**9.51%**	21.50%
	Skewness	0.0	0.1	0.0	**0.1**	0.0	0.0	-0.3
	Excess Kurtosis	1.9	2.4	2.1	2.0	1.9	1.7	**0.5**
	Certainty Equivalent *	-1.45%	-4.05%	-4.46%	-4.03%	-2.17%	-2.28%	**4.25%**
	VAR 1%	-1.95%	-1.92%	-1.89%	-1.91%	-1.77%	**-1.76%**	-3.54%
	VAR 5%	-0.92%	-0.91%	-0.90%	-0.99%	-0.90%	**-0.89%**	-2.40%
	Expected Shortfall 1%	-2.17%	-2.15%	-2.13%	-2.16%	**-2.07%**	-2.07%	-3.92%
	Expected Shortfall 5%	-1.40%	-1.40%	-1.37%	-1.41%	-1.33%	**-1.33%**	-3.00%
	LPM1	0.23%	0.24%	0.23%	0.25%	0.23%	**0.23%**	0.51%
BBVA	Profitability *	-14.6%	-15.8%	-16.6%	-17.0%	-17.0%	-17.1%	**-2.2%**
	Standard Deviation *	**10.85%**	10.86%	10.89%	11.13%	11.02%	11.04%	24.19%
	Skewness	-0.5	-0.5	-0.6	-0.5	-0.4	-0.4	**-0.2**
	Excess Kurtosis	2.6	2.8	2.7	2.7	2.6	2.5	**1.2**
	Certainty Equivalent *	-16.98%	-18.13%	-18.99%	-19.53%	-19.41%	-19.50%	**-13.96%**
	VAR 1%	-2.04%	-2.12%	-2.06%	-2.07%	**-2.04%**	-2.04%	-3.92%
	VAR 5%	-1.13%	**-1.08%**	-1.10%	-1.18%	-1.13%	-1.14%	-2.57%
	Expected Shortfall 1%	**-2.64%**	-2.70%	-2.69%	-2.77%	-2.69%	-2.68%	-4.99%
	Expected Shortfall 5%	**-1.67%**	-1.68%	-1.68%	-1.70%	-1.69%	-1.69%	-3.36%
	LPM1	**0.29%**	0.29%	0.29%	0.30%	0.30%	0.30%	0.60%

		GARCH 1	GARCH 2	GARCH 3	Utility decision	OLS D	OLS	Unhedged
REP	Profitability *	-9.4%	-10.0%	-9.8%	-10.3%	-11.7%	-11.9%	**-0.1%**
	Standard Deviation *	11.77%	**11.59%**	11.64%	11.76%	12.22%	12.50%	18.28%
	Skewness	-2.1	-1.8	-1.9	-1.9	-1.9	-1.8	**-0.4**
	Excess Kurtosis	13.4	10.7	10.9	12.3	12.0	11.4	**1.6**
	Certainty Equivalent *	-12.28%	-12.76%	-12.58%	-13.13%	-14.79%	-15.04%	**-6.84%**
	VAR 1%	**-2.28%**	-2.30%	-2.35%	-2.30%	-2.41%	-2.44%	-3.72%
	VAR 5%	-1.11%	**-1.09%**	-1.09%	-1.12%	-1.16%	-1.13%	-1.71%
	Expected Shortfall 1%	-3.85%	**-3.71%**	-3.76%	-3.81%	-3.91%	-3.94%	-3.97%
	Expected Shortfall 5%	-1.94%	-1.94%	-1.95%	**-1.92%**	-1.94%	-1.96%	-2.72%
	LPM1	0.27%	**0.27%**	0.27%	0.27%	0.29%	0.30%	0.44%
IBE	Profitability *	17.2%	17.2%	17.9%	16.5%	13.8%	13.6%	**25.0%**
	Transaction costs *	0.013%	0.006%	0.007%	0.004%	0.000%	0.000%	0.000%
	Standard Deviation *	**9.34%**	9.45%	9.55%	9.70%	11.93%	12.46%	13.49%
	Skewness	-1.9	-1.9	-1.8	-1.7	-0.9	-0.8	**-0.6**
	Excess Kurtosis	9.6	9.4	9.2	8.4	98.0	3.5	**2.2**
	Certainty Equivalent *	15.40%	15.34%	16.06%	14.55%	10.88%	10.45%	**21.38%**
	VAR 1%	-2.46%	-2.45%	-2.50%	**-2.29%**	-2.34%	-2.35%	-2.50%
	VAR 5%	**-0.68%**	-0.69%	-0.74%	-0.75%	-0.94%	-1.01%	-1.28%
	Expected Shortfall 1%	-3.07%	-3.10%	-3.10%	-3.04%	-3.29%	-3.32%	**-2.97%**
	Expected Shortfall 5%	-1.52%	-1.51%	-1.52%	**-1.48%**	-1.75%	-1.80%	-1.99%
	LPM1	**0.17%**	0.17%	0.17%	0.19%	0.26%	0.27%	0.28%
POP	Profitability *	-9.5%	-5.4%	-5.4%	-12.4%	-10.6%	-10.5%	**2.3%**
	Standard Deviation *	25.83%	26.24%	26.27%	**25.82%**	26.27%	26.36%	36.89%
	Skewness	0.0	0.2	0.2	0.1	0.2	0.2	**0.2**
	Excess Kurtosis	4.0	4.1	4.2	4.5	3.9	3.8	**0.6**
	Certainty Equivalent *	-22.81%	**-19.13%**	-19.17%	-25.69%	-24.40%	-24.30%	-24.77%
	VAR 1%	-3.78%	-3.74%	-3.72%	**-3.71%**	-3.76%	-3.79%	-5.75%
	VAR 5%	**-2.18%**	-2.20%	-2.19%	-2.22%	-2.22%	-2.26%	-3.54%
	Expected Shortfall 1%	-5.66%	-5.56%	-5.57%	-5.67%	-5.54%	**-5.51%**	-5.91%
	Expected Shortfall 5%	-3.35%	-3.33%	**-3.32%**	-3.34%	-3.33%	-3.34%	-4.50%
	LPM1	0.63%	0.62%	**0.62%**	0.63%	0.64%	0.64%	0.92%

Note: Best results are marked in bold. GARCH 1: The ratio is rebalanced daily; GARCH 2: The ratio is rebalanced each 10 days to the average hedge ratio over the previous 5 days; GARCH 3:The r ratio is rebalanced each 10 days to the previous day hedge ratio; OLS: The OLS ratio is calculated with the in-sample information and kept constant; OLS D: The OLS ratios is recalculated each 10 days with the new information; Utility decision: The desirability of applying a new ratio was appraised every 10 days in accordance with expected utility; * Annual basis

TABLE 9. Out-of-sample simulations. Relative gain in effectiveness under different measures**:** cross-hedge with IBEX 35 futures contract Vs. static OLS strategy.

	GARCH 1	GARCH 2	GARCH 3	Utility	OLS D
Certainty Equivalent					
TEF	**223%**	127%	66%	115%	7%
SAN	**36%**	-78%	-96%	-77%	5%
BBVA	**13%**	7%	3%	-0%	0%
REP	**18%**	15%	16%	13%	2%
IBE	47%	47%	**54%**	39%	4%
POP	6%	**21%**	21%	-6%	-0%
VAR 1%					
TEF	-4%	-7%	-6%	-8%	-1%
SAN	-11%	-9%	-7%	-8%	-0%
BBVA	0%	-4%	-1%	-1%	**0%**
REP	**7%**	6%	4%	6%	1%
IBE	-5%	-5%	-6%	**3%**	0%
POP	0%	1%	2%	**2%**	1%
VAR 5%					
TEF	**13%**	7%	9%	9%	3%
SAN	-4%	-2%	-2%	-11%	-1%
BBVA	1%	**5%**	4%	-4%	1%
REP	2%	**3%**	3%	1%	-3%
IBE	**33%**	31%	27%	25%	7%
POP	**4%**	3%	3%	2%	2%
ES 1%					
TEF	-3%	-3%	-3%	-3%	-1%
SAN	-5%	-4%	-3%	-4%	**0%**
BBVA	**2%**	-1%	-0%	-3%	-0%
REP	2%	**6%**	5%	3%	1%
IBE	7%	7%	6%	**8%**	1%
POP	-3%	-1%	-1%	-3%	-0%
ES 5%					
TEF	**3%**	-1%	1%	-1%	0%
SAN	-5%	-5%	-3%	-6%	-0%
BBVA	**1%**	1%	0%	-1%	0%
REP	1%	1%	1%	2%	1%
IBE	15%	16%	15%	**17%**	3%
POP	-0%	1%	**1%**	0%	0%
LPM 1					
TEF	**6%**	4%	4%	4%	1%
SAN	-3%	-4%	-4%	-8%	-0%
BBVA	**3%**	3%	1%	-1%	0%
REP	10%	**11%**	10%	9%	3%
IBE	**37%**	36%	36%	31%	5%
POP	2%	3%	**3%**	2%	0%

Note: Best results are marked in bold. GARCH 1: The ratio is rebalanced daily; GARCH 2: The ratio is rebalanced each 10 days to the average hedge ratio over the previous 5 days; GARCH 3:The r ratio is rebalanced each 10 days to the previous day hedge ratio; OLS: The OLS ratio is calculated with the in-sample information and kept constant; OLS D: The OLS ratios is recalculated each 10 days with the new information; Utility decision: The desirability of applying a new ratio was appraised every 10 days in accordance with expected utility.

TABLE 10. Out-of-sample simulations. Cross-correlations between stocks**:** GARCH ratios, spot-future conditional correlations and δ_t. Cross-hedges with IBEX 35 futures contract.

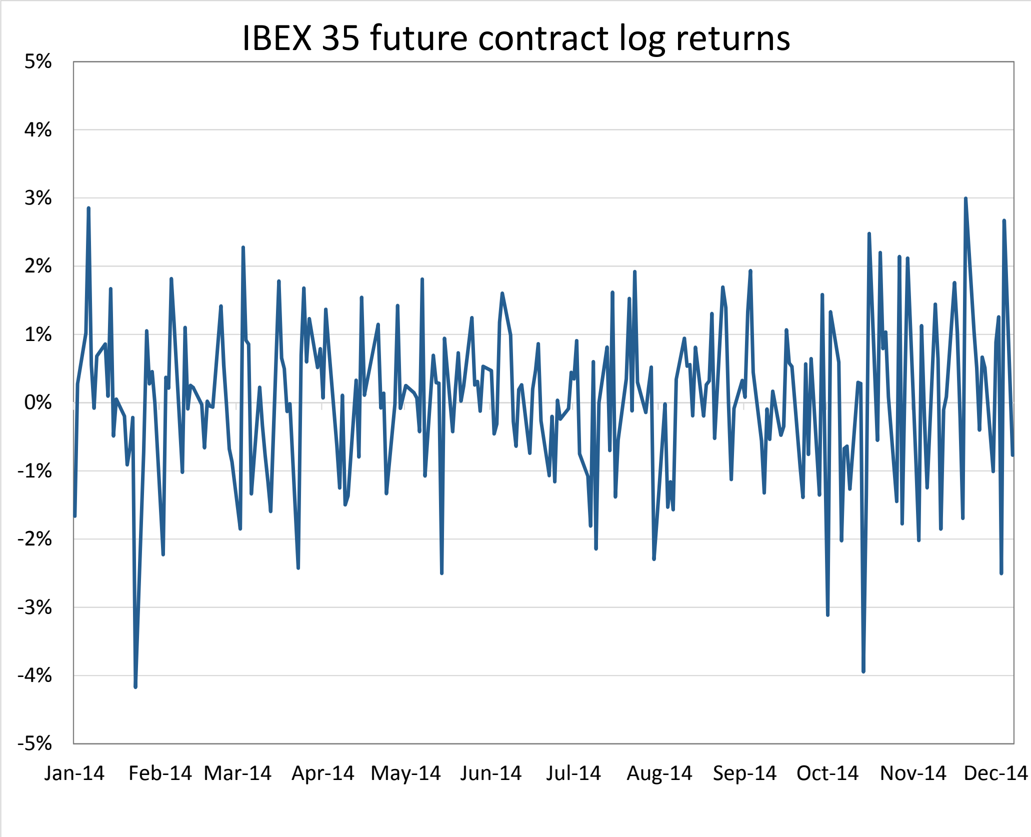
ρ_{AB} **Ratios**	TEF	SAN	BBVA	REP	IBE	POP
TEF	1	0,28	0,25	0,09	0,17	0,06
SAN	0,28	1	0,21	0,22	0,34	0,39
BBVA	0,25	0,21	1	0,32	0,14	0,55
REP	0,09	0,22	0,32	1	0,46	0,25
IBE	0,17	0,34	0,14	0,46	1	0,30
POP	0,06	0,39	0,55	0,25	0,30	1

ρ_{AB} ρ_{sf}	TEF	SAN	BBVA	REP	IBE	POP
TEF	1	0,08	0,48	0,04	-0,16	0,08
SAN	0,08	1	0,14	0,22	-0,17	-0,46
BBVA	0,48	0,14	1	-0,07	-0,09	-0,02
REP	0,04	0,22	-0,07	1	-0,08	0,02
IBE	-0,16	-0,17	-0,09	-0,08	1	0,34
POP	0,08	-0,46	-0,02	0,02	0,34	1

ρ_{AB} δ_t	TEF	SAN	BBVA	REP	IBE	POP
TEF	1	-0,19	0,19	0,09	0,14	0,03
SAN	-0,19	1	-0,03	0,10	-0,19	0,02
BBVA	0,19	-0,03	1	0,13	0,04	0,48
REP	0,09	0,10	0,13	1	0,23	0,22
IBE	0,14	-0,19	0,04	0,23	1	-0,01
POP	0,03	0,02	0,48	0,22	-0,01	1

Notes: ρ_{AB}: correlation between stock A and stock B. ρ_{sf}: correlation of the spot price return of the stock and the future price return of IBEX 35 future contract. δ_t: relative size of the specific noise to the common noise.

Appendix 2. – Figures



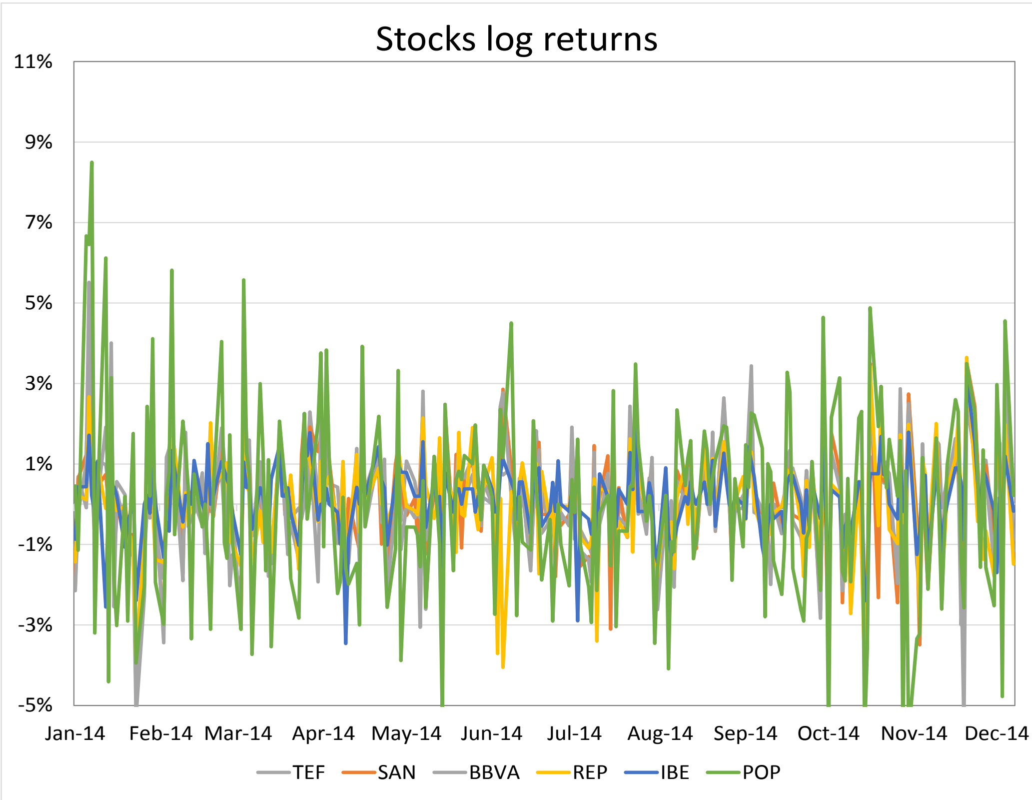
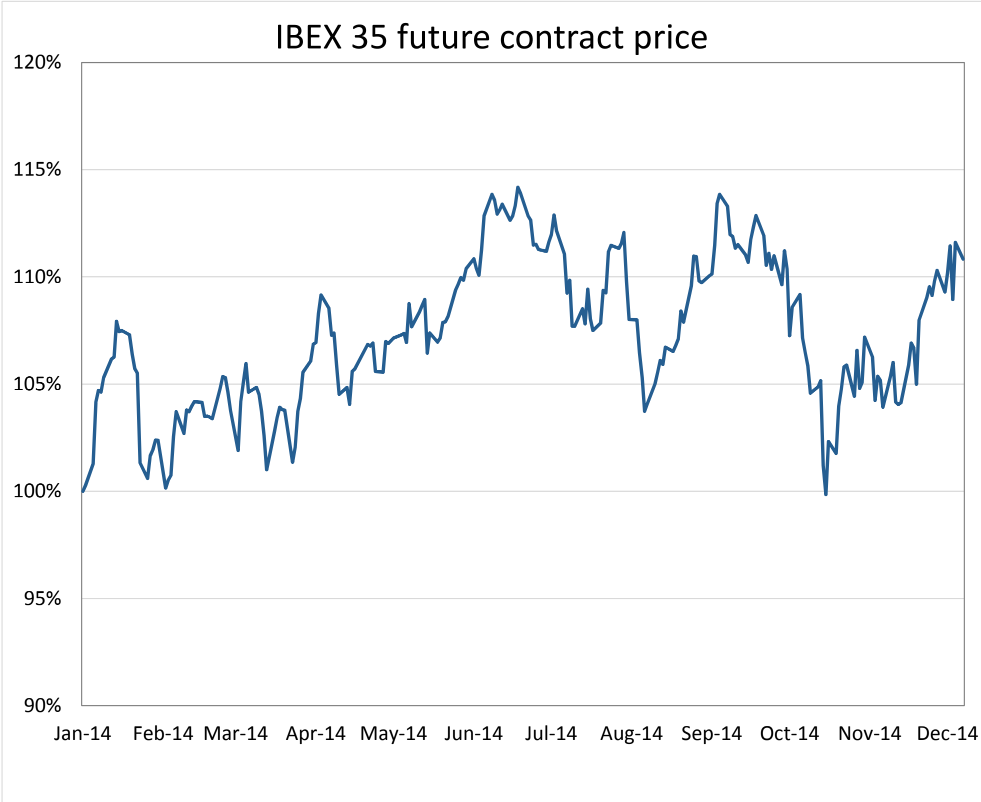


Figure 1. Log returns of out-of-sample stock spot prices and IBEX 35 future prices.



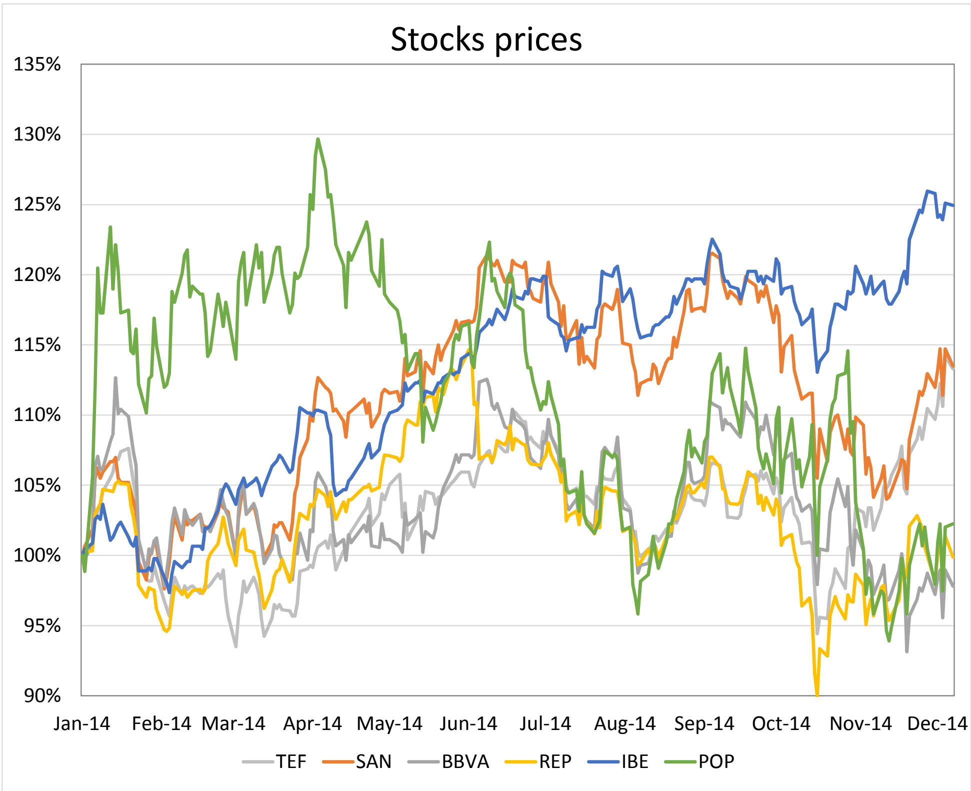
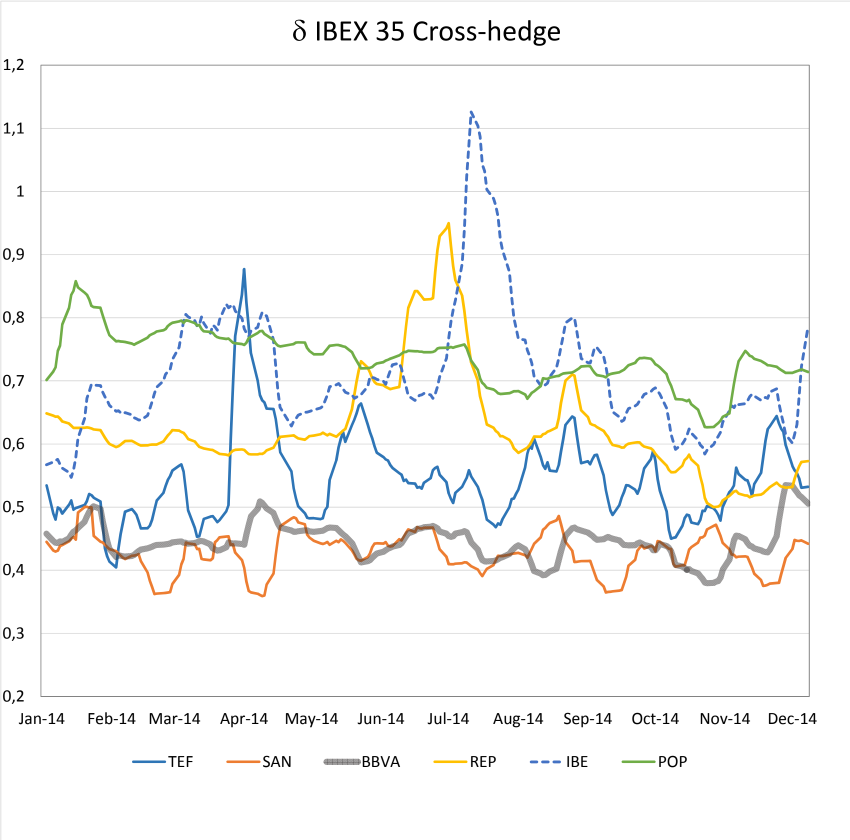


Figure 2. Out-of-sample IBEX 35 Futures and stocks prices evolution. January 2014=100%



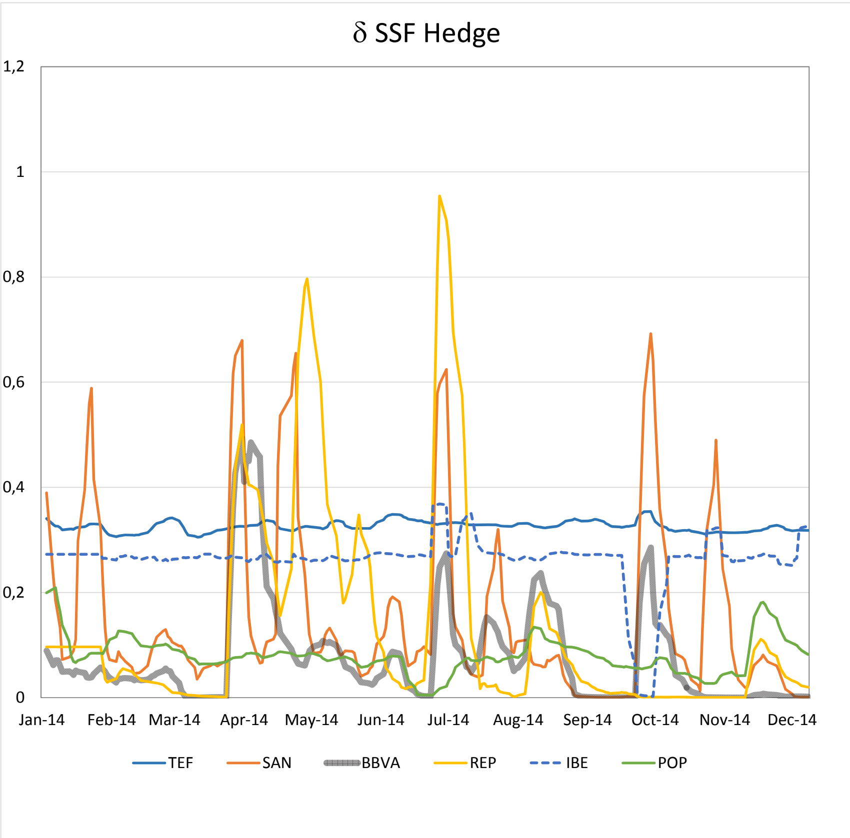
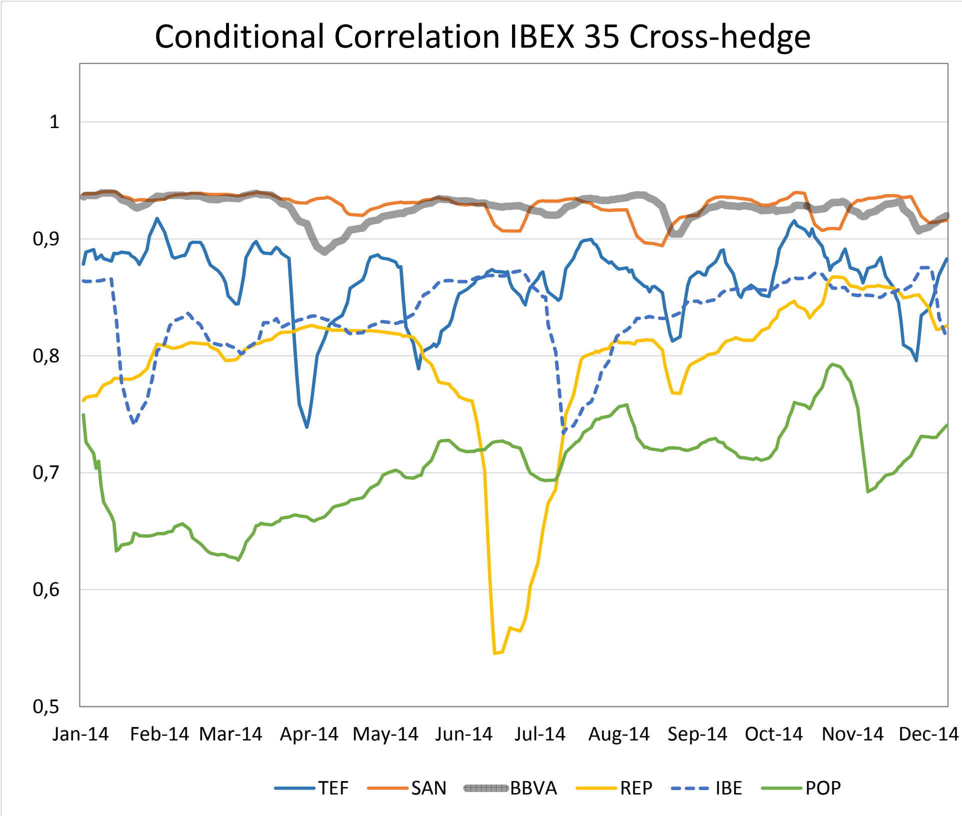


Figure 3. Out-of-sample simulations Relative importance of the specific noise as compared to the common noise. 5 days moving average.



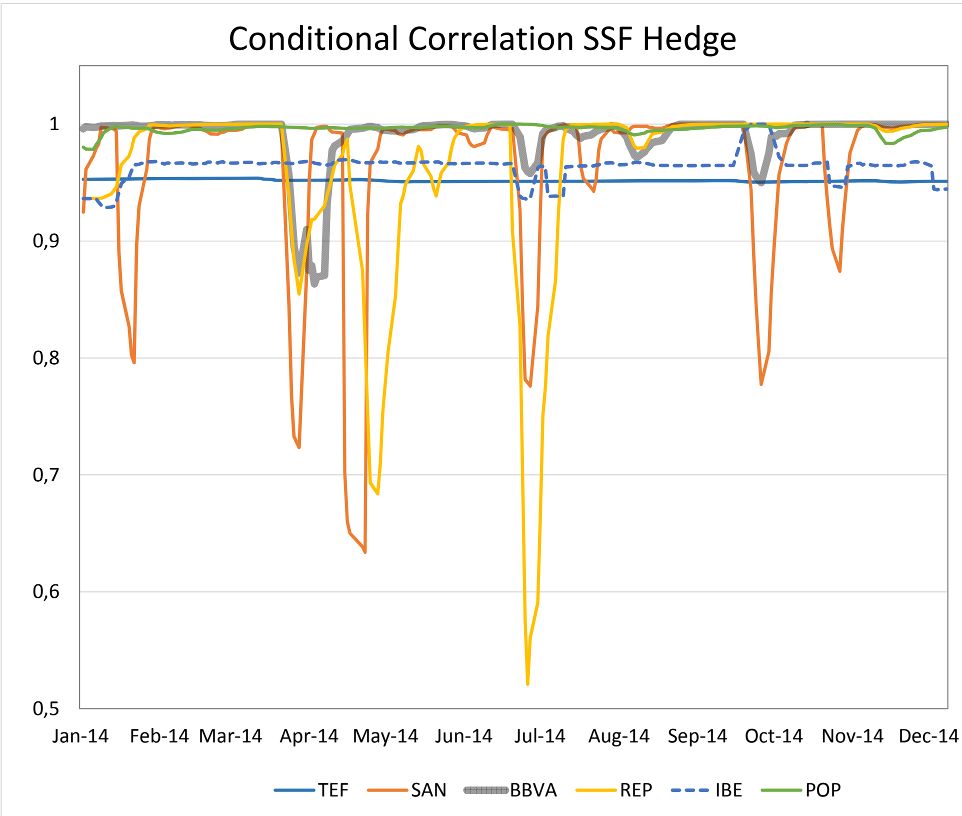
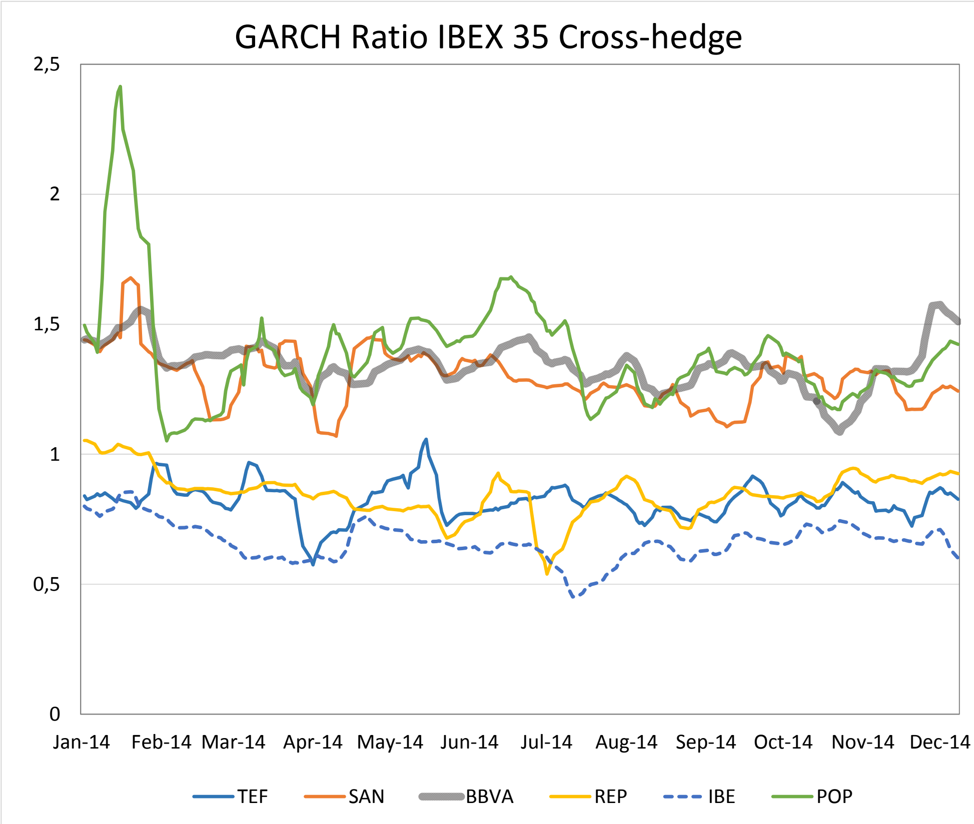


Figure 4: Out-of-sample simulations. Conditional correlation of returns between the spot position and the futures contract. 5 days moving average.



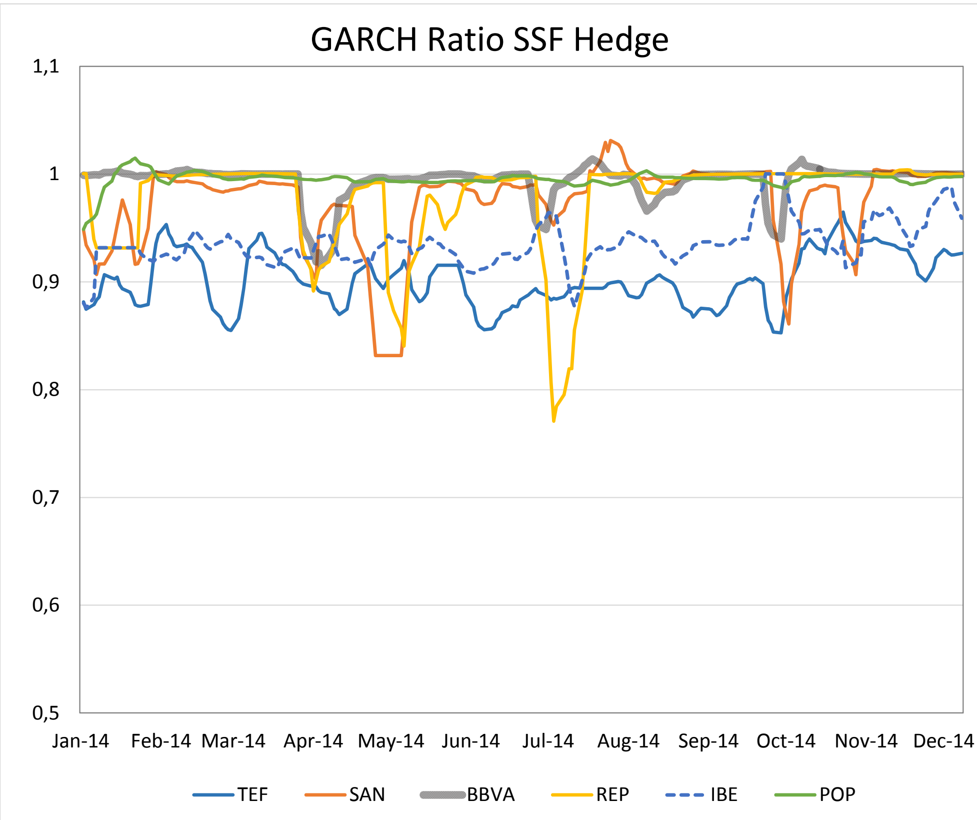


Figure 5. out-of-sample simulations. Ex-ante minimum variance GARCH ratio. 5 days moving average.

CHAPTER 3: Portfolio cross-hedging effectiveness: the role of liquidity

ABSTRACT: Usually, only imperfect hedging instruments are at hand. This paper analyses the effectiveness of cross-hedging strategies for stock portfolios when an index futures contract is used. In particular we build portfolios with securities traded in the Spanish stock market and we sort these portfolios according to their liquidity. We found that gain in volatility reduction is positively correlated with liquidity. The most liquid portfolios experimented a higher reduction in basis risk. We also show that the time-varying hedge ratio lead to a superior effectiveness relative to the ratio obtained from a regression of spot market returns on future market returns, especially in the case of portfolios with the lowest liquidity. Though the Spanish market could be considered as a developed market, our empirical findings suggest that, specific noises in spot and futures markets could be exploited to improve hedging effectiveness.

Key words: futures mispricing, cross-hedging effectiveness, liquidity

1. INTRODUCTION

When portfolio managers try to eliminate a particular risk, the futures contracts available at the market do not usually perfectly mirror the asset to be hedged. In this case, traders should manage risk with cross-hedging strategies, facing basis risk. In this paper we focus on the case where the composition of an equity portfolio does not replicate the composition of a market index and the hedger uses the futures contract written on this non-tradable stock index. In this paper we analyze the use of futures contracts written on the IBEX 35 stock index as a cross-hedging instrument for reduced portfolios that are built up with selected stocks that compose the index. Then we show how hedging effectiveness is affected by liquidity of the portfolios to be hedged.

Several theoretical approaches have been proposed in the literature in order to design an optimal hedge with futures contracts (see Chen et al., 2013, for an excellent review that considers minimum variance, mean-variance, expected utility, Sharpe ratio hedge, mean extended-Gini coefficient, semi variance, minimum generalized semi variance (GSV), mean-GSV and Value at Risk (VaR) approaches). Regardless the approach considered, the correlation between price changes plays a key role. We adopt the usual approach that takes into account not only the dynamic nature of market risk, but also the fact that the key idea of hedging is to combine spot and futures trading to form a portfolio with negligible fluctuations in its market value. And consequently, we consider the minimization of the variance of the hedged position as the relevant optimization criteria. The resulting optimal hedge ratio is then obtained as the ratio between the conditional covariance of spot and futures returns and the conditional variance of futures returns. These conditional moments have usually been estimated from a particular specification of the GARCH family of models (see, for example, Lee and Yoder, 2007, Ku et al., 2007, Choudhry, 2003 and 2004, Park and Switzer, 1995 among many others). In particular, a bivariate DCC-GARCH is considered for

We adopt the theoretical ratio proposed by Lafuente and Novales (2003) which considers the existence of a noise specific to the future market in addition to the noise common to spot and futures market returns that implies departures of futures traded quotes from its cost of carry valuation. This is consistent with previous empirical evidence on the absence of a common ARCH feature between spot and futures market returns. In particular, the relevant noises under our cross-hedging scenario are: a) the futures market specific noise, and b) the common noise for the spot market returns and the futures market returns, but not shared with the portfolio to be hedged.

In this paper we attempt to provide further insights on the relationship between liquidity and hedging effectiveness when using the IBEX 35 futures contract as a hedging instrument for portfolios that does not fully replicate the underlying stock index. A priori it is expected that liquidity matters. In order to assess our prior guess we have constructed four portfolios attending to liquidity of their individual components. In order to reproduce a more realistic situation we consider a potential rebalancing of the hedged position every 10 days, as a compromise between maintaining a static hedge ratio and changing the hedge too often. Our decision criteria is based on a standard expected utility function and transaction costs are explicitly taken into account. We compare the effectiveness of dynamic hedging strategies with the effectiveness associated to the ordinary least squares (OLS) ratios. We will consider a static OLS ratio estimated with the sample observation that we will call the OLS ratio, and an additional OLS ratio that varies with the arrival of new information and that we will call the dynamic OLS ratio. In order to check the robustness of our empirical findings we also consider alternative hedging effectiveness measures as the Certainty Equivalent (CE), the Value at Risk (VaR), the Expected Shortfall (ES) and Lower Partial Moments (LPM).

After identifying the GARCH structure of market returns with data for the period covering 2001-2011, empirical evidence obtained from out-of-sample simulations for the period 2012-2013 reveals a significant gain in volatility reduction when the hedging position is updated in accordance with expected utility.

To check the robustness of our empirical findings we perform out-of-sample simulations focusing on the financial crisis of 2007-2008. Conclusions for the year 2007 are qualitatively similar to those obtained with the full sample for the period 2012-13. However, high volatility and uncertainty associated to 2008 after the arising of the crisis lead to a non clear superiority of the GARCH ratio. The influence of high volatility time periods in the effectiveness of dynamic hedging strategies is also found in Sukcharoen et al. (2015).

The rest of the paper is organized as follows. Section 2 revisits the theory approach and provides the econometric approach to estimate conditional second moments of stock market returns. Section 3 describes the data and construction of portfolios used in the analysis. Section 4 discusses the empirical evidence on hedging effectiveness based on simulations of different hedging strategies. Finally, section 5 summarizes and makes concluding remarks.

2. DATA

Data for Spanish financial assets are collected from the database provided by *Bolsas y Mercados Españoles* (BME). We select stocks that have been listed along all the 2001-2013 period and have been part of the IBEX 35 composition at least once. After this initial filtering, we get 40 stocks.

As to the futures data, we have used daily closing quotes for the nearest-to-maturity IBEX 35 futures contract. We perform the rollover the last trading day of the previous maturity. We use the same criteria as in the First Chapter[10], who shows that is just the last trading day when the trading volume between of the nearest to maturity futures contract becomes lower than that of the next to maturity contract. We also have made the required price adjustments after the Euro currency adoption, as well as when splits and counter splits takes place.

We initially consider a sample period that covers from 2001 to 2006 and then we use the period 2007-2008 as the out-of-sample relevant time period. The period 2007-2008 is characterized by the arising of concerns about future potential growth in the world economy as a consequence of excessive risk taking by investment banks led to the global economic collapse of 2008 after the bankruptcy of Lehman Brothers. More particularly, in the case of the Spanish economy the global financial crisis triggered the bursting of the real estate bubble and led to the Spanish economy into a subsequent recession where cost of insurance against credit default rose dramatically. A second exercise considers data from 2001 to 2011, leaving 2012 and 2013 for out-of-sample simulations. The next time period considered for out-of-sample simulations is characterized by increasing debt sustainability concerns for peripheral countries in the euro-zone and the support of the European Central Bank through massive public debt purchases in order to keep risk premiums under control.

Figures 1A and 1B (see Appendix 2) depicts the time evolution of IBEX 35 stock index returns and stock index during the time period analyzed. Similar graphs for the portfolios considered are displayed in Figures 2A and 2B for the out-of-sample windows 2007-2008 and 2012-2013 respectively. Initially we use the full sample to focus on the period 2012-2013, that is characterized by relatively high volatility in 2012 that gradually reduces over time as a result of ECB interventions**.**

Table 1 (see Appendix 1) presents the main statistics for the return series computed as the first differences of the logs of closing prices. As expected, daily returns are on average very close to zero. Also, stock return distributions exhibit excess kurtosis and skewness, characteristics that are generally associated with conditional heteroskedasticity patterns.

Table 2 also presents empirical values of the Engle and Kozicki (1993) test for the null hypothesis that there is a linear combination of spot and futures market returns that is homoskedastic. We systematically reject the existence of a common ARCH feature between the returns of portfolio to be hedged and the returns of the hedging instrument, corroborating the existence of basis risk.

2.1 Portfolio construction

We sorted the selected 40 stocks in accordance with trading volume. Then we created portfolios using two alternative strategies. The first method uses relative weights based on the relative volume of each asset in year 2004. As an alternative way, we consider equally weighted portfolios. We refer to these two approaches as *W* and *EW*, respectively.

The most liquid portfolio is made up by 7 stocks that lie within the upper 86% of the trading volume distribution. We label this portfolio as portfolio *A*. Next we select the following 10 stocks in the cumulative trading volume distribution until reaching the 95% of the total volume. We refer this less liquid portfolio concerning these 10 stocks as portfolio *B*. We have discarded the remaining 23 stocks that account for about 5% of the total trading volume.

Our hypotheses to be tested can be summarized as follows:

Hypothesis 1: The most liquid portfolios are expected to have a more effective hedging than the less liquid portfolios.

Hypothesis 2: Regardless liquidity, the non-equally weighted portfolios are expected to have a greater variance reduction.

Hypothesis 3: Extreme volatility may reduce the potential advantage associated to the dynamic GARCH hedge ratio.

3. THE OPTIMAL HEDGE RATIO

The recent paper of Lien et al. (2014) discusses the reliability of the Ederington hedging effectiveness, that is, the percentage reduction in the return variance of the hedged portfolio relative to the return variance of the unhedged portfolio. They show that, using this measure, the OLS hedge ratio is likely to have a greater hedging effectiveness than the GARCH hedge ratio, regardless the specification used. Lien (2005) suggests as a potential explanation that the Ederington hedging effectiveness focuses on the unconditional variance while conditional variance minimization strategy is based on the idea that conditional and unconditional second order moments differ. Moreover, Kavussanos and Nomikos (2000) suggest that, for the GARCH hedge strategy to outperform the OLS hedge strategy, the variability of the resulting GARCH ratio must be sufficiently large. In accordance with this idea, Park and Jei (2010) find an inverse relationship between the variability of the GARCH hedge ratio and corresponding Ederington hedging effectiveness.

While it is not clear to justify the use of the Ederignton hedging effectiveness measure, we will consider the residual portfolio variance as the initial hedging effectiveness score. In accordance with this idea, we use the Lafuente and Novales (2003) approach, where the optimal hedge ratio is stated as follows:

$$\frac{h_t^*}{b_t} = \frac{\sigma_{s,t}^2 + \rho_{12,t}\sigma_{s,t}\sigma_{N,t}}{\sigma_{s,t}^2 + \sigma_{N,t}^2 + 2\rho_{12,t}\sigma_{s,t}\sigma_{N,t}} = \frac{1+\rho_{12,t}\delta_t}{1+\delta_t^2 + 2\rho_{12,t}\delta_t} \tag{1}$$

where $\delta_t = \frac{\sigma_{N,t}}{\sigma_{S,t}}$ represents the relative importance of the specific noise for futures market returns as compared to the common noise between spot and futures market returns, and $\rho_{12,t}$ represents the correlation between both noises.

3.1. Estimating time-varying conditional second order moments

Multivariate GARCH models are usually applied not only to the study of the relationships between volatilities and co-movements between stock market returns (Kearney and Patton, 2000), but also to estimate time-varying hedge ratios (Lien and Tse, 2002).

Given that a constant conditional correlation GARCH (CCC–GARCH) model, initially introduced by Bollerslev (1990) is too restrictive for the task at hand, we consider a bivariate GARCH DCC model as proposed in Engle (2002). As pointed out by Engle, this specification has clear computational advantages over multivariate GARCH models because the number of parameters to be estimated in the correlation process is independent of the number of series to be correlated. Moreover, DCC models are often the most accurate.

We represent the dynamics of spot and futures markets returns, $r_{s,t}$ and $r_{f,t}$, with an error correction model in which we define the error correction term as the spread between the logarithm of the spot price and the future price:

$$\begin{pmatrix} r_{s,t} \\ r_{f,t} \end{pmatrix} = \sum_{i=1}^{n} \begin{pmatrix} \alpha(i)_{11} & \alpha(i)_{12} \\ \alpha(i)_{21} & \alpha(i)_{22} \end{pmatrix} \begin{pmatrix} r_{s,t-i} \\ r_{f,t-i} \end{pmatrix} + \begin{pmatrix} \gamma_s \\ \gamma_f \end{pmatrix} \left(\ln S_{t-1} - \ln F_{t-1}\right) + \begin{pmatrix} \varepsilon_{s,t} \\ \varepsilon_{f,t} \end{pmatrix} \tag{2}$$

where Ω_{t-1} is the information set at time t-1 and Σ_t is the conditional variance-covariance matrix of innovations. We consider different distributions in order to simulate $\varepsilon_{s,t}$ and $\varepsilon_{\mathrm{f},t}$ market innovations: Normal Distribution, t-Student and GED (Generalized Error Distribution).

We represent the time evolution of the elements in the conditional variance-covariance matrix by a GARCH (p, q) specification with possible asymmetric effects:

$$\begin{aligned} \begin{pmatrix} \sigma^2_{s,t} \\ \sigma^2_{f,t} \end{pmatrix} &= \begin{pmatrix} \omega_s \\ \omega_f \end{pmatrix} + \sum_{i=1}^{p} \begin{pmatrix} A(i)_{11} & A(i)_{12} \\ A(i)_{21} & A(i)_{22} \end{pmatrix} \begin{pmatrix} \varepsilon^2{}_{s,t-i} \\ \varepsilon^2{}_{f,t-i} \end{pmatrix} + \sum_{j=1}^{q} \begin{pmatrix} B(j)_{11} & B(j)_{12} \\ B(j)_{21} & B(j)_{22} \end{pmatrix} \begin{pmatrix} \sigma^2_{s,t-1} \\ \sigma^2_{f,t-1} \end{pmatrix} \\ &+ \begin{pmatrix} D_{11} & 0 \\ 0 & D_{22} \end{pmatrix} \begin{pmatrix} \varepsilon^2{}_{s,t-1} I_{s,t-1} \\ \varepsilon^2{}_{f,t-1} I_{f,t-1} \end{pmatrix}, \qquad I_{k,t-1} = \begin{Bmatrix} 1, if\ \varepsilon_{k,t-1} < 0,\ k = s,f \\ 0, if\ \varepsilon_{k,t-1} \geq 0,\ k = s,f \end{Bmatrix} \end{aligned} \tag{3}$$

The diagonal elements in matrices A_i capture the ARCH effects, while the diagonal elements in matrices B_j measure the own GARCH effects. The off-diagonal elements capture the cross-effects in terms of volatility and disturbance spill over.

The structure p=q=1 appears to be a valid specification to capture the volatility dynamics.

With regard to the conditional correlation, the dynamics of the DCC model is:

$$\rho_{sf,t} = (1-\kappa_1-\kappa_2)\overline{\rho} + \kappa_1\rho_{sf,t-1} + \kappa_2\Psi_{t-1} \tag{4}$$

$$\Psi_{t-1} = \frac{\sum_{h=1}^{m}\eta_{s,t-h}\eta_{f,t-h}}{\sqrt{\left(\sum_{h=1}^{m}\eta^2{}_{s,t-h}\right)\left(\sum_{h=1}^{m}\eta^2{}_{f,t-h}\right)}},\ \eta_{k,t} = \frac{\varepsilon_{k,t}}{\sigma_{k,t}},\ k = s,f$$

When p=q=1 the elements of the variances vector are:

$$\sigma^2_{s,t} = \omega_s + \varepsilon^2{}_{s,t-1}(A_{11} + D_{11}I_{s,t-1}) + A_{12}\varepsilon^2{}_{f,t-1} + B_{11}\sigma^2_{s,t-1} + B_{12}\sigma^2_{f,t-1} \tag{5}$$

$$\sigma^2_{f,t} = \omega_f + A_{21}\varepsilon^2{}_{s,t-1} + \varepsilon^2{}_{f,t-1}(A_{22} + D_{22}I_{f,t-1}) + B_{21}\sigma^2_{s,t-1} + B_{22}\sigma^2_{f,t-1} \tag{6}$$

The conditional variances depend on the lagged squared conditional variances and the lagged squared errors with cross-effects between spot and future markets.

After the estimation of the conditional second order moments of spot and futures market returns, we use analytical expressions in Lafuente and Novales (2003) in order to recover the variances of the specific and the common noise, as well as their covariance.

$$\hat{\sigma}^2_{f,t} = \hat{\sigma}^2_{s,t} + \hat{\sigma}^2_{N,t} + 2\hat{\sigma}_{s,t}\hat{\sigma}_{N,t}\hat{\rho}_{12,t} \tag{7}$$

$$\hat{\sigma}_{sf,t} = \hat{\sigma}^2_{s,t} + \hat{\sigma}_{s,t}\hat{\sigma}_{N,t}\hat{\rho}_{12,t} \tag{8}$$

$$\hat{\rho}_{sf,\mathrm{t}} = \frac{\hat{\sigma}^2_{s,t} + \rho_{12,t}\sigma_{s,t}\sigma_{N,t}}{\sqrt{\hat{\sigma}^2_{s,t}(\hat{\sigma}^2_{s,t} + \hat{\sigma}^2_{N,t} + 2\rho_{12,t}\sigma_{s,t}\sigma_{N,t})}} \tag{9}$$

$$\hat{\rho}_{12,t} = \frac{\hat{\sigma}_{sf,t} - \sigma^2_{s,t}}{\hat{\sigma}_{s,t}\sqrt{\hat{\sigma}^2_{s,t} + \hat{\sigma}^2_{f,t} - 2\hat{\sigma}_{sf,t}}} \tag{10}$$

4. EMPIRICAL EVIDENCE

4.1. Spillover effects

Table 3 shows the point estimates of the parameters concerning the DCC-GARCH model for the periods 2001-2006 and 2001-2011, considering three different alternative distributions for innovations.

We find that the speed of adjustment to short-run price deviations from their long-run equilibrium differs from those reported in the First Chapter[10]. In particular our empirical findings suggest a more gradual adjustment. It should be also highlighted that the parameter associated to error correction term appears to be significant at conventional confidence levels in fewer cases. These results suggest that despite the IBEX 35 spot and futures markets are linked in the short and long-run as a consequence of arbitrage, the co-movements between our portfolios and the IBEX 35 do not systematically lead to the existence of a cointegration relationship.

The parameters that capture the cross-market interactions in mean ($\alpha(i)_{jk}, j \neq k$) reveal that the less liquid portfolios have a poor explanatory power about futures movements of the IBEX 35 futures market returns. This is most often case irrespective of the distributional assumptions of errors. As to the most liquid portfolio, we only find bidirectional causality for the equally weighted portfolio when the largest sample period (2001-2011) is used.

Volatility clustering in spot and futures market returns is corroborated by significant ARCH and GARCH coefficients. In general, we find significant asymmetric effects for all portfolios, corroborating that the increase in volatility is larger when the returns are negative than when they are positive. Our empirical findings also suggest not only that there is a clear volatility transmission channel between spot and futures market returns especially in the first estimation window, but also that the transmission occurs asymmetrically. The impact of the futures market on the spot market is stronger, with the exception of the *A_W* portfolio where the transmission appears to be the opposite than the spot to the futures market. This could be explained by the higher correlation of this portfolio with the IBEX 35. However spillover effects attenuate when the largest sample period is used, with the exception of the *A_W* portfolio which transmission from the spot to the futures market is even stronger than in the first subsample. Such patterns are explained by the inclusion of the global financial crisis in the full sample.

4.2. Decomposing the hedge ratio

The δ_t variable measures the relative importance of the specific noise as compared to the common noise. We observe (see Table 4) that δ_t tends to be higher as the correlation between the portfolios and the futures contract decreases. As expected, higher discrepancies in the relative weights between the portfolio to be hedged and the IBEX 35 are associated to a higher noise ratio. The most liquid portfolio with weights based on relative trading volume exhibits, on average, δ_t = 0.237[26]. For example, this value is higher than 0.200, the average value in the First Chapter[10] when a spot position in the IBEX is hedged with its future contract. When we consider an equally weighted portfolio with the most liquid assets the value becomes 0.357.

Less liquid portfolios have higher δ_t values, which we think is consitente with lower correlation that makes the idiosincratic risk to be higher. The average δ_t values are 0.553 and 0.533 for less liquid portfolios relative weighted and equally weighted respectively. Interestingly, different weighting methods have less impact on the change in δ_t value in the case of the less liquid portfolios compared to the more liquid portfolios. This variation is more pronounced in the first out-of-sample window and we believe is due to the relative difference in the correlation between the portfolios and the future of the IBEX 35 under different weighting methods. We obeserve, with the change in the weighting method, greater relative reduction in correlation with the future for the most liquid portfolios as can be seen in Table 4.

Figures 6, 7 and 8 present the time evolution of estimated noise ratios, as well as the conditional correlation and the optimal GARCH ratios. We observe that the *A_W* portfolio has a more stable δ_t in comparison with the *A_EW* portfolio. A similar finding is oberved when *B_W* and *B_EW* portfolios are compared. The lower correlation of the

[26] Average value for the out-of-sample periods.

equally weighted portfolios with the IBEX 35 future seems to be related with higher especific noise and more volatile δ_t . Not only the relative weights but also liquidity affect fluctuations. The less liquid portfolios have a more volatile noise ratio. Interestingly enough we observe an abrupt peak associated to the black Monday (01/21/2008) that marked the beginning of the subprime crisis.

4.3. Cross-hedging simulations

In this section we describe our empirical findings concerning the out-of-sample hedging effectiveness[27]. We have two initial estimations of the DCC model for the periods 2001-2006 and 2001-2011. For each one, we gradually incorporate out-of-sample data for the periods covering 2007-2008 and 2012-2013, respectively. We update our sample using a 10-day window, and then the model is re-estimated to forecast the hedge ratio for the next out-of-sample 10-days period. We consider that 10 days is a compromise between maintaining a static hedge ratio at the potential cost of effectiveness loss and changing the hedge too often which would imply high transaction costs. To forecast the out-of-sample ratio, two alternatives are used: a) the average hedge ratio computed over the last five trading days or b) the hedge ratio estimated the last day.

We initially compare the out-of-sample hedging effectiveness of the GARCH ratio with either the OLS ratio or the dynamic OLS ratio using the standard approach based on volatilities as follows:

$$Hedging\ effectiveness = 100x\left(\frac{Volatility(hedged\ \ position) - Volatility(Unhedged\ \ position)}{Volatility(Unhedged\ \ position)}\right)$$

where volatility is measured by the standard deviation of returns over the period chosen for comparison.

[27] We consider a position in IBEX 35 futures equal to the spot position value in each stock multiplied by the hedge ratio assuming that the spot position is large enough to be covered by IBEX-35 future. If needed, fine adjustments to complete the position are also made by Mini IBEX operations

Table 4[28] presents our empirical findings on hedging effectiveness using the foregoing measure when the GARCH ratio is updated on a daily basis. Tables 5[28] and 6[28] present the results of the alternative approach of a less frequent revision every 10 days.

As to the Hypothesis 1, as expected we find that liquidity matters. The most liquid portfolios achieve the highest reductions in volatility for all out-of-sample periods and for both, daily and every 10 days, rebalance frequencies. Compared with the dynamic and static OLS hedge ratio, an almost systematic improvement in hedging effectiveness is achieved using the GARCH ratio for the more liquid portfolios. However the GARCH ratio underperform for the less liquid portfolios once we rebalance the ratio each 10 days and with the exception of the year 2007. This result suggests that for the less liquid portfolios it would be interesting to analyze more frequent rebalances. We haven't´ found significant differences among the different distributions used in order to simulate disturbances with the exception of punctual worse results from GED disturbances simulations. Figure 3, 4 and 5 represent Table 4, 5 and 6 results in relative terms[29] respectively.

Findings in the First Chapter[10] for the IBEX 35 and other international indexes for the period 1997-2005 suggested that in mature futures markets with high trading volume the time-varying noise that characterizes basis risk can't be exploited to improve upon the hedging efficiency provided by a systematic static ratio. Those findings were in line with Roll et al. (2007) who presents empirical evidence suggesting that liquidity enhances the efficiency of the futures-cash pricing system. In our analysis liquidity improves the hedge effectiveness and on the other hand in the more liquid portfolios there are gains that can be exploited once the volatility structure is modelled versus the static ratios in line with Lafuente and Novales (2003) and the Third Chapter[11] and versus the dynamic OLS ratio.

As to the Hypothesis 2, the results confirm that the equally weighted portfolios achieve a lower variance reduction. This is a result that happens for the most liquid portfolios in all periods and in all rebalance strategies and for the less liquid portfolios

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[28] Simulations under Normal distribution, t-Student distribution and GED distribution are presented in panels A, B and C respectively.
[29] In Figures 3.B, 4.B and 5.B differences in volatility between GARCH and static OLS ratio are graphically represented in relative terms to the volatility reduction achieved with the static OLS ratio.

during the second window and also in all rebalance strategies. We believe this result is a consequence of changes in the correlation between the spot and futures markets when the weight criteria changes as we can see in Table 4, 5 and 6.

Finally, with regard to these cross-hedging simulations and as to the Hypothesis 3, we observe than in the acute volatility period during year 2008, the advantage of the GARCH strategy for the less liquid portfolios turns into underperformance in relation to the static OLS strategy. Nonetheless, this shift only happens when we reduce the frequency of rebalance as we can see comparing GARCH effectiveness for the less liquid portfolios in 2008 in Tables 4, 5 and 6. This may suggest, that during high volatility periods it is advisable to keep a high frequency rebalance or at least a high frequency monitoring of optimum ratios or otherwise implement a static strategy as in Sukcharoen et al. (2015).

In order to implement a more practical approach including transaction costs and a criteria to decide whether to rebalance the GARCH ratio or to keep the ratio constant, each certain days we consider the gain or loss in terms of utility, taking also into account the transaction costs from adjusting the position in the derivatives market. To this end, we consider a specification of the expected utility function: $E_t U(x) = E_t(x) - \gamma\sigma_t^2(x)$ where γ denotes the degree of risk aversion, with the level of risk being measured by the conditional variance of returns. Denoting transaction costs by τ and assuming a zero expected return, an investor would have an expected utility of $-\gamma\sigma_t^2(x^*)$ if the hedge ratio remains unchanged versus an expected utility equal to $-\tau - \gamma\sigma_t^2(x^{**})$ if the hedge ratio were updated from h_t^* / b_t to h_t^{**} / b_t. Thus, an investor will adjust the hedging position if and only if:

$$\tau - \gamma(\sigma_{s,t}^2 - 2\sigma_{sf,t}(h_t^{**} / b_t) + \sigma_{f,t}^2 (h_t^{**} / b_t)^2) > -\gamma(\sigma_{s,t}^2 - 2\sigma_{sf,t}(h_t^{*} / b_t) + \sigma_{f,t}^2 (h_t^{*} / b_t)^2)$$

where (h_t^{**} / b_t) denotes the hedge ratio applied as the result of the last revision of the futures position.

We consider a risk aversion coefficient of 4 and average costs of 0.0018%[30]. The optimal ratio obtained in the last trading day in each rolling sample, t, is applied to the following 10 trading days (from *t*+1 to *t*+10). Thus, over the out-of-sample period, we use the utility comparison rule every 10 trading days to decide on whether to change the ratio to the variance-minimizing ratio calculated in the immediately preceding period, or to maintain the same hedge ratio that was applied previously. The results obtained for each portfolio and distribution are presented in Table 7 in terms of aggregate utility for 2007-2008 and 2012-2013 as well as in terms of the utility gain relative to the non-hedged position. We observe similar results in relation to The Hypothesis 1 and 2 than in the simulations with the previous model that did not incorporate the utility criteria nor the decision rule based on it. The effectiveness in terms of utility gain is lower in the equally weighted portfolios when compared to the relative volume weighted portfolios with the exception of the less liquid portfolios during the first out-of-sample period. Managing the hedge ratio according to the utility comparison rule often provides significant utility gains against the OLS strategies, either dynamic or static, with the exception of *A_W* portfolio where it is very similar to the one obtained under the OLS ratio. The decision criteria based on the utility comparison rule provides very similar aggregate utility to the one emerging from applying the GARCH ratio from the previous period. We haven't found significant differences in terms of utility comparison among the distributions used to simulate the disturbances.

4.4. Beyond volatility: what about returns, asymmetry and kurtosis?

Finally, although the effectiveness criteria of minimum variance applied is the most widely accepted for financial hedges we introduce additional different criteria as measures that add more information on the hedged portfolio returns distribution in terms of risk of losses, kurtosis and profitability. In particular we consider the Certainty Equivalent (CE) with aversion parameter = 4 , $LPM_{1,0}$ and VaR and ES at 1% and 5% probabilities.

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[30] This corresponds to the MEFF Spanish commission of 0.225 € for the Mini IBEX future contract and the 2007 average value of the IBEX 35 future contract as we assume that corrections in the ratio are made by Mini IBEX operations. As to the transaction costs associated to the bid-ask spread, we use the recent 2.5 € mean half spread for the Mini IBEX future contract.

We consider the Certainty Equivalent (CE) for an investor with exponential utility on wealth W: $U(W) = -\exp(-\gamma W)$, with $\gamma > 0$ being the coefficient of absolute risk aversion. The Certainty Equivalent that the investor would accept for not taking the risk of the uncertain return on his/her portfolio is approximately given by:

$$CE \approx \mu - \frac{1}{2}\gamma\sigma^2 + \frac{\tau}{6}\gamma^2\sigma^3 - \frac{\kappa - 3}{24}\gamma^3\sigma^4$$

where μ, σ, τ and κ denote the mean, standard deviation, skewness and kurtosis of a given portfolio.

We also consider first order LPM that takes into account only the part of the returns distribution below certain return threshold τ.

$$LPM_{K,\tau}(X) = \mathrm{E}\left[\left|\min(X - \tau, 0)\right|^k\right]^{1/k} = \mathrm{E}\left[\max(\tau - \mathrm{X}, 0)^k\right]^{1/k}$$

We have chosen 0% threshold that is adequate to our hedging purpose in terms of returns, that value fluctuations of the hedged position were negligible. Under this threshold the first order LPM, k=1, can be interpreted as the expected average loss.

We also introduce VaR and ES at 1% and 5% probability with a time horizon equal to the out-of-sample periods. For a given portfolio, time horizon, and probability p, the p VaR is defined as a threshold loss value, such that the probability that the loss on the portfolio over the given time horizon exceeds this value is p. The ES at p% level is the expected return on the portfolio in the worst p% of the cases.

Table 8 displays the mean return, volatility, skewness, excess kurtosis, Certainty Equivalent, VaR, ES and $LPM_{1,0}$ for each hedge as well as for the spot position. Hedging reduces average return in half of the cases, in particular returns are reduced in all cases in 2007 and 2013 and are increased in all cases in 2008 and 2014. Hedging reduces volatility relative to the spot position in all cases in line with our results for individual stocks. Kurtosis either increases or reduces during 2007-2008 period, and increases in 2012-2013 period, this last result is also in line with our individual stocks analysis, indicating the possibility of large positive and negative extreme returns. With the exception of *A* portfolios in 2008 and 2012, the highest volatility periods, hedges produce positive asymmetry. As a result of the above effects the Certainty Equivalent increases most of the times, especially in 2008 and 2012, the years with higher volatility and higher excess kurtosis and lower returns in the spot positions. VaR, ES and $LPM_{1,0}$ improve in all cases suggesting improvement in the risk associated to the left tail of the returns distribution. There are no significant differences among distributions.

Table 9 displays the relative change in all these measures versus the unhedged position. In general, GARCH strategies perform better than OLS strategies under all measures.

5. CONCLUSIONS

This paper analyzes the use of index futures as a cross-hedging instrument for portfolios that share some stocks with the composition of the underlying index of the futures contract and the impact of liquidity in hedging effectiveness. We have used the theoretical model proposed by Lafuente and Novales (2003) that takes into consideration a specific noise in addition to the common noise shared with the spot market price.

We have analized daily closing data on futures prices for the IBEX 35 futures contract and spot prices for different portfolios over the period 2001-2013. In order to contrast the robustness of our results we have created portfolios with very different liquidity stocks and different weighting criteria and we have analyzed periods of very different characteristics. The existence of a noise specific to the futures market, as included in our econometric model, is validated by the rejection of a common ARCH feature underlying the heteroskedastic behaviour detected in spot and futures markets returns. We have implemented an asymmetric bivariate error-correction model with DCC-GARCH structure to estimate the conditional mean, variance and covariance of future and spot market returns. We have analyzed daily closing data during the 2001-2011 period and we have simulated out-of-sample hedges over 2007-2008 and 2012-2013 periods. We have also implemented other common hedging effectiveness measures in order to evaluate the impact of the hedge in the returns distribution.

The results show important volatility reductions up to 70% in the most liquid portfolios and an important relationship between idiosyncratic risk and hedging effectiveness that makes the most liquid portfolios, and among them the relative weighted portfolios, to achieve higher effectiveness. The results also show an improvement in hedging effectiveness of GARCH dynamic cross-hedging strategies as compared to the improvement that would be obtained by applying a static OLS ratio or a dynamic OLS ratio and we have found that this gain is higher in the least liquid portfolios and without significant differences among the distributions used to simulate the disturbances. The results also show that during a very high volatility period, as the year 2008, the dynamic strategies may fail to exceed static OLS ratio strategy. There are no significant differences in effectiveness among. Finally, the results obtained for CE, VaR, ES and LPM suggest that in terms of these measures GARCH strategies can also perform better than OLS dynamic ratio strategies and better than OLS static ratio strategies.

The advantage from the GARCH ratio is in line with the results obtained by Lafuente and Novales (2003) in their analysis of indexes hedge with their corresponding futures contract with data for the period 1993-1996, and with the results obtained in the Third Chapter[11] in the analysis of individual stocks cross-hedging with index futures with data for the 2009-2014 period. On the contrary, our results are in contrast with the results in the First Chapter[10] for different international indexes hedges with their corresponding future contracts with data for 1997-2006 that didn´t show a significant advantage for the GARCH ratio over the unitary ratio suggesting that in mature futures markets with high trading volume the time-varying noise couldn't be exploited. The results obtained in this study with the less liquid portfolios being more suitable for the GARCH strategy seems to indicate that the higher specific noise related to the common noise present in cross-hedges allows for exploiting better volatility clusters trough a GARCH dynamic ratio since the quick corrections of any arbitrage opportunity or equilibrium deviation that happens when the index is hedged by its futures contracts in a mature futures market do not happen. This is also confirmed by the significance and values of the error correction parameters found.

Low liquidity in the futures market allow to exploit the specific noise, in line with Roll et al. (2007) who presented evidence that liquidity enhances the efficiency of the futures pricing system, and that low liquidity in the spot market has a similar effect in cross-hedging. Our results also suggest that the higher specific noise in cross-hedging operations allows the GARCH ratio to achieve higher effectiveness when compared to a static ratio as in the Second Chapter results[10], and therefore when the liquidity is lower the advantage is higher.

REFERENCES

Andani, A., Lafuente, J.A. and Novales, A., 2009, Liquidity and hedging effectiveness under futures mispricing: international evidence, *Journal of Futures Markets 29, November 2009*, 1050-1066.

Chen, S.-S., Lee, C.-F. and Shrestha, K., 2013, Futures hedge ratios: a review, *Encyclopedia of Finance,* 871-890. Springer New York.

Choudhry, T., 2003, Short-run deviations and optimal hedge ratio: evidence from stock futures, *Journal of Multinational Financial Management* 13, 171-192.

Choudhry, T., 2004, The hedging effectiveness of constant and time-varying hedge ratios using three Pacific Basin stock futures, *International Review of Economics & Finance* 4, 371-385.

Cotter, J. and Hanly, J., 2012, Hedging effectiveness under conditions of asymmetry, *European Journal of Finance*, 18-2, 135-147.

Ederington, L.H., 1979. The hedging performance of the new futures markets. *Journal of finance* 34, 157-170.

Engle, R.F., 2002, Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models, *Journal of Business and Economic Statistics* 20, 339-350.

Engle, R.F. and Kozicki, S., 1993, Testing for common features, *Journal of Business and Economic Statistics* 11*,* 369–380.

Ku, Y.H., Chen, H. and Chen, K., 2007, On the application of the dynamic conditional correlation model in estimating optimal time-varying hedge ratios, *Applied Economics Letters 7*, 503-509.

Lafuente, J.A. and Novales, A., 2003, Optimal hedging under departures from the cost-of-carry valuation: Evidence from the Spanish stock index futures market, *Journal of Banking & Finance* 27, 1053-1078.

Lee, H. and Yoder, J., 2007, Optimal hedging with a regime switching time-varying correlations GARCH model, *Journal of Futures Markets* 27, 495-516.

Lien, D., 2005, A note on the superiority of the OLS hedge ratio, *Journal of Futures Markets* 25, 1121-1126.

Lien, D., Lee, G., Yang, L. and Zhou, C., 2014, Evaluating the Effectiveness of Futures Hedging, Handbook of Financial Econometrics and Statistics, 1891-1908. Springer, New York.

Park, T.H. and Switzer, L.N., 1995, Bivariate GARCH estimation of the optimal hedge ratios for stock index futures: A note, *Journal of Futures Markets* 15, 61–67.

Park, S. and Jei, Y., 2010, Estimation and hedging effectiveness of time-varying hedge ratio: Flexible bivariate GARCH approaches, *Journal of Futures Markets*, 30, 71-99.

Roll, R., Schwartz, E. and A. Subrahmanyam, 2007, Liquidity and the law of one price: The case of the futures-cash basis, *Journal of Finance*, 52, 5, 2201-2234.

Sukcharoen, K., Choi, H. and Leatham, D., 2015, Optimal gasoline hedging strategies using futures contracts and exchange-traded funds, *Applied Economics,* 2015, Vol. 47, Nº. 32, 3482-3498.

Appendix 1. - Tables

TABLE 1. Descriptive statistics on spot market returns and futures market returns.

	A_W	A_EW	B_W	B_EW	IBX1 *
Mean	-0.0001	-0.0002	0.0001	-0.0001	0.0000
Standar deviation	0.0169	0.0161	0.0147	0.0160	0.0157
Skewness	0.1994	0.1907	0.1109	0.2410	0.0498
Kurtosis	5.4945	6.1595	7.6954	12.8285	5.4587
Mean					
2007	0.0002	-0.0001	0.0002	0.0003	0.0003
2008	-0.0021	-0.0021	-0.0020	-0.0022	-0.0020
2012	-0.0008	-0.0014	0.0009	0.0005	-0.0002
2013	0.0007	0.0008	0.0007	0.0008	0.0008
Standar deviation					
2007	0.0100	0.0094	0.0132	0.0136	0.0106
2008	0.0266	0.0274	0.0245	0.0252	0.0250
2012	0.0201	0.0200	0.0153	0.0149	0.0175
2013	0.0134	0.0132	0.0115	0.0109	0.0118
Skewness					
2007	-0.2917	-0.2907	-0.5727	-0.6068	-0.4705
2008	0.1628	0.2179	0.2751	0.1778	-0.0979
2012	0.1179	0.1161	0.3325	0.2233	0.0855
2013	-0.1288	-0.1750	-0.0462	-0.1340	-0.0618
Kurtosis					
2007	0.8405	0.9734	1.7090	1.6260	1.2520
2008	3.3797	2.5920	2.5014	2.6169	3.2934
2012	1.4583	1.2865	1.4441	1.1697	1.0300
2013	0.8157	0.9101	0.1794	0.2893	0.6648

* IBEX 35 closest to maturity futures contract.
Note: daily basis

TABLE 2. Testing for common ARCH features. Portfolios and IBEX 35 future contract. Engle and Kozicki test.

k	1	2	3	4	5	6	7	8	9	10
Min TR^2										
A W	130.0	195.9	206.1	237.8	262.5	265.5	271.4	277.6	285.3	294.2
A EW	107.0	157.4	190.7	242.5	256.6	269.2	293.3	298.9	318.5	323.1
B W	23.9	35.9	40.2	53.2	88.7	96.7	100.7	102.0	102.4	104.5
B EW	34.7	54.1	59.3	83.6	107.9	112.9	127.3	132.2	131.9	135.4
Critical values										
a=0.05	6.0	11.1	15.5	19.7	23.7	27.6	31.4	35.2	38.9	42.6
a=0.01	9.2	15.1	20.1	24.7	29.1	33.4	37.6	41.6	45.6	49.6

Notes: The first panel shows the minimum T*R^2 in a set of regressions of $(r_{s,t}-dr_{f,t})^2$ on k lags of $r^2_{s,t}$, $r^2_{f,t}$ and $r_{s,t}r_{f,t}$, over a grid of values for d, where T denotes the sample size. The last two rows show critical values at the α-significance level.

TABLE 3. Maximum Likelihood estimation of the parameters involved in the DCC-GARCH model. Panel A presents Normal distribution estimates. Panel B presents t-Student distribution estimates. Panel C presents GED distribution estimates.

Panel A. Normal Distribution

	Estimation window 2001-2006				**Estimation window 2001-2011**			
	A_W	*A_EW*	*B_W*	*B_EW*	*A_W*	*A_EW*	*B_W*	*B_EW*
Spot mean equation								
α_{11}	-0.095	0.005	0.054	0.024	0.206 *	0.083	0.012	-0.003
α_{12}	0.085	-0.032	-0.075 **	-0.033	-0.174	-0.083 *	-0.027	0.010
γ_s	0.002	0.001 *	-0.003	-0.002	-0.002	0.000	-0.004	-0.006 **
Futures mean equation								
α_{21}	0.110	0.107 *	0.042	0.014	0.353 **	0.124 **	0.023	0.015
α_{22}	-0.132	-0.099 *	-0.034	-0.005	-0.338 **	-0.142 **	-0.037	-0.018
γ_s	0.003	0.001 **	0.002	0.004 *	0.000	0.001	-0.001	-0.003
Spot Variance equation								
ω_s	0.003	0.005 **	0.002	-0.001	0.005 **	0.002 **	0.001	0.002
A_{11}	0.056	0.131 *	0.172 **	0.350 **	0.045	0.059 **	0.028	0.094
A_{12}	-0.048	-0.026	-0.081 **	-0.265 **	-0.046	0.000	0.032	-0.005
B_{11}	1.134 **	0.539 **	0.643 **	0.426 **	1.046 **	0.854 **	0.950 **	0.888 **
B_{12}	-0.244	0.319	0.306 **	0.717 **	-0.151	0.053 **	-0.024	0.023
D_1	0.113 **	-0.007	0.068 **	0.085 *	0.154 **	0.062 *	0.026	0.005
Futures Variance equation								
ω_f	0.004 *	0.001 **	0.002 **	0.002 **	0.009 **	0.002 **	0.001 *	0.001
A_{21}	0.116	0.065 **	-0.007	-0.024	0.011	0.079 **	0.017	0.018
A_{22}	-0.123 *	-0.021	0.029 **	0.043 **	-0.039	-0.041 **	0.013	0.013
B_{21}	0.310	-0.139 *	-0.011 **	0.014	0.881 **	-0.101 **	-0.012	-0.010
B_{22}	0.582	1.039 **	0.921 **	0.886 **	-0.005	1.017 **	0.940 **	0.934 **
D_2	0.138 **	0.057 **	0.099 **	0.127 **	0.182 **	0.076 **	0.078	0.087 *
Correlation dynamics								
κ_1	0.118	0.055 **	0.014	0.009 **	0.139 **	0.055 **	0.030	0.044 *
κ_2	0.345	0.933 **	0.986 **	0.991 **	0.194 **	0.935 **	0.967 **	0.953 **

* Significant at the 5% level
** Significant at the 1% level
*** Multiplied by 1,000

TABLE 3. Maximum Likelihood estimation of the parameters involved in the DCC-GARCH model. Panel A presents Normal distribution estimates. Panel B presents t-Student distribution estimates. Panel C presents GED distribution estimates.

Panel B. T Distribution

	Estimation window 2001-2006				**Estimation window 2001-2011**			
	A_W	A_EW	B_W	B_EW	A_W	A_EW	B_W	B_EW
Spot mean equation								
α_{11}	-0.143	0.002	0.045	0.007	0.019	0.028	0.008	-0.008
α_{12}	0.131	-0.037	-0.066	-0.049 *	0.014	-0.029	-0.019	0.001
γ_s	0.003	0.001 **	-0.009 **	-0.009 **	0.001	0.001 *	-0.005 *	-0.006 **
Futures mean equation								
α_{21}	0.035	0.105	0.048	0.021	0.151 *	0.071	0.030	0.020
α_{22}	-0.060	-0.108 *	-0.059 *	-0.039	-0.132	-0.089 *	-0.038	-0.029
γ_s	0.004 **	0.001 **	-0.004	-0.004 *	0.003	0.001 **	-0.003	-0.004 *
Spot Variance equation								
ω_s	0.002 **	0.004 **	0.005 **	0.004	0.003 **	0.001 **	0.002	0.002 **
A_{11}	0.062	0.124 **	0.140 **	0.186 **	0.052	0.067 **	0.054	0.098 **
A_{12}	-0.046	-0.032	-0.075 **	-0.082	-0.048	-0.021	-0.012	-0.036
B_{11}	0.971 **	0.535 **	0.586 **	0.690 **	0.878 **	0.827 **	0.854 **	0.841 **
B_{12}	-0.060	0.336 **	0.314 *	0.186	0.050	0.099 **	0.077	0.081 *
D_1	0.101 **	0.008	0.078	0.054	0.117 **	0.055 **	0.047 *	0.030
Futures Variance equation								
ω_f	0.003 **	0.001 **	0.002 **	0.001 *	0.006 **	0.001 **	0.001 **	0.001 **
A_{21}	0.100 *	0.052 *	0.044 *	0.043 *	0.034	0.069 **	0.015	0.025
A_{22}	-0.107 **	-0.012	-0.011	-0.013	-0.061	-0.037 **	0.005	-0.001
B_{21}	0.214 *	-0.125 **	-0.070 *	-0.048 *	0.639 **	-0.100 **	-0.025	-0.024
B_{22}	0.699 **	1.033 **	0.986 **	0.979 **	0.264	1.029 **	0.958 **	0.959 **
D_2	0.121 **	0.056 **	0.064 **	0.065 **	0.147 **	0.065 **	0.078 **	0.074 **
Correlation dynamics								
κ_1	0.141 **	0.050 **	0.026 *	0.044 **	0.099 **	0.046 **	0.027 **	0.034 **
κ_2	0.534 **	0.939 **	0.974 **	0.955 **	0.461 *	0.945 **	0.968 **	0.964 **
Shape	7.195 **	8.850 **	6.213 **	5.769 **	5.749 **	6.776 **	6.363 **	6.201 **

* Significant at the 5% level
** Significant at the 1% level
*** Multiplied by 1,000

TABLE 3. Maximum Likelihood estimation of the parameters involved in the DCC-GARCH model. Panel A presents Normal distribution estimates. Panel B presents t-Student distribution estimates. Panel C presents GED distribution estimates.

Panel C. GED Distribution

	Estimation window 2001-2006				Estimation window 2001-2011			
	A_W	*A_EW*	*B_W*	*B_EW*	*A_W*	*A_EW*	*B_W*	*B_EW*
Spot mean equation								
α_{11}	0.028	0.018	0.155 *	0.101	0.402	0.209 *	0.067	0.017
α_{12}	-0.037	-0.018	-0.130 **	-0.059	-0.451 *	-0.222 *	-0.109 *	0.003
γ_s	0.000	0.001	0.002	0.001	-0.002	0.000	-0.001	-0.011 **
Futures mean equation								
α_{21}	0.319 *	0.098	0.072	0.005	0.589 **	0.250 *	0.044	0.019
α_{22}	-0.327 *	-0.057	-0.048	0.006	-0.643 **	-0.287 **	-0.086 *	-0.019
γ_s	0.001	0.001	0.006	0.008 *	-0.002	0.000	0.002	-0.007
Spot Variance equation								
ω_s	0.005 **	0.007 **	0.004	-0.008	0.010 **	0.003 **	0.019 **	0.001
A_{11}	0.019	0.173 **	0.591 *	0.677 **	0.007	0.058 **	0.574 **	0.026
A_{12}	0.004	-0.037	-0.485 **	-0.496 **	0.077	0.023	-0.388 **	0.073
B_{11}	1.313 **	0.580 **	0.005	0.094	0.935 *	0.884 **	-0.048	0.987 **
B_{12}	-0.461 **	0.276 **	1.254 **	1.454 **	-0.116	0.007	0.935 **	-0.074 *
D_1	0.168 **	-0.021	0.168	0.026	0.218 **	0.095 *	0.139 *	0.001
Futures Variance equation								
ω_f	0.007 **	0.002 **	0.003 **	0.004 **	0.011 **	0.003 **	0.004 **	0.002 *
A_{21}	0.135	0.105 **	-0.028	-0.032 *	0.125	0.103 **	0.076	0.018
A_{22}	-0.110	-0.046	0.074 *	0.082 *	-0.091	-0.058 **	0.045	0.010
B_{21}	0.417 **	-0.163 **	-0.001	0.010	0.145	-0.100 **	-0.067	0.012
B_{22}	0.432 **	1.057 **	0.852 **	0.835 **	0.689 **	1.008 **	0.898 **	0.909 **
D_2	0.208 **	0.066 **	0.181 **	0.181 **	0.252 **	0.115 **	0.168 **	0.117 **
Correlation dynamics								
κ_1	0.080 **	0.061 **	0.086 **	0.007 **	0.154 **	0.061 **	0.092 **	0.052
κ_2	0.260 *	0.927 **	0.665 **	0.993 **	0.157 **	0.927 **	0.890 **	0.943 **
Shape	0.541 **	0.531 **	0.612 **	0.642 **	0.674 **	0.628 **	0.655 **	0.694 **

* Significant at the 5% level
** Significant at the 1% level
*** Multiplied by 1,000

TABLE 4. Out-of-sample hedging effectiveness simulations. σ change. Daily rebalance of the hedge ratio. Panel A presents simulations of market innovations under Normal Distribution. Panel B: t-Student Distribution innovations. Panel C: GED Distribution innovations.

Panel A: Normal Distribution.

	GARCH ratio	σ_s	δ_t	ρ_{sf}	ρ_{sgarch}	Hedging effectiveness. Change in variance			Garch reduction vs			GARCH ratio	σ_s	δ_t	ρ_{sf}	ρ_{sgarch}	Hedging effectiveness. Change in variance			Garch reduction vs	
						GARCH	OLS	OLS Dyn	OLS	OLS Dyn							GARCH	OLS Dyn	OLS	OLS Dyn	OLS
A_W											***B_W***										
2007	0.976	1.00%	0.245	97.4%	-1.3%	**-75.94%**	-73.82%	-74.13%	-2.12%	-1.80%	**2007**	1.111	1.32%	0.448	89.7%	47.0%	**-54.96%**	-42.46%	-41.21%	-12.50%	-13.74%
2008	1.005	2.66%	0.234	98.1%	29.1%	**-80.52%**	-80.45%	-80.32%	-0.06%	-0.20%	**2008**	1.044	2.45%	0.442	92.1%	14.4%	-57.97%	-56.79%	-52.00%	-1.19%	-5.97%
2012	1.066	2.01%	0.233	97.5%	40.6%	**-77.13%**	-76.56%	-76.66%	-0.58%	-0.47%	**2012**	0.741	1.53%	0.657	81.6%	57.5%	**-42.15%**	-42.05%	-42.04%	-0.10%	-0.11%
2013	1.060	1.34%	0.237	96.1%	34.7%	-71.52%	-72.05%	**-72.18%**	0.53%	0.66%	**2013**	0.808	1.15%	0.663	78.0%	58.3%	-36.90%	-37.39%	**-37.39%**	0.49%	0.50%
A_EW											***B_EW***										
2007	0.860	0.94%	0.418	93.9%	23.6%	-64.44%	-65.10%	**-65.14%**	0.66%	0.70%	**2007**	1.188	1.36%	0.508	90.1%	35.5%	**-55.73%**	-44.71%	-43.60%	-11.02%	-12.13%
2008	0.966	2.74%	0.341	96.5%	43.9%	-72.93%	-63.33%	-66.81%	-9.60%	-6.12%	**2008**	1.060	2.52%	0.444	92.1%	16.6%	-56.82%	-57.94%	-54.23%	1.11%	-2.59%
2012	1.089	2.00%	0.335	95.3%	28.0%	**-69.95%**	-67.20%	-67.44%	-2.75%	-2.51%	**2012**	0.778	1.49%	0.596	86.7%	44.2%	-49.67%	**-49.80%**	-49.76%	0.14%	0.10%
2013	1.042	1.32%	0.335	95.1%	36.4%	-68.45%	-67.19%	-67.69%	-1.26%	-0.76%	**2013**	0.856	1.09%	0.583	84.8%	45.1%	-46.66%	**-46.95%**	-46.93%	0.30%	0.28%

Notes: σs: Spot position standard deviation; δt: Specific noise/common noise; ρsf: Correlation between spot and futures returns; ρsGARCH: Correlation between spot position and the hedged portfolio with the GARCH strategy; OLSDyn: Dynamic ordinary least squares strategy, the ratio is recalculated each 10 days with new information and applied to the following 10 days; OLS: The ordinary least squares ratio is calculated with the in-sample information and kept constant. When GARCH ratio performs better results are marked red; Best results are marked in bold.

TABLE 4. Out-of-sample hedging effectiveness simulations. σ change under daily rebalance of the hedge ratio. Panel A presents simulations of market innovations under Normal Distribution. Panel B: t-Student Distribution innovations. Panel C: GED Distribution innovations.

Panel B. t-Student Distribution.

	GARCH ratio	σ_s	δ_t	ρ_{sf}	ρ_{sgarch}	Hedging effectiveness. Change in variance			Garch reduction vs	
						GARCH	OLS	OLS Dyn	OLS	OLS Dyn
A_W										
2007	0.984	1.00%	0.244	97.4%	-7.5%	**-75.65%**	-73.82%	-74.13%	-1.82%	-1.51%
2008	1.016	2.66%	0.224	98.1%	19.3%	**-81.08%**	-80.45%	-80.32%	-0.63%	-0.76%
2012	1.087	2.01%	0.229	97.5%	30.2%	**-77.75%**	-76.56%	-76.66%	-1.19%	-1.09%
2013	1.075	1.34%	0.275	96.1%	30.5%	-71.94%	-72.05%	**-72.18%**	0.11%	0.24%
A_EW										
2007	0.852	0.94%	0.423	93.9%	25.4%	-64.64%	-65.10%	**-65.14%**	0.46%	0.50%
2008	0.977	2.74%	0.341	96.5%	40.3%	-73.32%	-63.33%	-66.81%	######	-6.52%
2012	1.081	2.00%	0.328	95.3%	30.1%	**-69.94%**	-67.20%	-67.44%	-2.74%	-2.50%
2013	1.031	1.32%	0.336	95.1%	39.2%	-68.32%	-67.19%	-67.69%	-1.13%	-0.63%

	GARCH ratio	σ_s	δ_t	ρ_{sf}	ρ_{sgarch}	Hedging effectiveness. Change in variance			Garch reduction vs	
						GARCH	OLS Dyn	OLS	OLS Dyn	OLS
B_W										
2007	1.059	1.32%	0.467	89.7%	53.3%	**-55.37%**	-42.46%	-41.21%	-12.91%	-14.16%
2008	0.979	2.45%	0.442	92.1%	27.9%	-58.12%	-56.79%	-52.00%	-1.34%	-6.12%
2012	0.737	1.53%	0.653	81.6%	58.3%	-41.87%	**-42.05%**	-42.04%	0.18%	0.17%
2013	0.784	1.15%	0.672	78.0%	60.8%	-36.86%	-37.39%	**-37.39%**	0.52%	0.53%
B_EW										
2007	1.100	1.36%	0.483	90.1%	50.3%	**-55.20%**	-44.71%	-43.60%	-10.49%	-11.60%
2008	0.991	2.52%	0.445	92.1%	25.9%	-57.92%	-57.94%	-54.23%	0.02%	-3.69%
2012	0.766	1.49%	0.587	86.7%	46.7%	-49.69%	**-49.80%**	-49.76%	0.11%	0.07%
2013	0.833	1.09%	0.590	84.8%	47.9%	-46.81%	**-46.95%**	-46.93%	0.14%	0.12%

Notes: σs: Spot position standard deviation; δt: Specific noise/common noise; ρsf: Correlation between spot and futures returns; ρsGARCH: Correlation between spot position and the hedged portfolio with the GARCH strategy; OLSDyn: Dynamic ordinary least squares strategy, the ratio is recalculated each 10 days with new information and applied to the following 10 days; OLS: The ordinary least squares ratio is calculated with the in-sample information and kept constant. When GARCH ratio performs better results are marked red; Best results are marked in bold.

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Panel C. GED Distribution.

	GARCH ratio	σ_s	δ_t	ρ_{sf}	ρ_{sgarch}	Hedging effectiveness. Change in variance: GARCH	OLS	OLS Dyn	Garch reduction vs: OLS	OLS Dyn
A_W										
2007	0.951	1.00%	0.254	97.4%	11.7%	**-76.16%**	-73.82%	-74.13%	-2.33%	-2.02%
2008	0.995	2.66%	0.241	98.1%	32.1%	-79.80%	**-80.45%**	-80.32%	0.65%	0.52%
2012	1.079	2.01%	0.235	97.5%	37.0%	**-77.41%**	-76.56%	-76.66%	-0.85%	-0.75%
2013	1.061	1.34%	0.237	96.1%	34.8%	-71.63%	-72.05%	**-72.18%**	0.42%	0.55%
A_EW										
2007	0.877	0.94%	0.409	93.9%	20.4%	-64.03%	-65.10%	**-65.14%**	1.07%	1.11%
2008	0.959	2.74%	0.342	96.5%	45.3%	-72.62%	-63.33%	-66.81%	-9.29%	-5.81%
2012	1.110	2.00%	0.342	95.3%	23.3%	**-69.77%**	-67.20%	-67.44%	-2.58%	-2.33%
2013	1.049	1.32%	0.336	95.1%	34.2%	-68.47%	-67.19%	-67.69%	-1.27%	-0.78%

	GARCH ratio	σ_s	δ_t	ρ_{sf}	ρ_{sgarch}	Hedging effectiveness. Change in variance: GARCH	OLS Dyn	OLS	Garch reduction vs: OLS Dyn	OLS
B_W										
2007	1.116	1.32%	0.506	89.7%	45.8%	-51.63%	-42.46%	-41.21%	-9.16%	-10.41%
2008	1.065	2.45%	0.447	92.1%	12.7%	-57.41%	-56.79%	-52.00%	-0.63%	-5.41%
2012	0.758	1.53%	0.687	81.6%	53.0%	-40.47%	**-42.05%**	-42.04%	1.59%	1.57%
2013	0.853	1.15%	0.645	78.0%	50.4%	-36.19%	-37.39%	**-37.39%**	1.20%	1.20%
B_EW										
2007	1.304	1.36%	0.544	90.1%	15.6%	-51.71%	-44.71%	-43.60%	-7.00%	-8.11%
2008	1.157	2.52%	0.476	92.1%	-1.4%	-55.78%	-57.94%	-54.23%	2.16%	-1.54%
2012	0.813	1.49%	0.606	86.7%	39.7%	-48.49%	**-49.80%**	-49.76%	1.31%	1.27%
2013	0.918	1.09%	0.563	84.8%	33.4%	-45.62%	**-46.95%**	-46.93%	1.33%	1.32%

Notes: σs: Spot position standard deviation; δt: Specific noise/common noise; ρsf: Correlation between spot and futures returns; ρsGARCH: Correlation between spot position and the hedged portfolio with the GARCH strategy; OLSDyn: Dynamic ordinary least squares strategy, the ratio is recalculated each 10 days with new information and applied to the following 10 days; OLS: The ordinary least squares ratio is calculated with the in-sample information and kept constant. When GARCH ratio performs better results are marked red; Best results are marked in bold.

TABLE 5. Out-of-sample hedging effectiveness simulations. σ change. The hedge ratio obtained for the last day in each rolling sample is applied to the following 10 trading days. Panel A presents simulations of market innovations under Normal Distribution. Panel B: t-Student Distribution innovations. Panel C: GED Distribution innovations.

Panel A. Normal Distribution.

	GARCH ratio	σ_s	δ_t	ρ_{sf}	ρ_{sgarch}	Hedging effectiveness. Change in variance			Garch reduction vs			GARCH ratio	σ_s	δ_t	ρ_{sf}	ρ_{sgarch}	Hedging effectiveness. Change in variance			Garch reduction vs	
						GARCH	OLS	OLS Dyn	OLS	OLS Dyn							GARCH	OLS Dyn	OLS	OLS Dyn	OLS
A_W											***B_W***										
2007	0.980	1.00%	0.245	97.4%	-4.1%	**-75.79%**	-73.82%	-74.13%	-1.97%	-1.66%	**2007**	1.112	1.32%	0.448	89.7%	45.5%	**-55.29%**	-42.46%	-41.21%	-12.83%	-14.08%
2008	1.001	2.66%	0.234	98.1%	37.7%	**-80.71%**	-80.45%	-80.32%	-0.25%	-0.38%	**2008**	1.067	2.45%	0.442	92.1%	-4.5%	-52.70%	-56.79%	-52.00%	4.09%	-0.69%
2012	1.064	2.01%	0.233	97.5%	43.9%	**-77.30%**	-76.56%	-76.66%	-0.74%	-0.64%	**2012**	0.738	1.53%	0.657	81.6%	59.1%	-41.84%	**-42.05%**	-42.04%	0.22%	0.20%
2013	1.061	1.34%	0.237	96.1%	34.1%	**-72.27%**	-72.05%	-72.18%	-0.22%	-0.09%	**2013**	0.809	1.15%	0.663	78.0%	55.7%	-35.93%	-37.39%	**-37.39%**	1.46%	1.47%
A_EW											***B_EW***										
2007	0.864	0.94%	0.418	93.9%	25.7%	**-65.25%**	-65.10%	-65.14%	-0.16%	-0.11%	**2007**	1.205	1.36%	0.508	90.1%	34.2%	**-55.70%**	-44.71%	-43.60%	-10.99%	-12.10%
2008	0.959	2.74%	0.341	96.5%	46.0%	-72.77%	-63.33%	-66.81%	-9.44%	-5.96%	**2008**	1.075	2.52%	0.444	92.1%	-0.5%	-52.83%	-57.94%	-54.23%	5.11%	1.40%
2012	1.094	2.00%	0.335	95.3%	30.3%	**-70.08%**	-67.20%	-67.44%	-2.89%	-2.64%	**2012**	0.774	1.49%	0.596	86.7%	46.4%	**-49.85%**	-49.80%	-49.76%	-0.05%	-0.09%
2013	1.042	1.32%	0.335	95.1%	34.8%	**-68.97%**	-67.19%	-67.69%	-1.77%	-1.28%	**2013**	0.854	1.09%	0.583	84.8%	41.3%	-45.20%	**-46.95%**	-46.93%	1.76%	1.74%

Notes: σs: Spot position standard deviation; δt: Specific noise/common noise; ρsf: Correlation between spot and futures returns; ρsGARCH: Correlation between spot position and the hedged portfolio with the GARCH strategy; OLSDyn: Dynamic ordinary least squares strategy, the ratio is recalculated each 10 days with new information and applied to the following 10 days; OLS: The ordinary least squares ratio is calculated with the in-sample information and kept constant. When GARCH ratio performs better results are marked red; Best results are marked in bold.

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Panel B. t-Student Distribution.

	GARCH ratio	σ_s	δ_t	ρ_{sf}	ρ_{sgarch}	Hedging effectiveness. Change in variance			Garch reduction vs			GARCH ratio	σ_s	δ_t	ρ_{sf}	ρ_{sgarch}	Hedging effectiveness. Change in variance			Garch reduction vs	
						GARCH	OLS	OLS Dyn	OLS	OLS Dyn							GARCH	OLS Dyn	OLS	OLS Dyn	OLS
A_W											***B_W***										
2007	0.987	1.00%	0.244	97.4%	-7.7%	**-75.75%**	-73.82%	-74.13%	-1.93%	-1.62%	**2007**	1.060	1.32%	0.467	89.7%	53.8%	**-55.47%**	-42.46%	-41.21%	-13.00%	-14.25%
2008	1.013	2.66%	0.224	98.1%	26.5%	**-81.34%**	-80.45%	-80.32%	-0.89%	-1.02%	**2008**	0.992	2.45%	0.442	92.1%	9.1%	-54.57%	-56.79%	-52.00%	2.22%	-2.56%
2012	1.086	2.01%	0.229	97.5%	35.8%	**-77.61%**	-76.56%	-76.66%	-1.05%	-0.95%	**2012**	0.735	1.53%	0.653	81.6%	59.4%	-41.58%	**-42.05%**	-42.04%	0.48%	0.46%
2013	1.077	1.34%	0.275	96.1%	28.7%	**-72.42%**	-72.05%	-72.18%	-0.37%	-0.24%	**2013**	0.783	1.15%	0.672	78.0%	59.1%	-36.30%	-37.39%	**-37.39%**	1.09%	1.09%
A_EW											***B_EW***										
2007	0.854	0.94%	0.423	93.9%	28.3%	**-65.38%**	-65.10%	-65.14%	-0.28%	-0.24%	**2007**	1.102	1.36%	0.483	90.1%	52.2%	**-55.75%**	-44.71%	-43.60%	-11.04%	-12.15%
2008	0.971	2.74%	0.341	96.5%	44.0%	-73.03%	-63.33%	-66.81%	-9.70%	-6.23%	**2008**	1.003	2.52%	0.445	92.1%	9.5%	-54.29%	-57.94%	-54.23%	3.64%	-0.06%
2012	1.086	2.00%	0.328	95.3%	32.5%	**-70.07%**	-67.20%	-67.44%	-2.87%	-2.63%	**2012**	0.763	1.49%	0.587	86.7%	49.0%	**-49.81%**	-49.80%	-49.76%	-0.01%	-0.05%
2013	1.030	1.32%	0.336	95.1%	38.3%	**-68.77%**	-67.19%	-67.69%	-1.57%	-1.08%	**2013**	0.831	1.09%	0.590	84.8%	45.3%	-45.83%	**-46.95%**	-46.93%	1.12%	1.10%

Notes: σs: Spot position standard deviation; δt: Specific noise/common noise; ρsf: Correlation between spot and futures returns; ρsGARCH: Correlation between spot position and the hedged portfolio with the GARCH strategy; OLSDyn: Dynamic ordinary least squares strategy, the ratio is recalculated each 10 days with new information and applied to the following 10 days; OLS: The ordinary least squares ratio is calculated with the in-sample information and kept constant. When GARCH ratio performs better results are marked red; Best results are marked in bold.

TABLE 5. Out-of-sample hedging effectiveness simulations. σ change. The hedge ratio obtained for the last day in each rolling sample is applied to the following 10 trading days. Panel A presents simulations of market innovations under Normal Distribution. Panel B: t-Student Distribution innovations. Panel C: GED Distribution innovations.

Panel C. GED Distribution.

	GARCH ratio	σ_s	δ_t	ρ_{sf}	ρ_{sgarch}	Hedging effectiveness. Change in variance			Garch reduction vs			GARCH ratio	σ_s	δ_t	ρ_{sf}	ρ_{sgarch}	Hedging effectiveness. Change in variance			Garch reduction vs	
						GARCH	OLS	OLS Dyn	OLS	OLS Dyn							GARCH	OLS Dyn	OLS	OLS Dyn	OLS
A_W											***B_W***										
2007	0.958	1.00%	0.254	97.4%	5.0%	**-76.02%**	-73.82%	-74.13%	-2.20%	-1.89%	**2007**	1.116	1.32%	0.506	89.7%	47.2%	-50.40%	-42.46%	-41.21%	-7.94%	-9.19%
2008	0.990	2.66%	0.241	98.1%	45.1%	-79.82%	**-80.45%**	-80.32%	0.64%	0.50%	**2008**	1.079	2.45%	0.447	92.1%	-6.8%	-51.18%	-56.79%	-52.00%	5.60%	0.82%
2012	1.078	2.01%	0.235	97.5%	40.6%	**-77.35%**	-76.56%	-76.66%	-0.79%	-0.69%	**2012**	0.748	1.53%	0.687	81.6%	57.6%	-41.15%	**-42.05%**	-42.04%	0.90%	0.89%
2013	1.063	1.34%	0.237	96.1%	33.5%	**-72.22%**	-72.05%	-72.18%	-0.17%	-0.04%	**2013**	0.849	1.15%	0.645	78.0%	49.1%	-35.24%	-37.39%	**-37.39%**	2.14%	2.15%
A_EW											***B_EW***										
2007	0.883	0.94%	0.409	93.9%	20.6%	-64.81%	-65.10%	**-65.14%**	0.29%	0.34%	**2007**	1.328	1.36%	0.544	90.1%	18.6%	-52.03%	-44.71%	-43.60%	-7.32%	-8.43%
2008	0.953	2.74%	0.342	96.5%	46.4%	-72.53%	-63.33%	-66.81%	-9.20%	-5.72%	**2008**	1.183	2.52%	0.476	92.1%	-18.6%	-45.48%	-57.94%	-54.23%	12.46%	8.76%
2012	1.114	2.00%	0.342	95.3%	25.6%	**-69.92%**	-67.20%	-67.44%	-2.72%	-2.48%	**2012**	0.811	1.49%	0.606	86.7%	40.0%	-48.67%	**-49.80%**	-49.76%	1.13%	1.09%
2013	1.052	1.32%	0.336	95.1%	31.3%	**-69.13%**	-67.19%	-67.69%	-1.93%	-1.44%	**2013**	0.921	1.09%	0.563	84.8%	28.6%	-43.24%	**-46.95%**	-46.93%	3.72%	3.70%

Notes: σs: Spot position standard deviation; δt: Specific noise/common noise; ρsf: Correlation between spot and futures returns; ρsGARCH: Correlation between spot position and the hedged portfolio with the GARCH strategy; OLSDyn: Dynamic ordinary least squares strategy, the ratio is recalculated each 10 days with new information and applied to the following 10 days; OLS: The ordinary least squares ratio is calculated with the in-sample information and kept constant. When GARCH ratio performs better results are marked red; Best results are marked in bold.

TABLE 6. Out-of-sample hedging effectiveness simulations. σ change. The average hedge ratio over the last five trading days in each rolling sample is applied to the following 10 trading days. Panel A presents simulations of market innovations under Normal Distribution. Panel B: t-Student Distribution innovations. Panel C: GED Distribution innovations.

Panel A. Normal Distribution.

	GARCH ratio	σ_s	δ_t	ρ_{sf}	ρ_{sgarch}	Hedging effectiveness. Change in variance			Garch reduction vs			GARCH ratio	σ_s	δ_t	ρ_{sf}	ρ_{sgarch}	Hedging effectiveness. Change in variance			Garch reduction vs	
						GARCH	OLS	OLS Dyn	OLS	OLS Dyn							GARCH	OLS Dyn	OLS	OLS Dyn	OLS
A_W											***B_W***										
2007	0.971	1.00%	0.245	97.4%	-0.7%	**-76.01%**	-73.82%	-74.13%	-2.19%	-1.87%	**2007**	1.101	1.32%	0.448	89.7%	50.4%	**-55.33%**	-42.46%	-41.21%	-12.87%	-14.11%
2008	0.999	2.66%	0.234	98.1%	33.0%	**-80.97%**	-80.45%	-80.32%	-0.51%	-0.65%	**2008**	1.047	2.45%	0.442	92.1%	5.5%	-52.16%	-56.79%	-52.00%	4.63%	-0.15%
2012	1.065	2.01%	0.233	97.5%	44.4%	**-77.38%**	-76.56%	-76.66%	-0.82%	-0.72%	**2012**	0.734	1.53%	0.657	81.6%	59.8%	**-42.28%**	-42.05%	-42.04%	-0.23%	-0.24%
2013	1.051	1.34%	0.237	96.1%	37.6%	**-72.51%**	-72.05%	-72.18%	-0.46%	-0.34%	**2013**	0.821	1.15%	0.663	78.0%	54.4%	-36.25%	-37.39%	**-37.39%**	1.14%	1.15%
A_EW											***B_EW***										
2007	0.855	0.94%	0.418	93.9%	28.5%	**-65.19%**	-65.10%	-65.14%	-0.09%	-0.04%	**2007**	1.181	1.36%	0.508	90.1%	38.5%	**-56.39%**	-44.71%	-43.60%	-11.68%	-12.79%
2008	0.953	2.74%	0.341	96.5%	48.4%	-73.10%	-63.33%	-66.81%	-9.77%	-6.29%	**2008**	1.059	2.52%	0.444	92.1%	7.4%	-52.55%	-57.94%	-54.23%	5.39%	1.68%
2012	1.083	2.00%	0.335	95.3%	32.9%	**-70.14%**	-67.20%	-67.44%	-2.94%	-2.70%	**2012**	0.767	1.49%	0.596	86.7%	48.5%	**-50.34%**	-49.80%	-49.76%	-0.54%	-0.58%
2013	1.032	1.32%	0.335	95.1%	38.9%	**-68.98%**	-67.19%	-67.69%	-1.79%	-1.29%	**2013**	0.874	1.09%	0.583	84.8%	38.0%	-45.45%	**-46.95%**	-46.93%	1.50%	1.48%

Notes: σs: Spot position standard deviation; δt: Specific noise/common noise; ρsf: Correlation between spot and futures returns; ρsGARCH: Correlation between spot position and the hedged portfolio with the GARCH strategy; OLSDyn: Dynamic ordinary least squares strategy, the ratio is recalculated each 10 days with new information and applied to the following 10 days; OLS: The ordinary least squares ratio is calculated with the in-sample information and kept constant. When GARCH ratio performs better results are marked red; Best results are marked in bold.

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Panel B. t-Student Distribution.

	GARCH ratio	σ_s	δ_t	ρ_{sf}	ρ_{sgarch}	Hedging effectiveness. Change in variance			Garch reduction vs			GARCH ratio	σ_s	δ_t	ρ_{sf}	ρ_{sgarch}	Hedging effectiveness. Change in variance			Garch reduction vs	
						GARCH	OLS	OLS Dyn	OLS	OLS Dyn							GARCH	OLS Dyn	OLS	OLS Dyn	OLS
A_W											***B_W***										
2007	0.978	1.00%	0.244	97.4%	-4.5%	**-75.84%**	-73.82%	-74.13%	-2.02%	-1.71%	**2007**	1.056	1.32%	0.467	89.7%	55.4%	**-55.53%**	-42.46%	-41.21%	-13.07%	-14.32%
2008	1.013	2.66%	0.224	98.1%	24.7%	**-81.45%**	-80.45%	-80.32%	-1.00%	-1.13%	**2008**	0.987	2.45%	0.442	92.1%	14.0%	-53.59%	-56.79%	-52.00%	3.19%	-1.59%
2012	1.083	2.01%	0.229	97.5%	36.3%	**-77.69%**	-76.56%	-76.66%	-1.14%	-1.03%	**2012**	0.728	1.53%	0.653	81.6%	60.9%	-41.90%	**-42.05%**	-42.04%	0.15%	0.14%
2013	1.067	1.34%	0.275	96.1%	32.3%	**-72.47%**	-72.05%	-72.18%	-0.42%	-0.29%	**2013**	0.798	1.15%	0.672	78.0%	57.5%	-36.75%	-37.39%	**-37.39%**	0.64%	0.64%
A_EW											***B_EW***										
2007	0.846	0.94%	0.423	93.9%	30.2%	**-65.24%**	-65.10%	-65.14%	-0.14%	-0.09%	**2007**	1.096	1.36%	0.483	90.1%	54.4%	**-55.89%**	-44.71%	-43.60%	-11.18%	-12.29%
2008	0.967	2.74%	0.341	96.5%	45.7%	**-73.43%**	-63.33%	-66.81%	-10.10%	-6.63%	**2008**	0.995	2.52%	0.445	92.1%	14.5%	-53.77%	-57.94%	-54.23%	4.16%	0.46%
2012	1.074	2.00%	0.328	95.3%	35.2%	**-70.11%**	-67.20%	-67.44%	-2.91%	-2.67%	**2012**	0.757	1.49%	0.587	86.7%	51.0%	**-50.14%**	-49.80%	-49.76%	-0.33%	-0.37%
2013	1.021	1.32%	0.336	95.1%	42.0%	**-68.73%**	-67.19%	-67.69%	-1.54%	-1.04%	**2013**	0.850	1.09%	0.590	84.8%	42.0%	-46.21%	**-46.95%**	-46.93%	0.74%	0.72%

Notes: σs: Spot position standard deviation; δt: Specific noise/common noise; ρsf: Correlation between spot and futures returns; ρsGARCH: Correlation between spot position and the hedged portfolio with the GARCH strategy; OLSDyn: Dynamic ordinary least squares strategy, the ratio is recalculated each 10 days with new information and applied to the following 10 days; OLS: The ordinary least squares ratio is calculated with the in-sample information and kept constant. When GARCH ratio performs better results are marked red; Best results are marked in bold.

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Panel C. GED Distribution.

	GARCH ratio	σ_s	δ_t	ρ_{sf}	ρ_{sgarch}	Hedging effectiveness. Change in variance			Garch reduction vs	
						GARCH	OLS	OLS Dyn	OLS	OLS Dyn
A_W										
2007	0.945	1.00%	0.254	97.4%	10.8%	**-76.07%**	-73.82%	-74.13%	-2.25%	-1.94%
2008	0.987	2.66%	0.241	98.1%	39.2%	-80.30%	**-80.45%**	-80.32%	0.15%	0.02%
2012	1.074	2.01%	0.235	97.5%	43.4%	**-77.40%**	-76.56%	-76.66%	-0.84%	-0.74%
2013	1.053	1.34%	0.237	96.1%	36.2%	**-72.34%**	-72.05%	-72.18%	-0.29%	-0.17%
A_EW										
2007	0.873	0.94%	0.409	93.9%	24.3%	-64.88%	-65.10%	**-65.14%**	0.22%	0.27%
2008	0.947	2.74%	0.342	96.5%	48.9%	-72.86%	-63.33%	-66.81%	-9.53%	-6.05%
2012	1.102	2.00%	0.342	95.3%	28.6%	**-70.03%**	-67.20%	-67.44%	-2.83%	-2.59%
2013	1.040	1.32%	0.336	95.1%	36.0%	**-69.16%**	-67.19%	-67.69%	-1.96%	-1.47%

	GARCH ratio	σ_s	δ_t	ρ_{sf}	ρ_{sgarch}	Hedging effectiveness. Change in variance			Garch reduction vs	
						GARCH	OLS Dyn	OLS	OLS Dyn	OLS
B_W										
2007	1.118	1.32%	0.506	89.7%	47.0%	-51.93%	-42.46%	-41.21%	-9.46%	-10.71%
2008	1.051	2.45%	0.447	92.1%	4.8%	-49.69%	-56.79%	-52.00%	7.10%	2.32%
2012	0.758	1.53%	0.687	81.6%	56.0%	-41.41%	**-42.05%**	-42.04%	0.65%	0.63%
2013	0.869	1.15%	0.645	78.0%	47.9%	-35.89%	-37.39%	**-37.39%**	1.50%	1.50%
B_EW										
2007	1.276	1.36%	0.544	90.1%	19.2%	-53.60%	-44.71%	-43.60%	-8.89%	-10.00%
2008	1.145	2.52%	0.476	92.1%	-8.1%	-45.42%	-57.94%	-54.23%	12.52%	8.81%
2012	0.808	1.49%	0.606	86.7%	43.0%	-48.77%	**-49.80%**	-49.76%	1.03%	0.99%
2013	0.930	1.09%	0.563	84.8%	26.5%	-43.36%	**-46.95%**	-46.93%	3.60%	3.58%

Notes: σs: Spot position standard deviation; δt: Specific noise/common noise; ρsf: Correlation between spot and futures returns; ρsGARCH: Correlation between spot position and the hedged portfolio with the GARCH strategy; OLSDyn: Dynamic ordinary least squares strategy, the ratio is recalculated each 10 days with new information and applied to the following 10 days; OLS: The ordinary least squares ratio is calculated with the in-sample information and kept constant. When GARCH ratio performs better results are marked red; Best results are marked in bold.

TABLE 7. Out-of-sample simulations of utility gains under different hedging strategies. Normal Distribution.

2007-2008	*A_W*	*A_EW*	*B_W*	*B_EW*
Aggregate utility				
Spot position	-0.75519	-0.71850	-1.00795	-1.07279
OLS ratio	-0.03632	-0.09239	-0.30539	-0.30044
OLS dynamic ratio (*)	-0.03709	-0.07859	-0.26187	-0.26694
GARCH hedge ratio (**)	-0.03568	-0.05997	-0.20254	-0.21077
GARCH hedge ratio with decision criterion (***)	-0.03554	-0.06040	-0.19899	-0.20973
Utility gain on the spot position				
OLS ratio	95.2%	87.1%	69.7%	72.0%
OLS dynamic ratio	95.1%	89.1%	74.0%	75.1%
GARCH hedge ratio (*)	95.3%	**91.7%**	79.9%	80.4%
GARCH hedge ratio with decision criterion (**)	**95.3%**	91.6%	**80.3%**	**80.5%**

2012-2013	*A_W*	*A_EW*	*B_W*	*B_EW*
Aggregate utility				
Spot position	-0.66147	-0.57907	-0.38758	-0.38984
OLS ratio	-0.03449	-0.06473	-0.13722	-0.10895
OLS dynamic ratio (*)	-0.03518	-0.06436	-0.13810	-0.10988
GARCH hedge ratio (**)	-0.03494	-0.05580	-0.13346	-0.10531
GARCH hedge ratio with decision criterion (***)	-0.03489	-0.05567	-0.13651	-0.10928
Utility gain on the spot position				
OLS ratio	**94.8%**	88.8%	64.6%	72.1%
OLS dynamic ratio (*)	94.7%	88.9%	64.4%	71.8%
GARCH hedge ratio (**)	94.7%	90.4%	**65.6%**	**73.0%**
GARCH hedge ratio with decision criterion (***)	94.7%	**90.4%**	64.8%	72.0%

Notes: Best results are marked in bold. (*) The ratio is recalculated each 10 days with new information and applied to the following 10 days. (**) The hedge ratio is changed every 10 days, applying the ratio from the last trading day in each rolling sample. (***) The desirability of applying a new ratio was appraised every 10 days, the decision being made in accordance with the expected utility.

TABLE 8. Out-of-sample simulations. Hedging effectiveness measures under different cross-hedging strategies with IBEX 35 futures contract.

PANEL A: 2007-2008

		GARCH 1	GARCH 2	GARCH 3	Utility	OLS Dyn.	OLS	Unhedged	GARCH 1	GARCH 2	GARCH 3	Utility	OLS Dyn.	OLS	Unhedged
					2,007							**2,008**			
A_W	Profitability *	-1.8%	-1.0%	-1.3%	-1.6%	-1.8%	-1.8%	**5.0%**	-1.7%	-4.1%	-3.6%	-3.8%	-2.1%	**-1.1%**	-49.3%
	Standard Deviation *	3.72%	3.74%	**3.71%**	3.74%	4.00%	4.05%	15.47%	8.02%	7.94%	7.84%	8.04%	8.10%	8.05%	41.18%
	Skewness	0.1	0.2	0.1	0.2	0.3	**0.3**	-0.3	-0.6	-0.4	-0.4	-0.6	-0.6	-0.6	**0.2**
	Excess Kurtosis	1.1	1.3	1.1	1.1	1.3	1.3	**0.8**	5.8	5.7	6.3	6.6	6.9	7.1	**3.4**
	Certainty Equivalent *	-2.09%	-1.27%	-1.60%	-1.88%	-2.10%	-2.15%	**0.16%**	-2.97%	-5.42%	-4.83%	-5.15%	-3.40%	**-2.37%**	-83.15%
	VAR 1%	-0.58%	-0.55%	**-0.55%**	-0.57%	-0.62%	-0.62%	-2.67%	-1.42%	-1.39%	-1.42%	-1.38%	**-1.38%**	-1.39%	-7.51%
	VAR 5%	**-0.41%**	-0.42%	-0.43%	-0.42%	-0.41%	-0.41%	-1.54%	-0.79%	-0.77%	**-0.76%**	-0.80%	-0.77%	-0.77%	-4.65%
	Expected Shortfall 1%	-0.73%	-0.70%	-0.71%	**-0.70%**	-0.73%	-0.74%	-2.94%	-2.15%	**-2.05%**	-2.08%	-2.14%	-2.15%	-2.16%	-9.47%
	Expected Shortfall 5%	-0.52%	-0.53%	**-0.52%**	-0.53%	-0.55%	-0.56%	-2.44%	-1.30%	-1.26%	**-1.24%**	-1.32%	-1.31%	-1.30%	-6.48%
	LPM1	0.09%	**0.09%**	0.09%	0.09%	0.10%	0.10%	0.37%	0.18%	0.19%	0.18%	0.18%	0.18%	**0.18%**	1.04%
A_EW	Profitability *	-6.0%	-7.6%	-7.4%	-7.2%	-6.7%	-6.7%	**-1.5%**	**-4.3%**	-6.9%	-7.3%	-4.4%	-13.4%	-14.9%	-49.8%
	Standard Deviation *	5.19%	**5.07%**	5.08%	5.09%	5.08%	5.09%	14.59%	11.49%	11.56%	**11.42%**	11.52%	14.09%	15.56%	42.44%
	Skewness	**0.0**	0.0	0.0	0.0	-0.1	-0.1	-0.3	0.1	0.3	0.3	0.0	0.5	**0.5**	0.2
	Excess Kurtosis	**-0.2**	0.0	-0.1	0.0	0.0	0.0	1.0	2.4	2.2	2.1	**1.9**	2.0	2.0	2.6
	Certainty Equivalent *	-6.56%	-8.13%	-7.93%	-7.69%	-7.20%	-7.17%	**-5.73%**	**-6.97%**	-9.56%	-9.86%	-7.11%	-17.35%	-19.76%	-85.59%
	VAR 1%	-0.75%	**-0.75%**	-0.76%	-0.76%	-0.79%	-0.79%	-2.50%	**-1.72%**	-1.82%	-1.75%	-1.87%	-2.00%	-2.38%	-7.83%
	VAR 5%	**-0.59%**	-0.60%	-0.61%	-0.61%	-0.61%	-0.62%	-1.59%	-1.20%	-1.14%	**-1.10%**	-1.23%	-1.50%	-1.68%	-4.87%
	Expected Shortfall 1%	**-0.79%**	-0.82%	-0.79%	-0.82%	-0.84%	-0.84%	-2.80%	-2.31%	-2.26%	**-2.25%**	-2.35%	-2.53%	-2.75%	-9.15%
	Expected Shortfall 5%	**-0.71%**	-0.71%	-0.71%	-0.71%	-0.73%	-0.73%	-2.32%	-1.66%	-1.65%	**-1.63%**	-1.72%	-1.96%	-2.17%	-6.46%
	LPM1	0.14%	0.14%	0.14%	0.14%	**0.14%**	0.14%	0.36%	0.28%	0.28%	0.28%	**0.28%**	0.36%	0.39%	1.08%
B_W	Profitability *	-1.4%	-3.1%	-3.5%	-2.4%	0.1%	0.3%	**4.6%**	4.3%	**10.0%**	8.0%	6.3%	-12.1%	-16.1%	-47.2%
	Standard Deviation *	9.20%	9.13%	**9.12%**	9.31%	11.75%	12.00%	20.42%	**15.94%**	17.94%	18.14%	17.28%	16.39%	18.20%	37.92%
	Skewness	**-0.2**	-0.3	-0.4	-0.2	-0.4	-0.4	-0.6	0.5	1.2	**1.4**	0.8	-0.1	0.0	0.3
	Excess Kurtosis	1.1	0.9	0.9	**0.6**	1.4	1.4	1.7	2.9	8.8	12.2	5.4	**1.0**	1.7	2.5
	Certainty Equivalent *	-3.08%	-4.73%	-5.20%	-4.09%	-2.70%	**-2.63%**	-3.82%	-0.79%	**3.68%**	1.57%	0.37%	-17.49%	-22.69%	-75.75%
	VAR 1%	**-1.48%**	-1.67%	-1.62%	-1.53%	-2.18%	-2.19%	-3.68%	**-2.32%**	-2.81%	-2.72%	-2.85%	-2.72%	-3.05%	-6.66%
	VAR 5%	**-1.03%**	-1.07%	-1.08%	-1.05%	-1.17%	-1.22%	-2.23%	-1.76%	-1.75%	**-1.73%**	-1.73%	-2.03%	-2.10%	-4.08%
	Expected Shortfall 1%	**-1.82%**	-1.95%	-1.90%	-1.87%	-2.58%	-2.63%	-4.57%	**-2.63%**	-3.38%	-3.41%	-3.07%	-2.97%	-3.32%	-7.53%
	Expected Shortfall 5%	-1.39%	-1.41%	-1.43%	**-1.38%**	-1.91%	-1.95%	-3.30%	**-2.17%**	-2.38%	-2.46%	-2.42%	-2.57%	-2.86%	-5.84%
	LPM1	**0.23%**	0.23%	0.23%	0.24%	0.29%	0.30%	0.49%	**0.37%**	0.37%	0.38%	0.38%	0.43%	0.47%	0.99%
B_EW	Profitability *	0.8%	-2.9%	-1.1%	-1.3%	1.7%	1.9%	**6.9%**	0.0%	**5.5%**	5.1%	0.8%	-16.4%	-19.8%	-54.0%
	Standard Deviation *	9.32%	9.32%	9.18%	**9.16%**	11.64%	11.87%	21.05%	16.87%	18.43%	18.54%	17.38%	**16.43%**	17.88%	39.07%
	Skewness	**-0.1**	-0.2	-0.2	-0.2	-0.5	-0.5	-0.6	0.8	0.9	**1.1**	0.7	-0.1	0.0	0.2
	Excess Kurtosis	1.2	1.0	1.0	**1.0**	1.3	1.3	1.6	4.4	5.5	7.6	4.2	**0.9**	1.7	2.6
	Certainty Equivalent *	-0.97%	-4.60%	-2.79%	-2.94%	-0.98%	**-0.91%**	-2.07%	-5.59%	**-1.19%**	-1.66%	-5.18%	-21.80%	-26.24%	-84.41%
	VAR 1%	**-1.49%**	-1.61%	-1.57%	-1.57%	-2.24%	-2.25%	-3.74%	-2.61%	-2.87%	-2.70%	**-2.51%**	-2.90%	-3.25%	-7.25%
	VAR 5%	-1.05%	-0.99%	-1.03%	**-0.97%**	-1.13%	-1.16%	-2.31%	**-1.67%**	-1.81%	-1.87%	-1.81%	-1.88%	-2.12%	-4.18%
	Expected Shortfall 1%	**-1.90%**	-2.00%	-1.96%	-1.90%	-2.63%	-2.67%	-4.74%	**-2.85%**	-3.13%	-3.43%	-2.91%	-3.08%	-3.54%	-8.22%
	Expected Shortfall 5%	**-1.35%**	-1.41%	-1.36%	-1.37%	-1.86%	-1.90%	-3.40%	**-2.23%**	-2.48%	-2.43%	-2.30%	-2.54%	-2.82%	-6.20%
	LPM1	**0.22%**	0.24%	0.23%	0.23%	0.28%	0.29%	0.50%	**0.40%**	0.41%	0.41%	0.40%	0.44%	0.47%	1.02%

Note: Best results are marked in bold. GARCH 1: The ratio is rebalanced daily; GARCH 2: The ratio is rebalanced each 10 days to the average hedge ratio over the previous 5 days; GARCH 3:The r ratio is rebalanced each 10 days to the previous day hedge ratio; OLS: The OLS ratio is calculated with the in-sample information and kept constant; OLS D: The OLS ratios is recalculated each 10 days with the new information; Utility decision: The desirability of applying a new ratio was appraised every 10 days in accordance with expected utility; * Annual basis.

TABLE 8. Out-of-sample simulations. Hedging effectiveness measures under different cross-hedging strategies with IBEX 35 futures contract.

PANEL B: 2012-2013

		GARCH 1	GARCH 2	GARCH 3	Utility	OLS Dyn.	OLS	Unhedged	GARCH 1	GARCH 2	GARCH 3	Utility	OLS Dyn.	OLS	Unhedged
					2,012							2,013			
A_W	Profitability *	**-14.8%**	-16.1%	-15.4%	-14.9%	-15.0%	-14.9%	-19.6%	-2.8%	-4.4%	-4.1%	-3.1%	-3.5%	-3.3%	**16.3%**
	Standard Deviation *	7.1%	7.1%	**7.1%**	7.4%	7.3%	7.3%	31.2%	5.9%	5.8%	**5.7%**	5.8%	5.77%	5.80%	20.75%
	Skewness	0.1	-0.1	-0.1	-0.1	-0.1	-0.1	**0.1**	**0.7**	0.4	0.2	0.3	0.3	0.3	-0.1
	Excess Kurtosis	1.9	**1.3**	1.5	1.4	1.4	1.4	1.5	4.2	1.8	1.3	1.3	1.6	1.4	**0.8**
	Certainty Equivalent *	**-15.79%**	-17.06%	-16.39%	-16.03%	-16.07%	-15.96%	-39.02%	-3.52%	-5.06%	-4.74%	-3.81%	-4.18%	-3.99%	**7.64%**
	VAR 1%	-1.21%	-1.20%	**-1.17%**	-1.26%	-1.23%	-1.23%	-4.90%	-0.91%	**-0.86%**	-0.89%	-0.92%	-0.88%	-0.90%	-3.45%
	VAR 5%	**-0.77%**	-0.79%	-0.78%	-0.80%	-0.79%	-0.79%	-3.41%	**-0.57%**	-0.58%	-0.60%	-0.62%	-0.61%	-0.62%	-2.06%
	Expected Shortfall 1%	**-1.47%**	-1.48%	-1.48%	-1.56%	-1.54%	-1.54%	-6.01%	-0.99%	-0.96%	-1.02%	-1.00%	**-0.96%**	-0.98%	-4.25%
	Expected Shortfall 5%	-1.10%	-1.10%	**-1.09%**	-1.16%	-1.14%	-1.15%	-4.55%	-0.79%	**-0.77%**	-0.79%	-0.81%	-0.79%	-0.79%	-2.97%
	LPM1	**0.20%**	0.21%	0.21%	0.21%	0.21%	0.21%	0.78%	**0.15%**	0.15%	0.15%	0.15%	0.15%	0.15%	0.48%
A_EW	Profitability *	-32.4%	-32.8%	-32.4%	-31.3%	-30.6%	**-30.4%**	-34.7%	-0.1%	-1.0%	-1.1%	0.8%	0.7%	1.1%	**18.9%**
	Standard Deviation *	9.29%	9.25%	**9.23%**	9.34%	10.06%	10.14%	30.91%	6.46%	6.36%	**6.35%**	6.42%	6.62%	6.72%	20.48%
	Skewness	-0.8	-0.8	-0.8	-0.8	-0.6	-0.5	**0.1**	0.3	0.3	0.2	**0.4**	0.0	0.0	-0.2
	Excess Kurtosis	7.8	7.7	7.8	7.6	6.0	5.8	**1.3**	2.1	1.4	1.3	1.8	1.0	1.0	**0.9**
	Certainty Equivalent *	-34.12%	-34.51%	-34.07%	-33.10%	-32.66%	**-32.50%**	-53.81%	-0.92%	-1.77%	-1.87%	-0.04%	-0.16%	0.19%	**10.45%**
	VAR 1%	-1.45%	-1.48%	-1.45%	**-1.42%**	-1.53%	-1.54%	-5.06%	-1.06%	**-0.96%**	-1.01%	-0.96%	-1.17%	-1.21%	-3.53%
	VAR 5%	**-0.94%**	-0.96%	-0.97%	-1.08%	-1.09%	-1.08%	-3.39%	-0.68%	-0.65%	-0.68%	**-0.64%**	-0.70%	-0.71%	-2.07%
	Expected Shortfall 1%	-2.53%	-2.56%	-2.53%	-2.52%	**-2.49%**	-2.49%	-5.87%	-1.13%	-1.10%	-1.17%	**-1.08%**	-1.19%	-1.22%	-4.15%
	Expected Shortfall 5%	-1.52%	**-1.52%**	-1.52%	-1.52%	-1.63%	-1.64%	-4.53%	-0.90%	-0.87%	-0.89%	**-0.83%**	-0.94%	-0.96%	-2.94%
	LPM1	0.29%	0.29%	0.29%	**0.28%**	0.30%	0.30%	0.81%	0.16%	0.16%	0.16%	**0.16%**	0.16%	0.16%	0.47%
B_W	Profitability *	23.7%	23.4%	23.8%	24.0%	**24.6%**	24.5%	21.1%	1.4%	4.0%	2.7%	2.5%	2.6%	2.5%	**16.8%**
	Standard Deviation *	13.73%	13.80%	**13.70%**	13.85%	13.75%	13.76%	23.73%	11.22%	11.39%	11.33%	11.40%	11.13%	**11.13%**	17.77%
	Skewness	**0.4**	0.4	0.4	0.4	0.4	0.4	0.3	0.2	0.2	**0.3**	0.2	0.2	0.2	0.0
	Excess Kurtosis	6.2	6.1	6.1	5.7	5.5	5.5	**1.4**	0.7	1.0	1.1	0.7	0.3	0.3	**0.2**
	Certainty Equivalent *	19.97%	19.62%	20.08%	20.16%	**20.85%**	20.77%	9.87%	-1.12%	1.46%	0.11%	-0.05%	0.10%	-0.01%	**10.48%**
	VAR 1%	-2.03%	-2.00%	-2.00%	-2.00%	**-1.99%**	-1.99%	-3.40%	-1.77%	-1.76%	**-1.75%**	-1.79%	-1.76%	-1.76%	-2.71%
	VAR 5%	**-1.16%**	-1.34%	-1.17%	-1.29%	-1.26%	-1.27%	-2.50%	-1.09%	-1.13%	-1.12%	**-1.07%**	-1.08%	-1.09%	-1.83%
	Expected Shortfall 1%	-2.82%	-2.78%	-2.78%	-2.77%	**-2.75%**	-2.75%	-3.98%	-2.00%	-1.97%	-1.98%	-1.95%	-1.87%	**-1.87%**	-2.97%
	Expected Shortfall 5%	-1.85%	-1.87%	**-1.84%**	-1.89%	-1.84%	-1.84%	-3.13%	-1.52%	-1.51%	-1.52%	-1.51%	**-1.45%**	-1.45%	-2.42%
	LPM1	0.27%	0.28%	**0.27%**	0.28%	0.27%	0.27%	0.52%	0.28%	**0.28%**	0.28%	0.28%	0.28%	0.28%	0.42%
B_EW	Profitability *	15.6%	14.1%	15.4%	15.2%	**16.0%**	16.0%	12.3%	1.6%	4.8%	2.8%	5.1%	3.5%	3.4%	**18.5%**
	Standard Deviation *	11.65%	11.61%	**11.50%**	11.87%	11.62%	11.63%	23.15%	8.99%	9.23%	9.19%	9.36%	**8.94%**	8.94%	16.85%
	Skewness	0.2	0.1	0.1	0.0	0.1	0.1	**0.2**	0.1	0.1	0.1	**0.2**	0.1	0.1	-0.1
	Excess Kurtosis	2.2	2.0	2.0	1.7	1.9	1.9	**1.2**	0.8	1.1	1.3	1.0	0.4	0.4	**0.3**
	Certainty Equivalent *	12.90%	11.40%	12.73%	12.42%	**13.33%**	13.25%	1.62%	0.00%	3.06%	1.14%	3.36%	1.95%	1.80%	**12.82%**
	VAR 1%	**-1.79%**	-1.79%	-1.80%	-1.85%	-1.84%	-1.85%	-3.28%	-1.54%	-1.48%	-1.53%	-1.51%	-1.41%	**-1.40%**	-2.81%
	VAR 5%	**-1.12%**	-1.13%	-1.13%	-1.14%	-1.13%	-1.13%	-2.46%	-0.98%	-0.98%	-0.99%	-0.95%	-0.92%	**-0.91%**	-1.84%
	Expected Shortfall 1%	**-2.25%**	-2.26%	-2.26%	-2.29%	-2.28%	-2.28%	-3.97%	-1.63%	-1.61%	-1.68%	-1.59%	**-1.58%**	-1.58%	-2.85%
	Expected Shortfall 5%	-1.58%	-1.62%	**-1.57%**	-1.73%	-1.61%	-1.61%	-3.14%	-1.28%	-1.29%	-1.31%	-1.29%	-1.21%	**-1.20%**	-2.35%
	LPM1	0.25%	0.25%	0.25%	0.26%	**0.25%**	0.25%	0.53%	0.22%	**0.22%**	0.22%	0.22%	0.22%	0.22%	0.39%

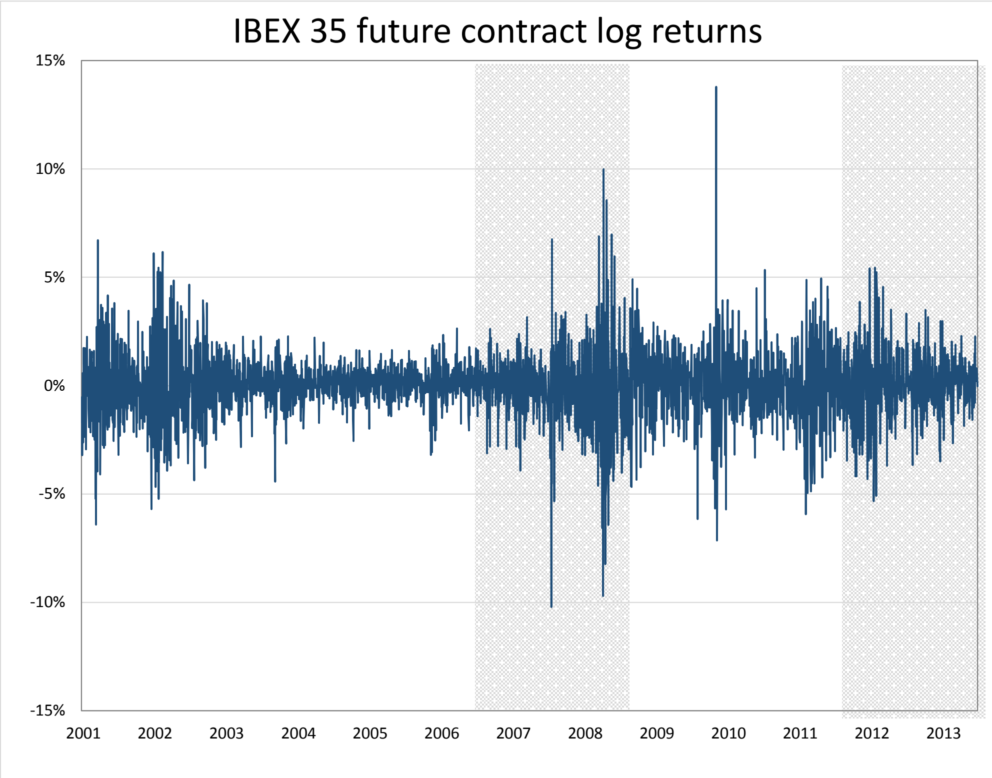
Note: Best results are marked in bold. GARCH 1: The ratio is rebalanced daily; GARCH 2: The ratio is rebalanced each 10 days to the average hedge ratio over the previous 5 days; GARCH 3:The r ratio is rebalanced each 10 days to the previous day hedge ratio; OLS: The OLS ratio is calculated with the in-sample information and kept constant; OLS D: The OLS ratios is recalculated each 10 days with the new information; Utility decision: The desirability of applying a new ratio was appraised every 10 days in accordance with expected utility; * Annual basis.

TABLE 9. Out-of-sample simulations. Relative gain in effectiveness under different measures: cross-hedge with IBEX 35 futures contract Vs. static OLS strategy.

	GARCH 1	GARCH 2	GARCH 3	Utility	OLS D	GARCH 1	GARCH 2	GARCH 3	Utility	OLS D	GARCH 1	GARCH 2	GARCH 3	Utility	OLS D	GARCH 1	GARCH 2	GARCH 3	Utility	OLS D
CE			**2007**					**2008**					**2012**					**2013**		
A W	3%	**41%**	25%	12%	2%	**-25%**	-128%	-103%	-117%	-43%	**1%**	-7%	-3%	-0%	-1%	**12%**	-27%	-19%	4%	-5%
A EW	**8%**	-13%	-11%	-7%	-0%	**65%**	52%	50%	64%	12%	-5%	-6%	-5%	-2%	**-0%**	-591%	-1050%	-1102%	**-119%**	-185%
B W	-17%	-80%	-98%	-56%	**-3%**	97%	**116%**	107%	102%	23%	-4%	-6%	-3%	-3%	**0%**	-14824%	**19554%**	1557%	-534%	1373%
B EW	**-6%**	-406%	-206%	-223%	-8%	79%	**95%**	94%	80%	17%	-3%	-14%	-4%	-6%	**1%**	-100%	70%	-37%	**87%**	8%
VAR 1%			**2007**					**2008**					**2012**					**2013**		
A W	7%	11%	**11%**	9%	0%	-2%	0%	-2%	0%	**1%**	2%	2%	**5%**	-2%	0%	-2%	**4%**	1%	-3%	1%
A EW	5%	**5%**	4%	4%	0%	**28%**	24%	27%	22%	16%	5%	4%	6%	**8%**	0%	12%	**21%**	17%	21%	4%
B W	**33%**	24%	26%	30%	1%	**24%**	8%	11%	7%	11%	-2%	-0%	-0%	-1%	**0%**	-1%	0%	**1%**	-2%	-0%
B EW	**34%**	29%	30%	31%	1%	20%	12%	17%	**23%**	11%	**3%**	3%	3%	-0%	0%	-10%	-5%	-9%	-7%	**-1%**
VAR 5%			**2007**					**2008**					**2012**					**2013**		
A W	**2%**	-2%	-4%	-1%	1%	-3%	-0%	**1%**	-4%	1%	**3%**	-0%	1%	-2%	-0%	**8%**	6%	2%	-1%	1%
A EW	**5%**	3%	2%	1%	0%	28%	32%	**34%**	27%	10%	**13%**	11%	11%	-0%	-1%	5%	9%	5%	**10%**	1%
B W	**16%**	12%	11%	14%	4%	16%	16%	**18%**	17%	3%	**9%**	-6%	8%	-1%	1%	-0%	-4%	-3%	**2%**	0%
B EW	10%	15%	12%	**16%**	3%	**21%**	15%	12%	15%	11%	**1%**	-0%	0%	-1%	-0%	-7%	-7%	-8%	-4%	**-0%**
ES 1%			**2007**					**2008**					**2012**					**2013**		
A W	1%	5%	4%	**5%**	0%	0%	**5%**	4%	1%	0%	**5%**	4%	4%	-1%	0%	-1%	2%	-5%	-2%	**2%**
A EW	**6%**	2%	6%	3%	0%	16%	18%	**18%**	14%	8%	-2%	-3%	-2%	-1%	**0%**	8%	11%	5%	**12%**	3%
B W	**31%**	26%	28%	29%	2%	**21%**	-2%	-3%	8%	11%	-2%	-1%	-1%	-1%	**0%**	-7%	-5%	-6%	-4%	**-0%**
B EW	**29%**	25%	27%	29%	2%	**19%**	11%	3%	18%	13%	**1%**	1%	1%	-0%	0%	-3%	-2%	-7%	-1%	**0%**
ES 5%			**2007**					**2008**					**2012**					**2013**		
A W	6%	5%	**6%**	5%	0%	0%	3%	**5%**	-1%	-1%	4%	4%	**5%**	-1%	0%	0%	**3%**	0%	-1%	1%
A EW	**3%**	2%	3%	2%	0%	24%	24%	**25%**	21%	10%	7%	**7%**	7%	7%	0%	7%	9%	7%	**14%**	2%
B W	29%	28%	27%	**29%**	2%	**24%**	17%	14%	15%	10%	-0%	-1%	**0%**	-2%	0%	-5%	-4%	-5%	-4%	**0%**
B EW	**29%**	26%	29%	28%	2%	**21%**	12%	14%	19%	10%	2%	-0%	**3%**	-7%	0%	-6%	-7%	-9%	-7%	**-0%**
LPM1			**2007**					**2008**					**2012**					**2013**		
A W	7%	**9%**	9%	7%	1%	-2%	-5%	-2%	-2%	**-1%**	**3%**	1%	2%	-1%	0%	**1%**	-1%	0%	-0%	0%
A EW	-2%	-2%	-2%	-2%	**0%**	28%	28%	29%	**29%**	8%	5%	5%	5%	**6%**	1%	5%	3%	4%	**5%**	1%
B W	**23%**	21%	21%	19%	2%	**22%**	21%	19%	20%	9%	-0%	-1%	**0%**	-2%	0%	0%	**1%**	1%	-1%	0%
B EW	**22%**	18%	20%	20%	2%	**16%**	14%	14%	15%	7%	-0%	-2%	-0%	-5%	**0%**	0%	**1%**	-0%	-1%	0%

Note: Best results are marked in bold. GARCH 1: The ratio is rebalanced daily; GARCH 2: The ratio is rebalanced each 10 days to the average hedge ratio over the previous 5 days; GARCH 3:The r ratio is rebalanced each 10 days to the previous day hedge ratio; OLS: The OLS ratio is calculated with the in-sample information and kept constant; OLS D: The OLS ratios is recalculated each 10 days with the new information; Utility decision: The desirability of applying a new ratio was appraised every 10 days in accordance with expected utility

Appendix 2. – Figures



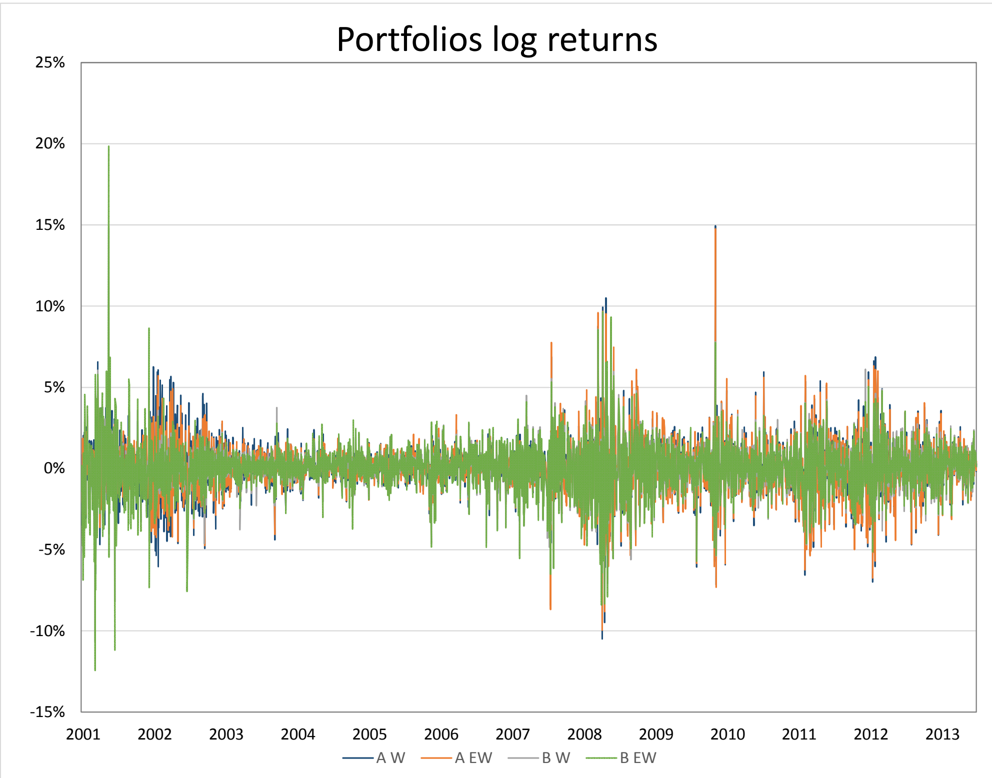


Figure 1. Log returns of out-of-sample stock spot prices and IBEX 35 future prices.

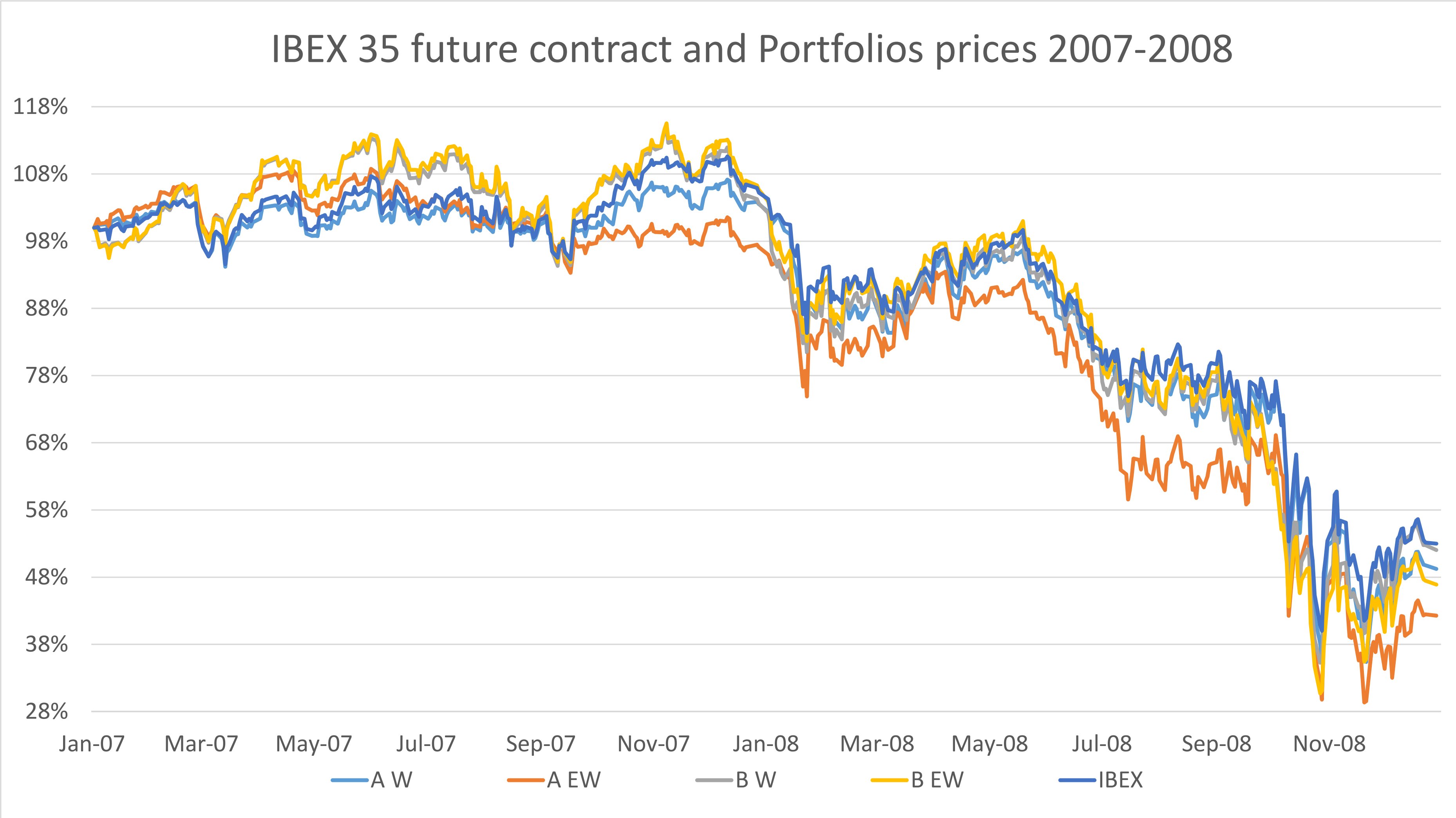


Figure 2 A. Out-of-sample IBEX 35 future contract price and portfolios prices 2007-2008 evolution. January 2007=100%

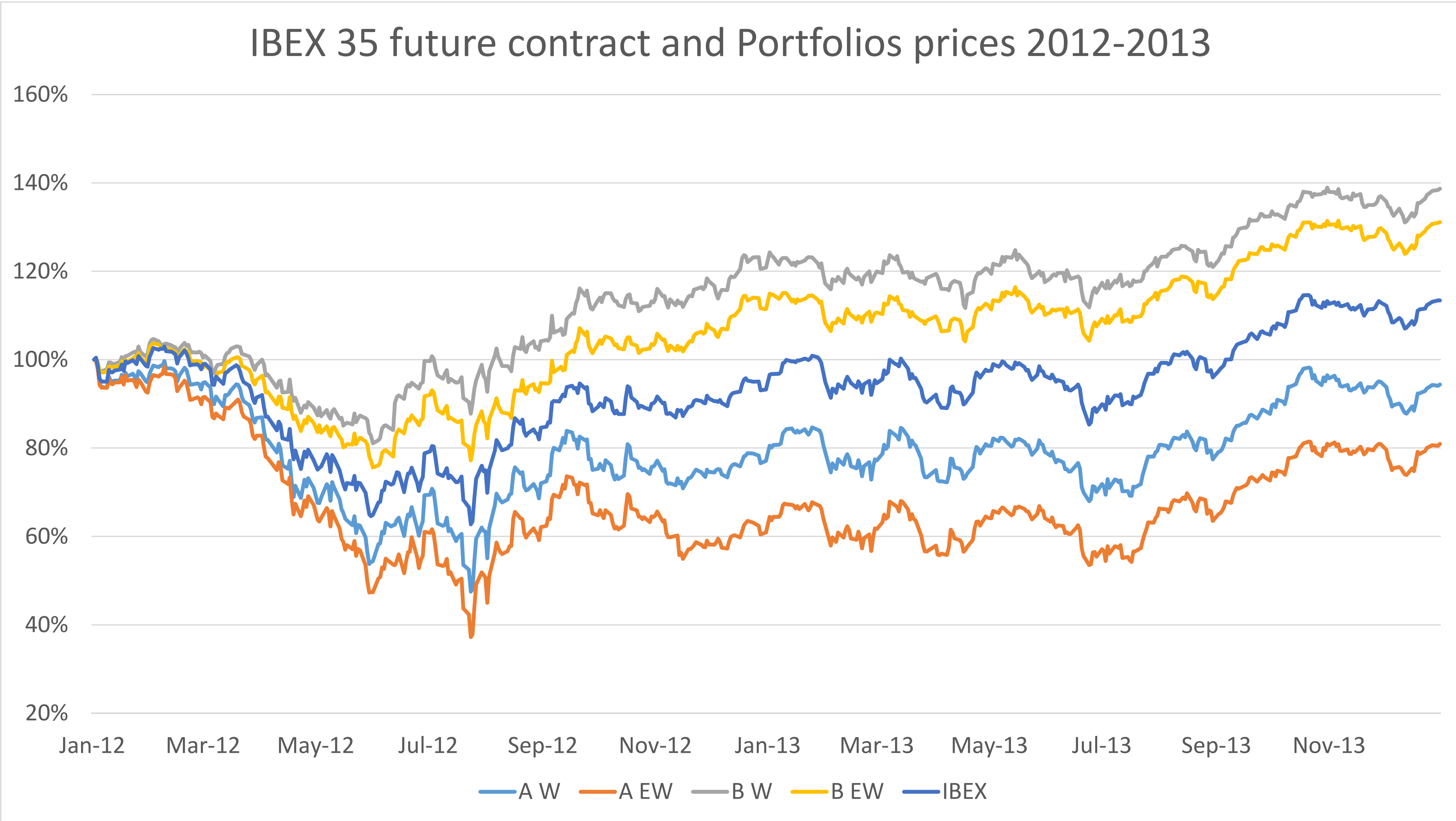


Figure 2 B. Out-of-sample IBEX 35 future contract price and portfolios prices 2012-2013 evolution. January 2012=100%

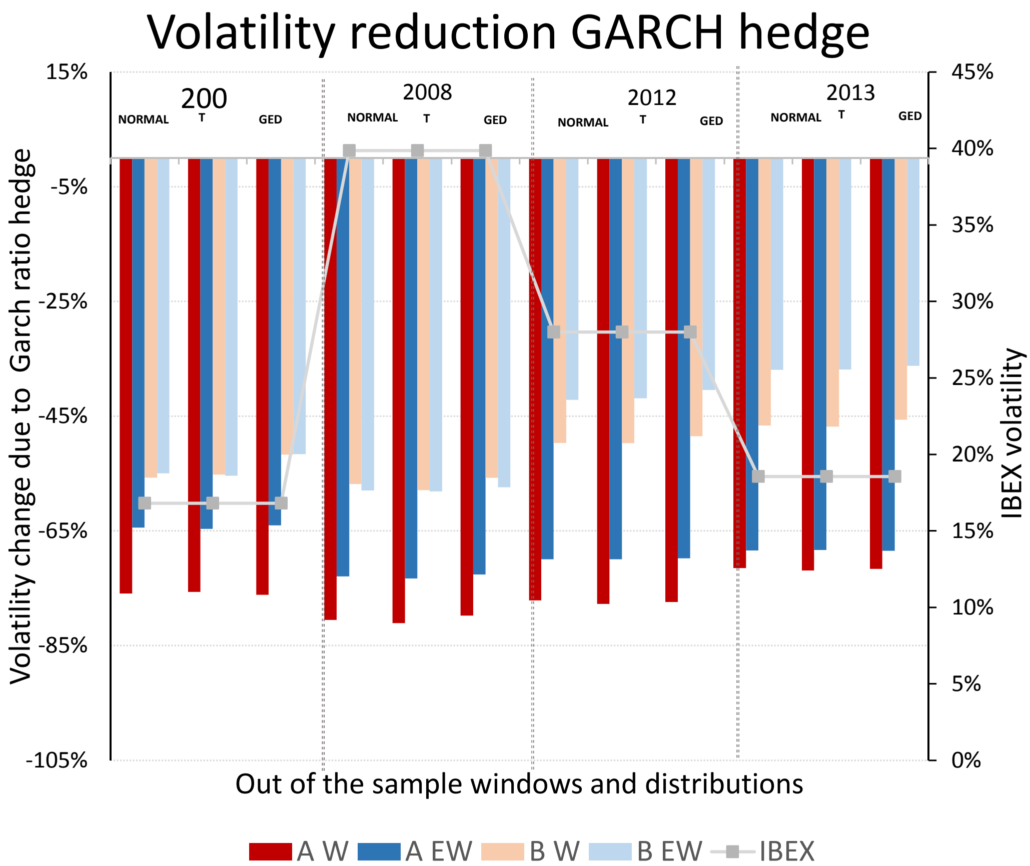


Fig. 3.A

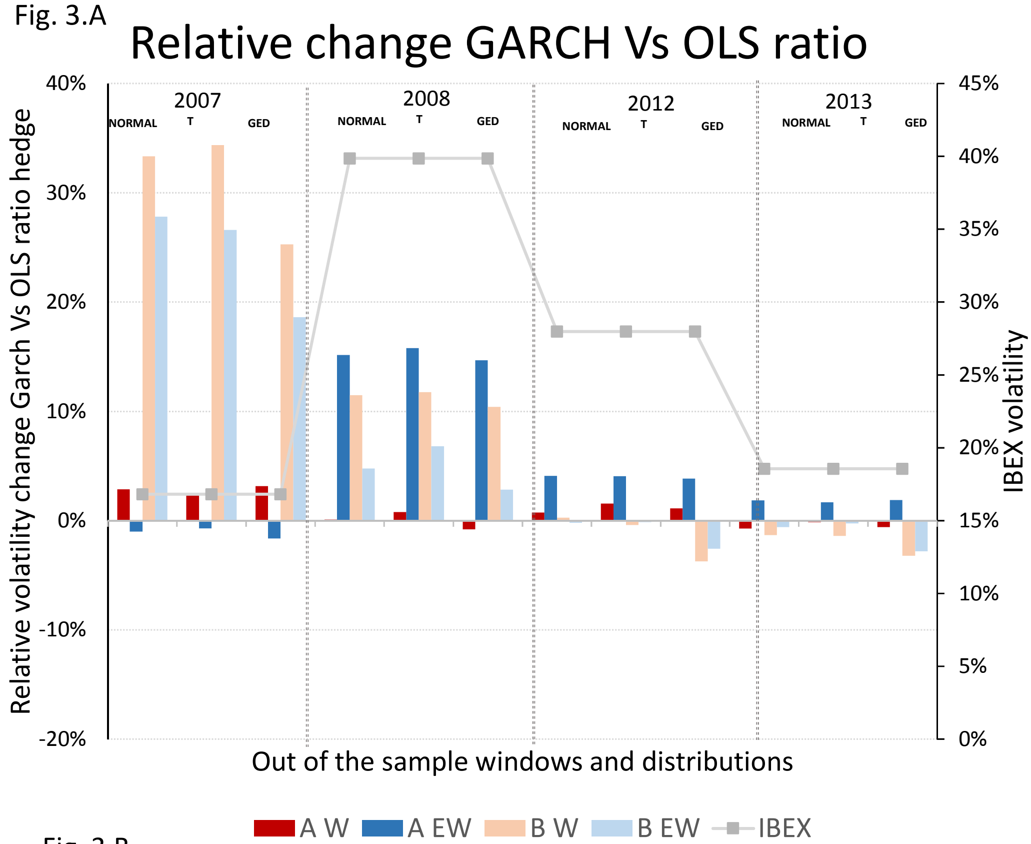


Fig. 3.B

Figure 3. GARCH ratio Out-of-sample effectiveness and different market innovation distributions. Daily rebalance of the ratio. A: Out-of-sample IBEX 35 cross hedge effectiveness. B: Relative volatility change GARCH Vs OLS static ratio hedge

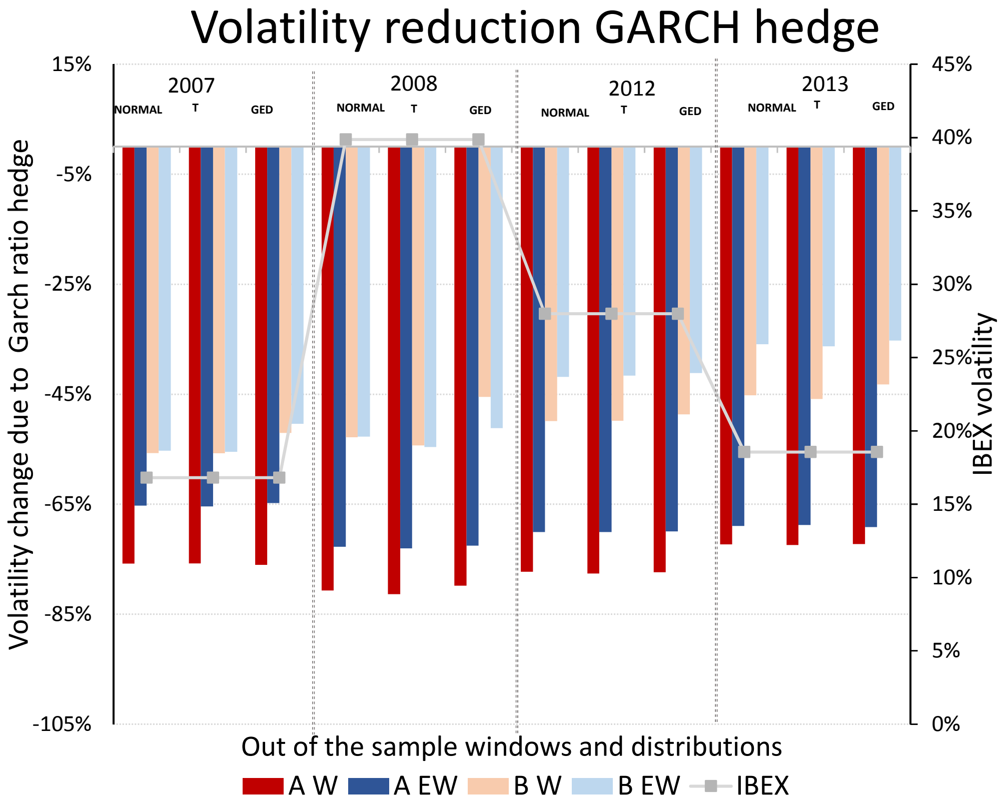


Fig. 4.A

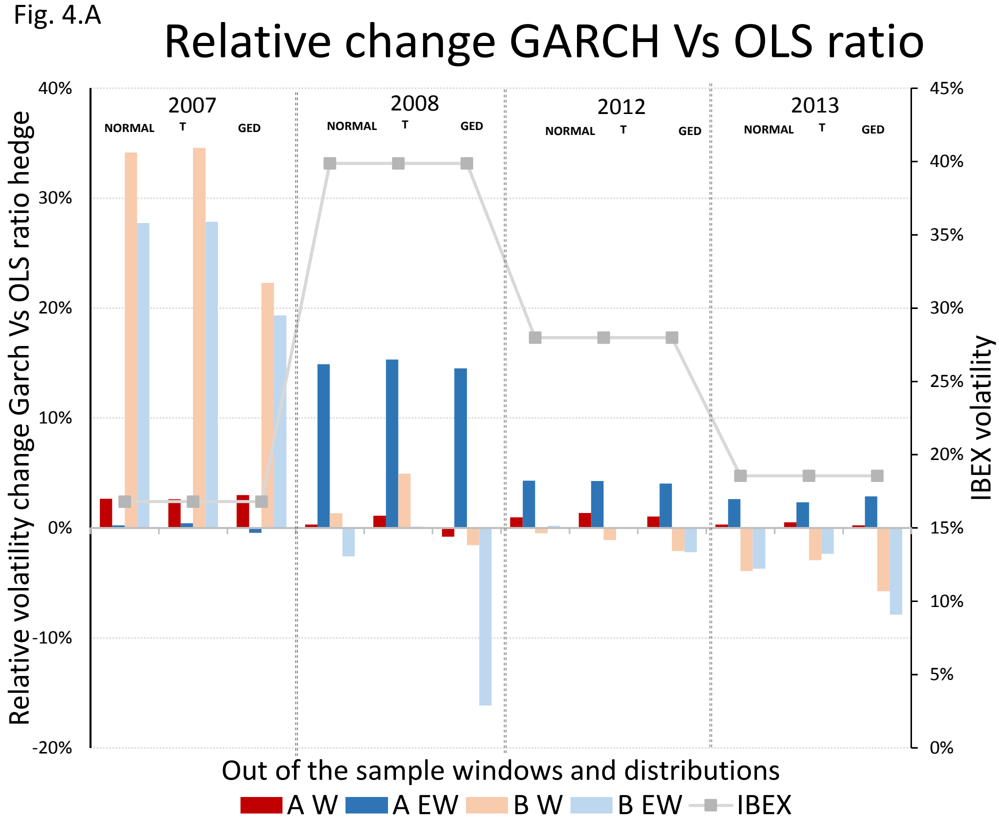


Fig. 4.B

Figure 4. GARCH ratio out-of-sample effectiveness and different market innovation distributions. The ratio is recalculated each 10 days with new information. The average hedge ratio of the the last 5 days in each rolling sample is applied to the following 10 trading days. A: Out-of-sample IBEX 35 cross hedge effectiveness. B: Relative volatility change GARCH Vs OLS static ratio hedge

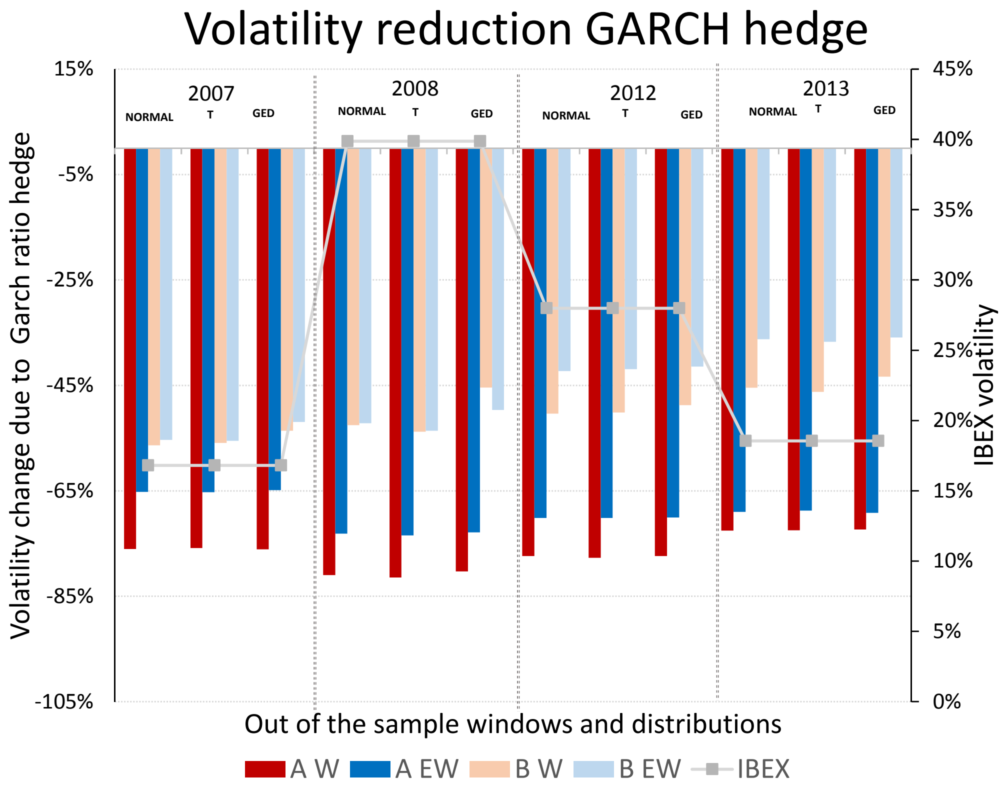


Fig. 5.A

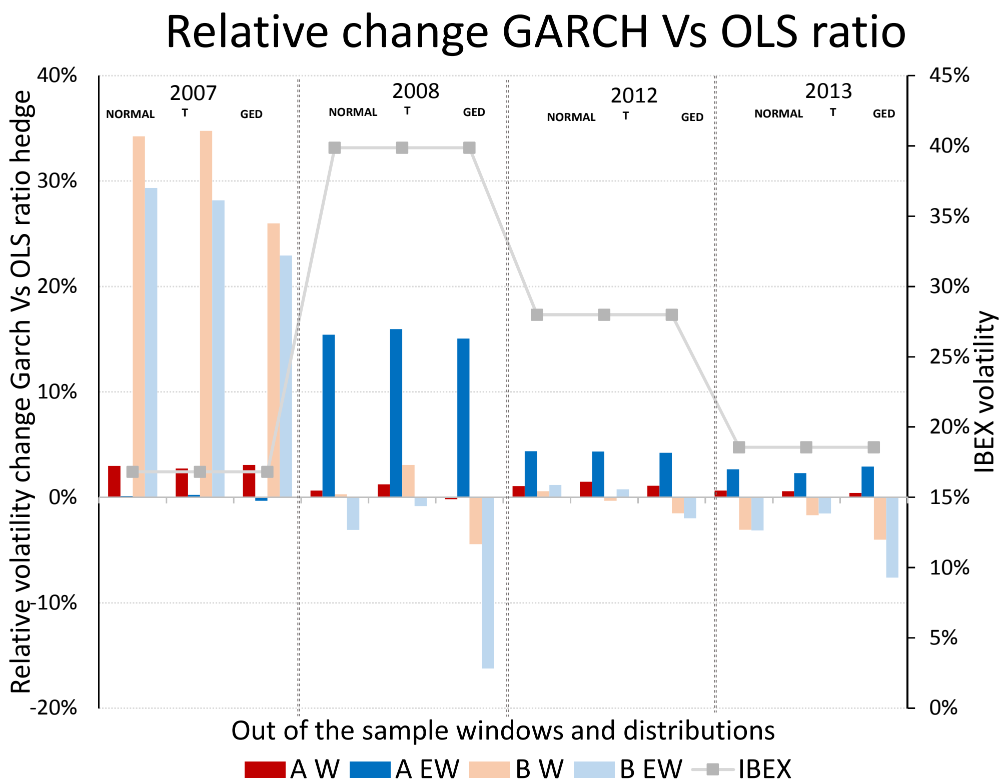


Fig. 5.B

Figure 5. GARCH ratio effectiveness and different market innovation distributions. The ratio is recalculated each 10 days with new information. The ratio obtained for the last day is applied to the following 10 days. A: Out-of-sample IBEX 35 cross hedge effectiveness. B: Relative volatility change GARCH Vs OLS static ratio hedge

Figure 6. A. *A_W* and *A_EW* portfolios out-of-sample simulations. Relative importance of the specific noise as compared to the common noise.

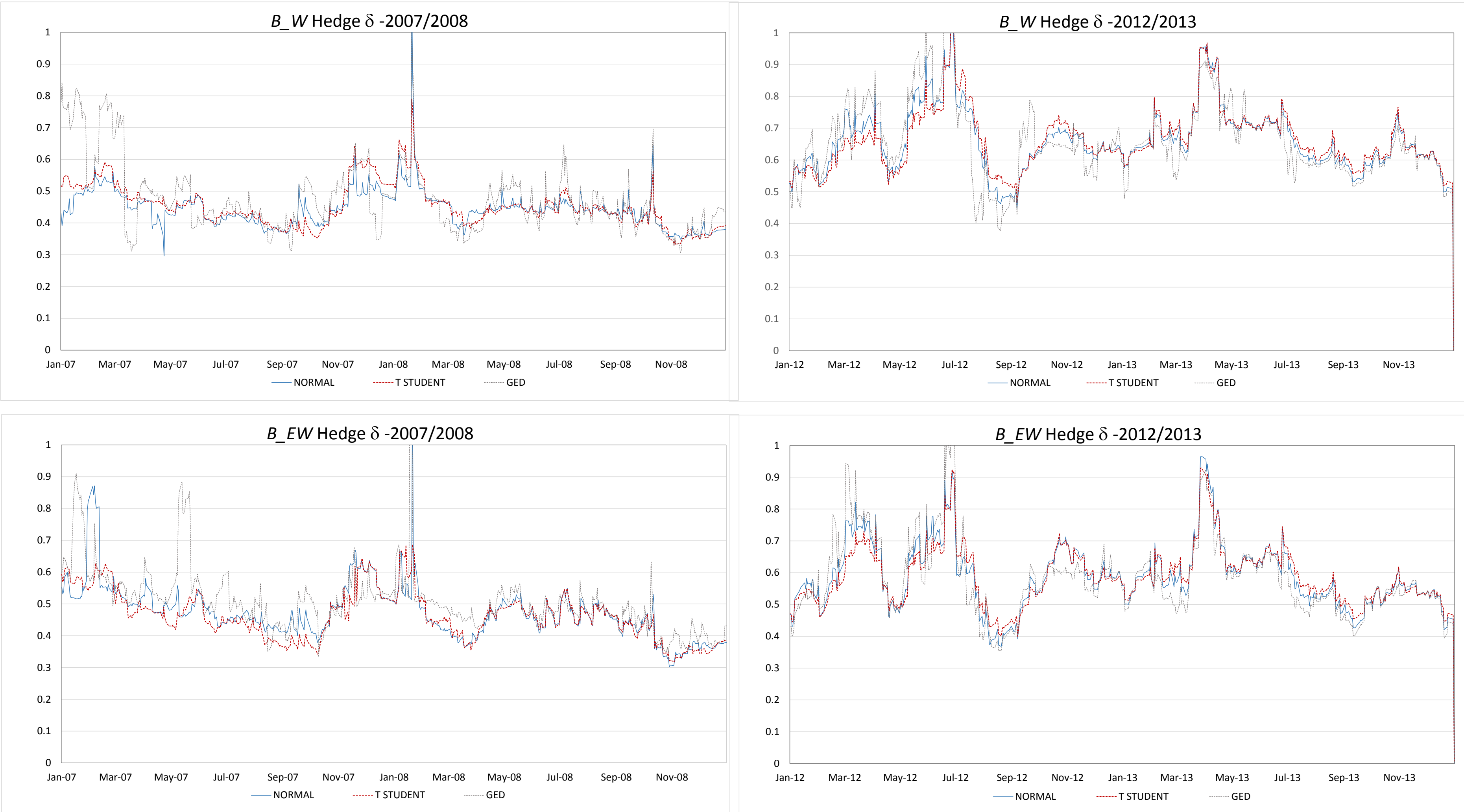


Figure 6. B. *B_W* and *B_EW* portfolios out-of-sample simulations. Relative importance of the specific noise as compared to the common noise.

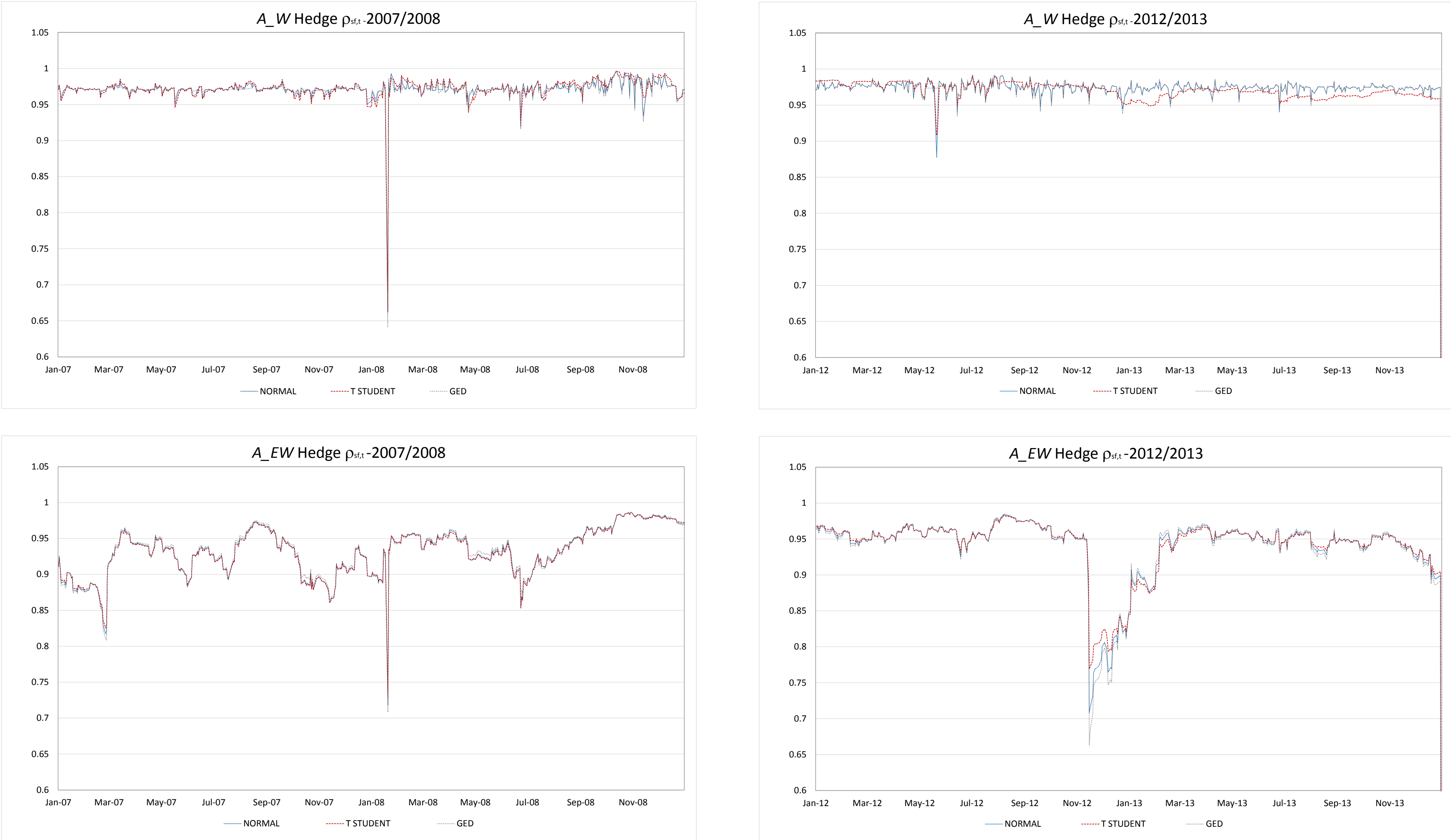


Figure 7. A. *A_W* and *A_EW* portfolios out-of-sample simulations. Conditional correlation spot portfolio – IBEX 35 future.

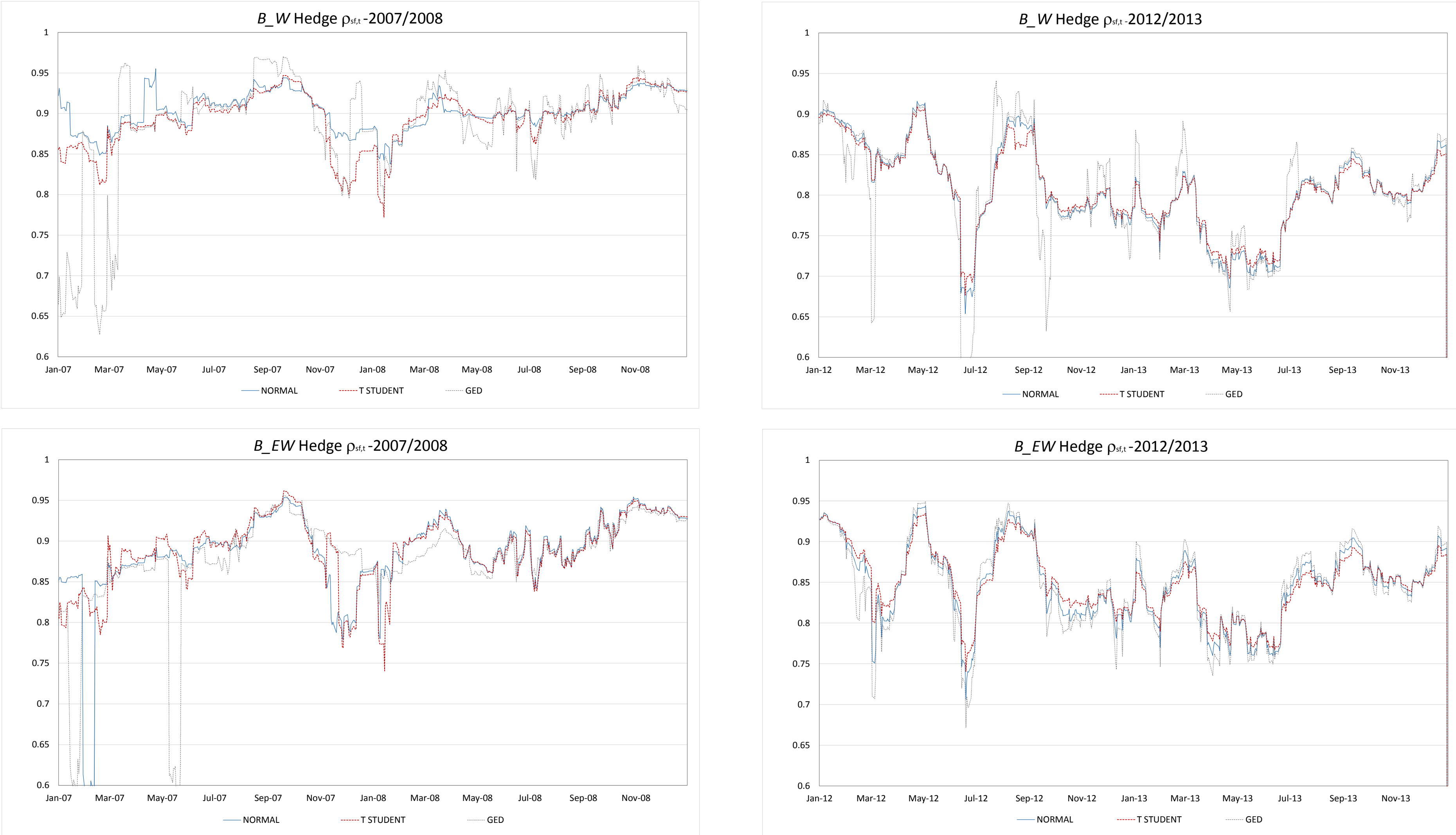


Figure 7. B. *B_W* and *B_EW* portfolios out-of-sample simulations. Conditional correlation spot portfolio – IBEX 35 future.

Figure 8. A. *A_W* and *A_EW* portfolios out-of-sample simulations. Minimum variance DCC GARCH ratio.

Figure 8. B. *B_W* and *B_EW* portfolios out-of-sample simulations. Minimum variance DCC GARCH ratio.

SUMMARY AND CONCLUSIONS

This thesis analyzes the use of index futures as a hedging instrument for indexes, individual stocks and portfolios under different time periods, distinct liquidity conditions of the assets and portfolios being hedged and various stages of development of the futures markets involved. We also consider the use of single stock futures (SSF) as hedging instruments for their underlying stocks. We have adopted Lafuente and Novales (2003) specification of price futures process that is consistent with deviations from the "cost of carry" model. Such deviations are due to the existence of a noise specific to the future market, in addition to a noise common to spot and futures market returns. For all the hedging situations considered in the thesis, we estimate a bivariate error-correction model with a DCC-GARCH structure and possible asymmetric effects to represent the conditional mean, variance and covariance of future and spot market returns and we use these results to simulate realistic out-of-sample hedging operations. Although the cointegration relationship between the spot position and the index future in the case of portfolios and stocks is rejected, the inclusion of an error term does not bias the estimation of the rest of parameters since the error term parameters are then not statistically significant. On the other hand, if cointegration relationship is disregarded and it exists, it could lead to a smaller than optimal position in the hedging instrument and a relatively poor hedging performance as shown by Lien (1996).

In order to test the prediction capabilities of our framework we simulate out-of-sample hedging strategies. After an initial in-sample estimation, we incorporate new information in 10-day windows of out-of-sample observations estimating again the model for each new window. We then rebalance the hedge using the new information and we apply the rebalanced hedge to the following 10 trading days. In addition to this automatic rebalance, we have defined a decision criteria under which he hedge is rebalanced only if the expected utility of rebalancing exceeds the expected utility from keeping the hedge ratio from the previous 10-day window. In this utility decision criteria we have incorporated the associated transaction costs. Thus we have simulated the practical situation where a financial agent estimates the model every few days and decides to rebalance the position or to maintain the previous portfolio unchanged. We think that 10 days is a good compromise between changing the hedge too often with consequently higher transaction costs or to keep it constant at the cost of a potential loss in effectiveness.

As futures prices we have used daily settlement prices of nearest to maturity contracts obtained from MEFF *(Mercado Español de Futuros Financieros*), Reuters and Bloomberg data services. For spot prices we have used BME *(Bolsas y Mercados Españoles)* databases and Reuters and Bloomberg data services. The null hypothesis on the existence of a common ARCH feature (Engle and Kozicki (1993)) underlying the heteroskedastic behavior detected in spot and futures markets returns is rejected, validating the existence of a noise specific to the futures market, as it is incorporated in our econometric model.

Chapter 1: Liquidity and hedging effectiveness under futures mispricing: international evidence

In this chapter, we extend Lafuente and Novales (2003) model to different international markets. We analyze hedging effectiveness for NIKKEI 225, FTSE 100, DAX, S&P 500 and IBEX 35 in order to determine whether that advantage of the GARCH strategy maintains over time, through the different development stages of a given market and through different markets. We used 1997-2005 data to estimate the model, and 2006 for out-of-sample simulations.

The results show that hedging effectiveness is high with variance reductions of 80% and higher. GARCH dynamic strategies do not lead to a systematic improvement in hedging effectiveness, as compared to the improvement that would be obtained by applying a static unit ratio. These results are in sharp contrast with those obtained using intraday data for the period 1993-1996 by Lafuente and Novales (2003) for the Spanish market. One reason might be that our analysis uses daily data, which implies a loss of information on price fluctuations that may bias upward the estimation of co-movement between spot and futures prices, moving optimal hedge ratios closer to 1.

But we believe that what is really central to explain the different results is the fact that the IBEX 35 futures Spanish market in 2006 was in a significantly more mature stage and with a sufficiently high level of activity that would quickly correct any arbitrage opportunity. Indeed, our results are consistent with the trend detected in Lafuente and

Novales (2003) about the optimal hedge ratio for the Spanish market gradually coming closer to 1 towards the end of the 1993-1996 sample period, thereby limiting the potential gain in hedging effectiveness obtained from the dynamic GARCH ratio. The similar conclusions we have reached for fully developed index futures markets in the US, Japan and Germany reinforce that interpretation.

The empirical evidence for the Spanish futures market is also consistent with McMillan and Quiroga (2008). These authors show that the equilibrium speed of adjustment between spot and futures market prices was reduced after the introduction of the mini-futures contract in the Spanish market in November 2001, the effect being particularly pronounced after the second year, when mini-futures contracts started being more heavily traded.

Even more significantly, the result that noisy deviations from the no-arbitrage relationship in mature market prices may be of no consequence for improving the efficiency of hedging a spot portfolio with futures contracts goes along the lines of Roll et al. (2007), who have shown evidence that liquidity enhances the efficiency of the futures-cash pricing system for the S&P 500 stock index futures market.

Chapter 2: Cross-hedging effectiveness of individual stocks

In this chapter we study the use of SSF and index futures as hedging and cross-hedging instruments for the underlying stock of the SSF contract. In particular, we analyze if a dynamic stochastic minimum strategy improves the effectiveness of the static and dynamic OLS hedge ratios. We have analyzed daily settlement data on futures markets and daily closing data on spot markets over the 2010-2014 period.

Hedging effectiveness is high for the stocks with higher correlation with the hedging instrument, reaching 55% reduction in variance for the assets with the highest correlation, and 30% for the assets with the lowest correlation. Minimum variance GARCH hedge ratios systematically achieve a superior hedging effectiveness in cross-hedges between individual stocks and the futures on the stock market index, as compared to the improvement that would be obtained by applying a static OLS ratio. This advantage is also found in terms of the rest of other performance measures we have implemented based on utility, left tail characteristics or threshold returns.

The advantage of the GARCH ratio is in line with the results obtained by Lafuente and Novales (2003) for 1993-1996 as well as by our analysis of the cross-hedging of portfolios with IBEX 35 futures. The GARCH strategy is superior to the static ratio for cross-hedging operations with a liquid stock market index futures contract. We believe that the main reason to explain the GARCH advantage found in a mature market like the IBEX 35 futures is the nature of the cross-hedge itself. The higher importance of the specific noise relative to the common noise allows for exploiting volatility clusters trough a GARCH dynamic ratio markets even in mature markets, a result for which we also find evidence when analysing portfolio hedging in the next chapter.

When we introduce other measures that take into consideration the impact of the hedge on the profitability, the results do not show a clear conclusion regarding to hedge or not to hedge, as this will depend on each investor preferences. An investor concerned just about risk, understood as the variability of the returns, or just about left tail risk or downside risk, should enter into a cross-hedge with IBEX-35 futures contracts for the six analyzed stocks. But a common situation is that investors are concerned not only about minimization of the two mentioned risks but also about maximization of profits and under such circumstances the risk aversion profile is necessary to assess the decision to hedge.

With regard to the effectiveness of the SSF hedge operations, due to issues regarding the nature of data on volume and price we have not been able to properly analyze its hedging effectiveness. Given the underdevelopment of SSF market we believe that at this stage, the cross-hedge with the index future may be a more realistic approach despite of being, in theory, less effective.

Chapter 3: Portfolio cross-hedging effectiveness: the role of liquidity

We have analyzed the use of index futures as a cross-hedging instrument for portfolios with different liquidity and weighting criteria and different degrees of correlation with the underlying asset. We have used the theoretical minimum variance model proposed by Lafuente and Novales (2003). In this analysis we have used, normal distribution, t-Student distribution and GED distribution assumptions for the innovations in order to simulate market disturbances. The GED distribution performs worse than the alternative distributions in some years while the normal distribution and the t-Student distribution achieve almost the same performance. We have used daily closing data during the 2001-2013 period and we have simulated out-of-sample hedges with the ratio calculated from the estimated econometric specification during two periods with disparate, but remarkable circumstances: 2007-2008 and 2012-2013.

Cross-hedging effectiveness for the most liquid portfolios with relative volume weighting criteria, 80% variance reduction, is close to that achieved for index hedging operations with their futures contracts. Lower liquidity portfolios also achieve high effectiveness with results close to 70% variance reduction, although significantly lower than the most liquid. The weighting criteria also affect the effectiveness, with the equally weighting portfolios performing worse, especially for the most liquid portfolios.

The results show that GARCH dynamic cross-hedging strategies do lead to an improvement in hedging effectiveness as compared to a static OLS ratio. This advantage from the GARCH ratio is in line with the results obtained by Lafuente and Novales (2003) for 1993-1996. The results obtained in chapter 1 for different international indexes and their nearest to maturity futures contracts for the 1993-1996 period do not show a significant advantage for the GARCH ratio over the static ratio, suggesting that in mature futures markets with high trading volume the existence of a specific, time-varying noise could not be exploited for hedging purposes. The results obtained in this chapter show that the GARCH strategy advantage seems to confirm the liquidity/maturity hypothesis.

One explanation for the advantage of GARCH hedge ratios found in this analysis of portfolio hedging might be again that the higher specific noise relative to the common noise, allows for a better exploitation of volatility clusters through a GARCH dynamic ratio. This may be because the rapid corrections of any arbitrage opportunity or deviation from equilibrium that arises when the index is hedged through its futures contracts do not occur in the case of cross-hedges. This seems to be confirmed by the lack of statistical significance of most of the error correction parameters and by the values close to zero of the statistically significant parameters. Nonetheless, we have also found some evidence that during high volatility periods, dynamic strategies can perform worse than static strategies and, under such circumstances, more complex regime switching and copula models might help to improve hedging strategies.

When we introduce other measures that take into consideration the impact of the hedge on the profitability, the results, similarly to our analysis of stocks cross-hedges, do not show a clear conclusion regarding to hedge or not to hedge, as this will depend on each investor preferences. In this chapter results we observe that during periods of high market volatility and high market losses, all the implemented measures recommend to hedge for all portfolios. These additional measures in general terms also show that GARCH hedging strategies perform better than OLS strategies.

General conclusions

Our findings across all the assets and hedging operations we have analyzed suggest that:

6. Indexes, individual stocks and portfolios have very different risk characteristics that significantly affect the hedging effectiveness achieving up to 80%, 50% and 70% variance reduction respectively.

7. Minimum variance GARCH hedge ratios achieve superior hedging effectiveness in perfect hedges between IBEX 35 and its futures when the futures market was not mature enough. These findings are in line with McMillan and Quiroga (2008) and Roll et al. (2007).

8. When index futures contracts from a mature futures market are used in cross hedging operations of individual stocks or stocks portfolios, GARCH strategies achieve a superior performance in comparison to strategies based on static OLS ratios. These results suggest that the GARCH advantage is not exclusively related to futures market maturity.

9. During very high volatility periods, when investors tend to care more about risk, the GARCH dynamic strategy may be less effective than the static OLS ratio. This is consistent with Sukcharoen et al. (2015).

10. Hedging improves, relative to the unhedged position, not only in terms of variance reduction but also under the CE, VaR, ES and LPM measures. The Certainty Equivalent criterion that takes into consideration volatility and risk aversion in addition to negative asymmetry and excess kurtosis, shows a systematic improvement from hedging during high volatility periods. The impact of cross-hedges on the hedged position in terms of all the considered measures show the importance of taking into consideration each investor individual risk profile in order to decide to hedge.

11. Minimum variance GARCH strategies also achieve superior hedging effectiveness under the alternative effectiveness indicators we have analyzed as compared to applying a static OLS ratio. We find this to be an important result because our minimum variance GARCH approach is cost-effective in terms of complexity and shows a good performance under other effectiveness measures. Optimization for other common risk and return measures is not easy and, to the best of our knowledge, the gains found in the academic literature for optimized strategies for VaR, ES, LPM, etc., are not conclusive enough.

We have found that in the Spanish case, the initial results showing effectiveness of the GARCH hedge of IBEX 35 using its futures contract were conditioned by the degree of maturity of the Spanish futures market. We think that this is an important contribution and additional research testing this result is advisable in order to generalize such statement to other markets since it would have important consequences regarding the adoption of the proper hedging strategy.

The relationship found between high volatility and the performance of dynamic strategies suggests the convenience of studying how regime switching models with a moderate complexity may help in this issue. There is research on these models that shows promising results although at the cost of complex techniques.

Unfortunately, the lack of quality prices in Spanish SSF that makes MEFF to adjust settlement prices to the cost of carry valuation most of the time, does not allow us to conclude much regarding SSF effectiveness as hedging instruments nor regarding the potential advantage of GARCH strategies. The low volume in SSF Spanish market is related, in our opinion, to some regulatory and reputational issues together with the uncertainty of dividend payment dates that can cause the hedge to fail if the payment day is not anticipated properly at the roll-up time. Total return SSF contracts might soon be introduced in the Spanish market. That would be a good opportunity to evaluate again if such futures contracts are suitable for effective hedges and whether GARCH strategies achieve any advantage in comparison to a static ratio strategy.

It would be interesting to study how cross-hedging strategies with different hedging instruments may affect the effectiveness of each hedging strategy. With this regard, a first logical step would be to extend the analysis to futures on other international indexes as hedging instrument for Spanish assets.

Finally, we believe that the characterization of the future prices process introduced by Lafuente and Novales (2003) helps to explain the effectiveness of hedging strategies based on the relationship between the common and specific noises. More research within this framework in other markets and assets may help to understand how to improve hedging strategies under different circumstances and different investor preferences.