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**IMPACT OF INTEREST RATE CHANGES ON THE
DISTRIBUTION OF SPANISH BANK STOCK RETURNS**

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A mis padres, a Blanch y a Dani

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Contents

Introducción	1
Capítulo 1: Impacto del Riesgo de Interés sobre las Acciones del Sector Bancario Español	
1. Introducción.....	11
2. Revisión de la literatura.....	15
3. Metodología.....	19
4. Datos empleados.....	25
5. Resultados empíricos.....	29
5.1. Propiedades de los datos.....	29
5.2. Interpretación de los resultados.....	30
5.3. Importancia relativa del riesgo de mercado y del riesgo de interés.....	36
5.4. Análisis por subperiodos.....	37
6. Conclusiones.....	39
Anexo: Tablas y Gráficos.....	42
Tabla 1.1: Medición del Riesgo de Interés en el Sector Bancario.....	43
Tabla 1.2: Listado de bancos y composición de las carteras.....	44
Tabla 1.3: Principales estadísticos descriptivos de las series de rendimientos de las carteras bancarias.....	45
Tabla 1.4: Estimación del modelo GARCH (1,1)-M ampliado por máxima verosimilitud.....	46
Tabla 1.5: Importancia relativa de los factores de riesgo.....	47
Tabla 1.6: Estimación del modelo GARCH (1,1)-M extendido con variable ficticia.....	47
Gráfico 1.1: Evolución de los diferentes tipos de interés.....	48
Gráfico 1.2: Rendimientos mensuales de las carteras G , M y P VS rendimiento de la cartera de mercado.....	48
Chapter 2: Linear and Non-Linear Interest Rate Sensitivity of Bank Stock Returns in Spain	
1. Introduction.....	51
2. Literature Review.....	54
3. Data.....	57
4. Methodology.....	61

4.1. Parametric models	61
4.1.1. Linear Model	61
4.1.2. Nonlinear Model.....	62
4.1.3. Asymmetric Sign and Size Model.....	64
4.2. Nonparametric Model.....	66
5. Empirical results	68
6. Conclusions	79
Annex: Tables and Graphs	79
Table 2.1: List of Banks, Composition of Bank Portfolios and Descriptive Statistics of Bank and Market Weekly Returns.....	82
Table 2.2: Descriptive Statistics of Level and First Differences of Interest Rates.....	84
Table 2.3: Exposure of Bank Portfolios to Interest Rate.....	85
Table 2.4: Economic significance of linear and nonlinear exposures	87
Table 2.5: Asymmetry in Interest Rate Exposure.....	87
Table 2.6: Adjustment Measures: R^2 and Sum of Squared Residuals	88
Table 2.7: Percentage of individual banks with significant interest rate exposure	89
Table 2.8: Descriptive Statistics of Residuals	90
Table 2.9: Correlation matrix between residuals and the dependent variable.....	93
Table 2.10: Wilcoxon signed-rank test for residuals	94
Graph 2.1: Returns on Bank and Market Portfolios and Level of Interest Rates.....	95
Graph 2.2: Nonparametric Model: Values of the estimated parameter \hat{b}	96
Graph 2.3: Fitted vs Actual Values and Residuals	98

Chapter 3: Determinants of Interest Rate Exposure of the Spanish Banking

Industry

1. Introduction	105
2. Literature review.....	109
3. Data.....	113
3.1. First stage data: Equity and interest rate market data.....	115
3.2. Second stage data: bank-specific characteristics	116
4. Methodology.....	122
4.1. First stage: Estimation of banks' interest rate exposure.....	122

4.2. Second stage: Association between interest rate exposure and bank-specific characteristics	124
4.2.1. Model specification	126
4.2.1.1. Model with the absolute value of the empirical durations as the dependent variable	126
4.2.1.2. Regime switching model with zero threshold	127
4.2.1.3. Regime switching model with optimal threshold	128
4.2.2. Estimation methods	129
4.2.3 Principal component analysis	133
5. Empirical results	134
5.1. First stage: estimation of the empirical duration coefficients.....	134
5.2 Second stage: identification of the determinants of exposure to IRR	138
5.2.1. Model with the absolute value of the empirical durations as dependent variable	138
5.2.2. Model that takes into account the sign of the interest rate exposure.....	139
5.2.2.1 Univariate model	140
5.2.2.2 Multivariate model	141
5.2.3. Two-regimes model with optimal threshold.....	142
5.2.3.1 Univariate analysis	142
5.2.3.2 Multivariate analysis	143
5.2.4. Principal component analysis	148
6. Concluding remarks.....	150
Annex: Tables and Graphs	153
Table 3.1: List of Banks and Descriptive Statistics of Bank and Market Monthly Returns.....	154
Table 3.2: Variables: Definitions, Expected Signs and Literature Review	155
Table 3.3: Descriptive statistics of the bank-specific characteristics in pre-euro and post-euro periods	156
Table 3.4: Correlation matrix of the bank characteristics	157
Table 3.5: Descriptive Statistics of the Estimated Sensitivity of Bank Stock Returns to Interest Rate Movements and Market Returns	158
Table 3.6: Univariate analysis: model with the absolute value of the empirical durations as dependent variable.....	159
Table 3.7: Univariate analysis: Regime switching model with zero threshold	160
Table 3.8: Multivariate analysis: Regime switching model with zero threshold	162

Table 3.9: Descriptive statistics of the optimal thresholds.....	163
Table 3.10: Univariate analysis: OLS estimation of regime switching model with optimal threshold.....	164
Table 3.11: Optimal threshold T^* for the multivariate model.....	166
Table 3.12: Multivariate analysis: OLS estimation of regime switching model with optimal threshold.....	166
Table 3.13: Multivariate analysis: Estimation of regime switching model with optimal threshold and individual effects.....	168
Table 3.14: Multivariate analysis: Dynamic panel-data estimation, two-step System GMM.....	170
Table 3.15: Principal Component Analysis.....	172
Table 3.16: Optimal threshold T^* for the model with principal components.....	173
Table 3.17: Principal Components: Dynamic panel-data estimation, two-step System GMM.....	174
Graph 3.1: Level of Interest Rates.....	175
Resumen	176
References	195

Introducción

El riesgo de interés es uno de los más importantes riesgos financieros a que se enfrentan las entidades bancarias en su condición de intermediarios financieros. De acuerdo con el Comité de Supervisión Bancaria de Basilea (2004), el riesgo de interés puede ser definido como el riesgo de que los resultados y/o el valor de mercado de una entidad financiera se vean afectados de forma adversa por los movimientos de los tipos de interés. Dado que las variaciones de los tipos de interés pueden tener efectos perjudiciales tanto sobre los resultados como sobre el valor económico de los activos, pasivos y posiciones fuera de balance de los bancos, dos perspectivas separadas, aunque complementarias, para la evaluación del riesgo de interés pueden ser distinguidas. La perspectiva de los beneficios se centra en el impacto de los cambios de los tipos de interés sobre los beneficios de las entidades financieras. En cambio, la perspectiva del valor económico se concentra en el efecto de las variaciones de los tipos de interés sobre el valor económico de los activos, pasivos y posiciones fuera de balance de las entidades bancarias. Esta última perspectiva considera el impacto de los movimientos de los tipos de interés sobre el valor actual de los flujos de caja esperados de las entidades bancarias y, por consiguiente, proporciona una visión más amplia de los efectos potenciales de los cambios en los tipos de interés que la ofrecida por la perspectiva de los beneficios.

El riesgo de interés es inherente al negocio bancario y es generalmente atribuido a dos razones esenciales. Primero, las entidades financieras mantienen básicamente en su balance activos y pasivos financieros fijados en términos nominales (no ajustados a la inflación) y, por tanto, especialmente sensibles a los cambios de los tipos de interés. Segundo, las entidades bancarias realizan normalmente una función de transformación de plazos en virtud de la cual financian préstamos y créditos a largo plazo con depósitos a corto plazo. El desequilibrio resultante entre el plazo hasta el vencimiento o fecha de depreciación de los activos y pasivos bancarios introduce volatilidad en los resultados y el valor neto de los bancos ante cambios de los tipos de interés. Este desequilibrio da lugar al denominado riesgo de depreciación, que constituye la modalidad más destacada de riesgo de interés. Aparte del riesgo de depreciación, las entidades bancarias están sujetas a otros tipos de riesgo de interés como por ejemplo el riesgo de base, el riesgo de curva de rendimiento, o el riesgo de opcionalidad. Por todo ello, la industria bancaria es típicamente catalogada como uno de los sectores con mayor exposición al riesgo de interés.

La medición y gestión del riesgo de interés en la industria bancaria han cobrado gran interés en los últimos años debido a la combinación de diversos factores. Por un lado, la elevada volatilidad de los tipos de interés ha tenido un significativo impacto sobre los costes e ingresos bancarios. Por otro, el énfasis a nivel internacional sobre la supervisión y control de los riesgos bancarios de mercado, entre ellos el riesgo de interés, materializado en el nuevo Acuerdo de Capitales de Basilea (Basilea II), ha contribuido también a la creciente relevancia del riesgo de interés. Asimismo, el margen financiero o de intermediación, directamente vinculado a la evolución de los tipos de

interés, constituye todavía la principal fuente de resultados bancarios a pesar del creciente peso de los ingresos vía comisiones.

La correcta comprensión del efecto del riesgo de interés sobre las entidades bancarias representa una cuestión con implicaciones fundamentales en términos de gestión del riesgo, valoración bancaria, selección de carteras, implementación de la política monetaria y supervisión de la estabilidad del sistema financiero.

A este respecto, la sensibilidad de las entidades de crédito ante los movimientos de los tipos de interés ha sido objeto de una extensa corriente de investigación desde 1980, concentrada mayoritariamente en el mercado estadounidense (véanse, entre otros, los trabajos de Lynge y Zumwalt, 1980; Akella y Chen, 1990; Elyasiani y Mansur, 1998 y 2004; Benink y Wolff, 2000; Verma y Jackson, 2008). El grueso de esta literatura ha adoptado un enfoque de mercado de capitales, según el cual la exposición al riesgo de interés es típicamente cuantificada como la sensibilidad del rendimiento de las acciones bancarias ante los cambios de los tipos de interés en el marco del modelo de regresión lineal de dos factores introducido por Stone (1974). Este enfoque extiende el clásico modelo de mercado mediante la adición de un factor representativo de los cambios de los tipos de interés al rendimiento de la cartera de mercado en un intento de describir más correctamente el comportamiento del rendimiento de las acciones bancarias. La incorporación de un factor de cambio de los tipos de interés es asimismo consistente con el modelo intertemporal de valoración de activos (ICAPM) de Merton (1973) y el modelo basado en la teoría de valoración por arbitraje (APT) de Ross (1976).

Esta tesis doctoral se plantea como objetivo primordial ofrecer un análisis exhaustivo de la incidencia del riesgo de interés sobre el sector bancario español examinando diversas cuestiones escasamente o no abordadas hasta la fecha y

empleando para ello diferentes procedimientos econométricos. En línea con una parte importante de la literatura sobre riesgo de interés en la industria bancaria, la presente tesis se centra en el impacto de los movimientos de los tipos de interés sobre el rendimiento de las acciones bancarias. Dado que el precio de una acción bancaria representa el valor actual de los flujos de caja futuros esperados generados por la entidad financiera en cuestión a lo largo del tiempo, este enfoque basado en el mercado de capitales puede ser encuadrado dentro de la perspectiva del valor económico de la entidad bancaria. Esta tesis se estructura en tres Capítulos organizados de la forma que se comenta a continuación.

El Capítulo Primero, titulado “*Impacto del riesgo de interés sobre las acciones del sector bancario español*”, está dedicado a la medición del efecto del riesgo de interés sobre el sector bancario español. A diferencia de la literatura tradicional sobre riesgo de interés de las acciones bancarias, limitada básicamente al estudio del impacto de los cambios en el nivel de los tipos de interés, el presente trabajo examina de forma conjunta la repercusión de las variaciones de los tipos de interés y de la volatilidad de tipos sobre la distribución de rendimientos de las acciones bancarias cotizadas en el mercado bursátil español. El objetivo esencial es determinar si la volatilidad de los tipos de interés juega un papel importante en el proceso generador de rendimientos de las acciones bancarias y, en consecuencia, debe ser incorporada a los modelos de valoración del riesgo de interés. Con tal fin, se propone una versión ampliada del clásico modelo bifactorial de Stone (1974) que es estimada mediante la aplicación de metodología de tipo GARCH (heterocedasticidad condicional autorregresiva generalizada) univariante. En concreto, el análisis empírico es llevado a cabo sobre diversas carteras de acciones bancarias construidas atendiendo a criterios de tamaño de

las entidades de crédito y utilizando diferentes variables representativas de los tipos de interés de mercado. Asimismo, se analiza si la introducción del euro como moneda única en el marco de la Unión Monetaria Europea a partir del 1 de enero de 1999 ha alterado significativamente el grado de exposición al riesgo de interés de las entidades financieras españolas.

El Capítulo Segundo, titulado “*Linear and Nonlinear Interest Rate Sensitivity of Bank Stock Returns in Spain*”, contiene un exhaustivo análisis del impacto del riesgo de interés sobre el sector bancario español basado en el empleo de diferentes formas funcionales para la medición de dicho efecto. En particular, el tradicional enfoque de exposición lineal y simétrica con origen en el modelo de Stone (1974) es extendido para permitir la posibilidad de un componente de exposición no lineal o la existencia de asimetrías. En esencia, el objetivo central es dilucidar si el perfil de exposición lineal habitualmente analizado continúa siendo el más relevante o si patrones más complejos (de carácter no lineal o asimétrico) deben ser también tomados en consideración en los modelos de valoración del riesgo de interés de las acciones bancarias. Con tal fin, diversas funciones no lineales, como por ejemplo la función cuadrática, la función cúbica, la función seno hiperbólico o la función seno hiperbólico inverso han sido empleadas para detectar la presencia de un efecto no lineal de los cambios de los tipos de interés sobre el rendimiento de las acciones bancarias. Además, se ha examinado la existencia de asimetrías tanto de signo (impacto diferente de las subidas y de las bajadas de tipos) como de tamaño (impacto distinto de los cambios de tipos de gran y pequeña cuantía). Asimismo, se ha cuantificado la exposición al riesgo de interés mediante un modelo de regresión no paramétrica, cuya principal ventaja reside en que no necesita imponer una forma funcional concreta.

Este trabajo constituye el primer estudio hasta la fecha en abordar de una forma tan completa y pormenorizada, investigando la presencia de relaciones lineales, no lineales y no paramétricas, la medición del impacto del riesgo de interés sobre el comportamiento bursátil del sector bancario español. Con el objeto de alcanzar una mayor comprensión de la incidencia del riesgo de interés, el análisis empírico es efectuado desde una doble vertiente, esto es, a nivel de acciones bancarias individuales y a nivel de carteras construidas según un criterio de tamaño de las entidades financieras análogo al empleado en el Capítulo Primero. A su vez, también se examina si la entrada del euro ha afectado sustancialmente a la naturaleza de la exposición al riesgo de interés de las entidades de crédito.

El Capítulo Tercero, titulado “*Determinants of Interest Rate Exposure of the Spanish Banking Industry*”, tiene como objetivo principal identificar los principales factores determinantes del grado de exposición al riesgo de interés de los bancos españoles, utilizando para ello un amplio conjunto de características bancarias, representativas tanto de las operaciones bancarias típicas (dentro de balance) como de las crecientemente relevantes operaciones fuera de balance. Como se ha comentado antes, el análisis de la sensibilidad del rendimiento de las acciones bancarias con respecto a los movimientos de los tipos de interés ha dado lugar a un extenso cuerpo de literatura. Sin embargo, el estudio de los determinantes de la exposición al riesgo de interés de las entidades de crédito ha sido objeto de un nivel de atención muy inferior. Este Capítulo pretende cubrir este importante vacío en el caso español y sus aportaciones básicas son las que se exponen seguidamente:

- 1) Constituye el primer trabajo en abordar específicamente esta cuestión en el marco del sector bancario español. De hecho, el grueso de la literatura se ha

centrado en la industria financiera de algunos de los países con mayores niveles de desarrollo, básicamente Estados Unidos y, sólo de forma más reciente, Japón, Alemania y Australia.

- 2) Dedicar una especial atención a la cuestión de si la introducción de la moneda única europea a partir de enero de 1999, con sus implicaciones en términos de mayor estabilidad financiera inducida por la política monetaria europea común y de expansión de los mercados financieros del área del euro, ha tenido un impacto significativo sobre los factores determinantes de la exposición al riesgo de interés del sector bancario español.
- 3) A nivel metodológico, representa el primer trabajo que aplica técnicas de datos de panel para el análisis de los determinantes del riesgo de interés. En un intento de controlar posibles problemas de heterogeneidad no observada, potencial endogeneidad de las variables y persistencia del riesgo de interés, diferentes técnicas de datos de panel son utilizadas, con un especial énfasis en el estimador dinámico de sistema basado en el método generalizado de los momentos desarrollado por Arellano y Bover (1995), y Blundell y Bond (1998).
- 4) Permite distinguir dos regímenes en cuanto a la exposición al riesgo de interés. En otras palabras, los determinantes más importantes no tienen por qué ser los mismos para todas las entidades bancarias, sino que pueden diferir en función del grado de exposición al riesgo de interés de las mismas. Con tal fin, se propone y estima un modelo de cambio de régimen con umbral óptimo donde éste es seleccionado a través de un procedimiento secuencial, como el valor de la sensibilidad ante los cambios de los tipos de interés estimada (duración empírica de las acciones bancarias) que lleva a un mejor ajuste estadístico del modelo.

- 5) La identificación de los determinantes clave del grado de exposición al riesgo de interés se realiza siguiendo una estrategia empírica basada en el contenido informativo o poder explicativo de las variables bancarias, y no simplemente en la significatividad estadística del estadístico t .

La evidencia obtenida en el caso español puede tener importantes implicaciones para la industria bancaria de países actualmente inmersos en un proceso de profunda transformación de su sector financiero similar al ocurrido en España a raíz de su entrada en la Unión Europea. Un buen ejemplo en este sentido pueden ser los países del centro y este de Europa recientemente integrados en la Unión Europea.

Capítulo 1

Impacto del Riesgo de Interés sobre las Acciones del Sector Bancario Español

1. Introducción

El riesgo asociado a las variaciones de los tipos de interés constituye una de las principales formas de riesgo que afectan a las entidades financieras y tiene su origen en la peculiar naturaleza del negocio bancario. Este riesgo es inherente al tradicional papel de las entidades de crédito como intermediarios financieros que realizan una función de transformación de plazos consistente en financiar préstamos y créditos a largo plazo mediante depósitos a la vista y a corto plazo. En el entorno bancario, el riesgo de interés puede ser definido como el riesgo de que los resultados y/o el valor de mercado de una entidad se vean afectados de manera adversa por los movimientos de los tipos de interés.

En la actualidad es generalmente aceptado que el riesgo de interés puede proceder de diversas fuentes. El riesgo de reprecación representa la modalidad de riesgo de interés más conocida y surge por diferencias en la sensibilidad de los activos y pasivos bancarios ante movimientos de los tipos de interés, motivadas por desequilibrios en el plazo hasta el vencimiento o los períodos de reprecación. Según esto, ante un cambio de tipos el período de reprecación medio del activo no va a coincidir con el del pasivo, de tal forma que los flujos futuros de cobros y pagos por intereses no van a variar en la misma magnitud, con la consiguiente repercusión sobre los resultados y el valor de las entidades.

Otras manifestaciones del riesgo de interés son: el riesgo de curva de rendimiento, referido a la posibilidad de que cambios no anticipados en la pendiente y en la forma de la curva de rendimientos tengan efectos perjudiciales sobre el valor y los resultados de las entidades; el riesgo de base, derivado de una correlación imperfecta entre los tipos base o de referencia de operaciones activas y pasivas con similares períodos de reprecación; y el riesgo de opcionalidad, con origen en las opciones

incorporadas en numerosas operaciones activas, pasivas y fuera de balance que pueden llevar a vencimientos reales de las operaciones sustancialmente diferentes de los fijados contractualmente.¹ Por todo ello, la industria bancaria es típicamente catalogada como uno de los sectores con mayor exposición al riesgo de interés.

Además, el riesgo de interés en el ámbito del sector bancario ha cobrado una significación especial en los últimos años debido al sustancial incremento de la variabilidad de los tipos de interés y al hecho de que las fluctuaciones de los tipos de interés afectan directamente a los flujos de costes y de ingresos de las entidades bancarias. Esto ha provocado la creciente preocupación de las autoridades supervisoras por el cumplimiento de los requerimientos mínimos de capital necesarios para cubrir los riesgos bancarios, entre ellos el riesgo de interés (Acuerdos de Capital de Basilea I y II).

En este contexto, se ha desarrollado un amplio cuerpo de literatura dedicado al estudio de la exposición de las entidades financieras al riesgo de interés basado en la cuantificación de dicha exposición mediante la estimación de la sensibilidad del rendimiento de las acciones bancarias ante los movimientos de los tipos de interés.

El conocimiento del efecto de las variaciones de los tipos de interés sobre las acciones bancarias constituye una información extremadamente relevante para una adecuada gestión del riesgo de interés. De hecho, la toma de decisiones de los diferentes agentes afectados por la exposición al riesgo de interés, tales como gestores de las propias entidades financieras, inversores, autoridades supervisoras e incluso académicos, puede verse ampliamente condicionada por esta información.

Este trabajo se plantea como objetivo primordial examinar la incidencia del riesgo de interés sobre el comportamiento bursátil del sector bancario español. Para ello, se aplica metodología de tipo GARCH (heterocedasticidad condicional autorregresiva

¹ Ejemplos de productos con opciones incorporadas a favor de los clientes bancarios incluyen préstamos y depósitos bancarios con posibilidad de cancelación anticipada.

generalizada) sobre diferentes carteras de acciones bancarias construidas según el tamaño de las entidades. Su principal aportación consiste en analizar por primera vez en el caso español de manera conjunta el impacto de los cambios de los tipos de interés y de la volatilidad de tipos sobre la distribución de los rendimientos de las acciones bancarias. Específicamente, la literatura sobre riesgo de interés del mercado bursátil español [véase, por ejemplo, los trabajos de Ferrer et al. (1999), Ferrer et al. (2008) y Jareño (2006 y 2008)] ha quedado circunscrita al enfoque tradicional, limitándose al estudio del efecto de las variaciones de los tipos de interés sobre el rendimiento de las acciones, mientras que la repercusión de la volatilidad de los tipos sobre los rendimientos bursátiles ha sido ignorada.

La investigación empírica concerniente a la repercusión del riesgo de interés sobre la industria bancaria se ha centrado mayoritariamente en el mercado estadounidense. Sin embargo, la extensión de este análisis al caso español resulta especialmente interesante considerando que nuestro sistema financiero, a diferencia del de los países anglosajones, se ha caracterizado por un mayor peso relativo de los bancos respecto a los mercados de capitales en la financiación de empresas y particulares. Además, las entidades españolas responden al modelo de banca universal típico de la Europa continental, ofreciendo una amplia gama de productos y servicios financieros frente a la banca especializada predominante en el caso estadounidense. Estas diferencias confieren relevancia al estudio de la exposición al riesgo de interés del sector bancario español para comprobar si los resultados obtenidos en Estados Unidos pueden ser extrapolados a mercados con distintas características.

Asimismo, el presente trabajo también puede contribuir a esclarecer si el tamaño institucional representa un determinante significativo del grado de exposición al riesgo de interés de las entidades de crédito. En este sentido, varios motivos han sido

esgrimidos para justificar las diferencias en términos de riesgo de interés existentes entre bancos de distinto tamaño.

Por un lado, los bancos más grandes pueden tener un cierto incentivo a asumir mayores niveles de riesgo debido a economías de escala en sus actividades de gestión de riesgos, a sus mayores posibilidades de diversificación de productos y clientes, a su mayor capacidad para atraer y retener personal cualificado y a su más fácil acceso a los mercados financieros globales.² Por otro, es también posible que los bancos de mayor dimensión muestren una actitud más agresiva hacia el riesgo a causa de un problema de riesgo moral derivado de su estatus “demasiado grande para fracasar”, en virtud del cual las entidades incurren en excesivos riesgos al confiar plenamente en el respaldo del banco central en caso de graves dificultades. En contraposición, los bancos de menor tamaño presentan un comportamiento más averso al riesgo debido a su acceso más limitado a los mercados e innovaciones financieras y, en consecuencia, se centran más en la actividad bancaria tradicional y menos en la especulación.

La evidencia empírica obtenida en este trabajo ofrece varios resultados interesantes. En primer lugar, confirma la relevancia del riesgo de interés en el ámbito del sector bancario español, poniendo de relieve que tanto los cambios de los tipos de interés como su volatilidad tienen un impacto negativo significativo sobre la distribución de rendimientos de las acciones bancarias. En segundo lugar, los tipos de interés a largo plazo se revelan como los que ejercen una influencia más significativa. En tercer y último lugar, parece existir una relación positiva entre el tamaño bancario y el grado de exposición al riesgo de interés.

El resto del trabajo queda estructurado del siguiente modo. En la sección 2 se lleva a cabo una breve revisión de la literatura sobre riesgo de interés en el sector bancario. La

² En relación con este aspecto, puede verse Amor et al. (2008).

sección 3 describe la metodología aplicada, mientras que la sección 4 presenta los datos empleados. La sección 5 contiene los resultados obtenidos en el análisis empírico. Por último, la sección 6 recoge las conclusiones más relevantes.

2. Revisión de la literatura

La incidencia del riesgo de interés sobre el rendimiento de las acciones de las entidades financieras ha sido objeto de estudio por parte de una importante corriente de literatura desarrollada a lo largo de las tres últimas décadas y centrada mayoritariamente en el caso estadounidense. El grueso de la investigación empírica ha sido efectuada en el ámbito del modelo de regresión lineal de dos índices introducido por Stone (1974) [al respecto pueden verse, entre otros, los trabajos de Flannery y James (1984), Sweeney y Warga (1986), Madura y Zarruk (1995) y Faff y Howard (1999)]. Esta formulación representa una versión ampliada del clásico modelo de mercado de Sharpe y Lintner, caracterizada por la inclusión de un factor representativo de los cambios de los tipos de interés como variable explicativa adicional junto al rendimiento de la cartera de mercado en un intento de describir más correctamente el proceso generador de rendimientos de las acciones bancarias.

Dentro de este marco, si bien es cierto que se puede apreciar una considerable variedad de metodologías aplicadas, períodos muestrales seleccionados, frecuencias de datos utilizadas, especificaciones del modelo planteadas y variables de tipo de interés empleadas, también lo es que existe un amplio consenso en torno a algunas cuestiones. En primer lugar, la gran mayoría de los trabajos documentan una relación negativa significativa entre los movimientos de los tipos de interés y el rendimiento de las acciones bancarias [véanse, por ejemplo, Flannery y James (1984), Kwan (1991) y Elyasiani y Mansur (1998)]. La explicación más frecuente apunta al habitual

desequilibrio de vencimientos y duraciones entre activos y pasivos bancarios, fruto de la transformación de plazos típicamente desarrollada por las entidades financieras. A este respecto, la mayor sensibilidad del activo con respecto al pasivo frente a las variaciones de los tipos de interés debido a su mayor plazo medio hasta vencimiento provoca que en caso de subidas de tipos las entidades experimenten una reducción de su margen financiero, ya que las operaciones de pasivo tenderán a repreciarse antes que las de activo, con el subsiguiente efecto negativo sobre el valor de las entidades, mientras que en caso de bajadas de tipos se producirá el efecto contrario. En segundo lugar, por lo general se observa una mayor sensibilidad de las acciones bancarias ante los cambios de los tipos de interés a largo plazo que ante las variaciones de los tipos a corto. En tercer lugar, la exposición de las entidades financieras al riesgo de interés ha ido disminuyendo con el paso del tiempo, previsiblemente a causa de la mayor disponibilidad de instrumentos derivados susceptibles de ser utilizados con fines de cobertura y al desarrollo de mejores sistemas de medición y gestión del riesgo de interés.

Los trabajos iniciales sobre el riesgo de interés de las entidades bancarias se basaron en el empleo de técnicas de regresión convencionales bajo las tradicionales hipótesis de linealidad, independencia y varianza condicional constante de los rendimientos de las acciones [véanse, por ejemplo, Lynge y Zumwalt (1980), Flannery y James (1984) y Sweeney y Warga (1986)].

Con posterioridad, diversos estudios [véanse, entre otros, Yourougou (1990), Akella y Chen (1990) y Kwan (1991)] presentaron evidencia contraria a la hipótesis de varianza condicional constante, mostrando que la sensibilidad del rendimiento de las acciones bancarias ante los cambios de los tipos de interés varía de forma sustancial en el tiempo en función de las condiciones económicas, siendo especialmente acusada

durante períodos de elevada variabilidad de tipos. De hecho, la no consideración del carácter variable en el tiempo del riesgo de interés puede desembocar en la obtención de estimadores sesgados e ineficientes.

En un intento de capturar explícitamente la naturaleza cambiante en el tiempo de la sensibilidad de las acciones del sector bancario ante los cambios de los tipos de interés, ha aparecido un cuerpo de trabajo más reciente basado en el empleo de metodología de tipo GARCH [véanse, por ejemplo, Song (1994), Elyasiani y Mansur (1998 y 2004), Tai (2000), Faff et al. (2005), o Joseph y Vezos (2006)]. Esta corriente asume la hipótesis de varianza condicional de los rendimientos variable en el tiempo. Además, a diferencia de la literatura previa, no se limita al estudio del efecto de las variaciones de los tipos de interés sino que también pone un especial énfasis en el impacto de la volatilidad de tipos sobre la distribución de rendimientos de las acciones bancarias.

En concreto, Song (1994) es el trabajo pionero en la aplicación de la metodología ARCH (heterocedasticidad condicional autorregresiva) en el sector bancario, demostrando la idoneidad de este enfoque. Posteriormente, Elyasiani y Mansur (1998) y Ryan y Worthington (2004) emplean modelos GARCH-M (GARCH en media) de tipo univariante para examinar tanto el efecto de las variaciones como de la volatilidad de los tipos de interés sobre la distribución de rendimientos de diversas carteras bancarias en los mercados estadounidense y australiano, respectivamente. Siguiendo un enfoque parecido, Joseph y Vezos (2006) utilizan un modelo EGARCH (GARCH exponencial) univariante en el mercado estadounidense. Por su parte, Tai (2000) y Faff et al. (2005) proponen modelos GARCH-M multivariantes para examinar el impacto dual de los cambios de los tipos de interés y de la volatilidad de tipos sobre los rendimientos de carteras bancarias en los mercados estadounidense y australiano,

respectivamente. De forma similar, Elyasiani y Mansur (2004) aplican un modelo GARCH multivariante en el sector bancario estadounidense. La Tabla 1.1 contiene un resumen de los principales objetivos y resultados de estos trabajos.

En lo que concierne al caso español, la evidencia disponible relativa al riesgo de interés del sector financiero es considerablemente inferior al caso estadounidense, si bien se pueden destacar algunos trabajos interesantes. Al respecto, con el propósito de determinar la relevancia del riesgo de interés en el comportamiento de los distintos sectores bursátiles Ferrer et al. (1999) utilizan un modelo unifactorial cuya única variable explicativa recoge el impacto de los cambios de tipos sobre los rendimientos bursátiles sectoriales. Por su parte, Ferrer et al. (2008) examinan la exposición al riesgo de interés de las empresas españolas, también a nivel sectorial, en el ámbito del modelo bifactorial de Stone centrándose exclusivamente en el efecto de los cambios de los tipos de interés y empleando técnicas de regresión móvil. En ambos estudios se constata que el sector bancario constituye, junto con los sectores de construcción y eléctrico, uno de los más afectados por los movimientos de los tipos de interés.

Desde una perspectiva distinta, Jareño (2006 y 2008) propone una extensión del clásico modelo de Stone (1974) y un enfoque híbrido entre el modelo de Stone y el modelo de tres factores de Fama y French (1993), respectivamente, para analizar por separado el efecto de los cambios de los tipos de interés reales y de la tasa de inflación esperada sobre el mercado de acciones a nivel sectorial. En ambos trabajos se pone de manifiesto que el sector bancario español presenta una significativa sensibilidad negativa ante las variaciones de los tipos de interés reales, mientras que la inflación esperada no tiene un impacto significativo.

3. Metodología

La formulación tradicionalmente empleada para medir la sensibilidad de las acciones bancarias ante los movimientos de los tipos de interés es el modelo de dos índices introducido por Stone (1974), cuya expresión analítica es la siguiente:

$$R_{it} = \alpha_i + \lambda_i R_{mt} + \theta_i \Delta I_t + \varepsilon_{it} \quad (1.1)$$

donde R_{it} denota el rendimiento de la acción de la entidad bancaria i en el periodo t , R_{mt} el rendimiento de la cartera de mercado en el periodo t , λ_i la sensibilidad del rendimiento de la acción i ante los movimientos generales del mercado, ΔI_t los cambios del tipo de interés en el periodo t , θ_i la sensibilidad del rendimiento de la acción i ante las variaciones de los tipos de interés independientemente del efecto que estas variaciones tienen sobre el mercado bursátil en su conjunto y, finalmente, ε_{it} indica el término de error.

El coeficiente θ_i puede ser visto como una estimación de la duración de la acción bancaria i y, por consiguiente, representa un indicador del grado de exposición al riesgo de interés de la entidad financiera i .

Dada la habitual tendencia a la agrupación de la volatilidad (*volatility clustering*) en la mayor parte de las series temporales financieras, el modelo contenido en (1.1) ha sido ampliado con el fin de capturar el carácter cambiante en el tiempo de la varianza condicional del rendimiento de las acciones bancarias. En este contexto, la metodología GARCH ha sido expresamente desarrollada para ocuparse de los potenciales problemas derivados de la presencia de heterocedasticidad condicional. Esta aproximación combina una especificación relativamente simple con una memoria larga del proceso de volatilidad y dentro de la misma se encuadran los modelos ARCH introducidos por

Engle (1982), así como los procesos GARCH propuestos por Bollerslev (1986) y las extensiones ARCH-M y GARCH-M de Engle et al. (1987).

Específicamente, la rama de investigación sobre riesgo de interés en el sector bancario con mayor protagonismo en la literatura reciente es la basada en la aplicación de los modelos GARCH-M [véanse a este respecto, por ejemplo, Elyasiani y Mansur (1998), Ryan y Worthington (2004), Tai (2000) o Faff et al. (2005)]. El rasgo distintivo de estos procesos es su capacidad para capturar la dinámica variable en el tiempo de la prima de riesgo, así como la posible relación existente entre riesgo y rendimiento esperado.

El modelo aquí propuesto es una versión extendida de un modelo GARCH(1,1)-M univariante y viene descrito por el siguiente sistema de ecuaciones:

$$R_{it} = \omega_i + \lambda_i R_{it} + \theta_i \Delta I_t + \gamma_i \log h_{it} + \varepsilon_{it} \quad (1.2)$$

$$h_{it} = \alpha_0 + \alpha_1 \varepsilon_{it-1}^2 + \beta h_{it-1} + \delta_i VCI_{t-1} \quad (1.3)$$

$$\varepsilon_{it} | \Omega_{t-1} \sim N(0, h_{it}) \quad (1.4)$$

donde h_{it} refleja la varianza condicional del rendimiento de la acción i en el período t , VCI_{t-1} es la volatilidad del tipo de interés en el período $t-1$ y ε_{it} es un término de error gaussiano de media cero y varianza h_{it} , dependiente del conjunto de información relevante disponible en $t-1$, Ω_{t-1} . Finalmente, ω_i , λ_i , θ_i , γ_i , α_0 , α_1 , β , y δ_i son los parámetros a estimar. Los mismos deben satisfacer las condiciones de estacionariedad, de tal forma que $\alpha_0, \alpha_1, \beta \geq 0$ y $\alpha_1 + \beta < 1$.

En lo concerniente a la especificación planteada, se ha considerado más oportuno usar un modelo GARCH univariante que un enfoque multivariante. Ello

obedece a que en el caso concreto del presente estudio parece claro desde un punto de vista económico que la causalidad va desde el riesgo de interés y el riesgo de mercado en dirección al rendimiento de las acciones bancarias, mientras que es ciertamente difícil justificar un efecto de retroalimentación del rendimiento de las acciones bancarias sobre el rendimiento de mercado y las fluctuaciones de los tipos de interés. Es por ello que la modelización adicional incorporada por un proceso multivariante para analizar posibles efectos de transmisión de volatilidad entre la variable dependiente y las variables independientes no parece necesaria para el estudio del riesgo de interés del sector bancario. Por consiguiente, la mayor sencillez operativa junto con el intento de evitar problemas en la estimación derivados del incremento exponencial del número de parámetros a estimar en los modelos multivariantes representan argumentos de peso a favor del empleo de una especificación GARCH univariante. Adicionalmente, la presencia de posibles efectos asimétricos en el impacto de los cambios positivos y negativos de los tipos de interés sobre las acciones bancarias ha sido examinada. Los resultados contrarios a la existencia de asimetrías significativas justifican la no utilización de modelos GARCH asimétricos.

El empleo de un proceso GARCH-M de orden (1,1) viene apoyado por numerosos trabajos empíricos que muestran que los modelos GARCH(1,1) capturan adecuadamente el comportamiento heterocedástico condicional de gran cantidad de series temporales financieras. En este sentido, se pueden destacar, entre otros, los trabajos de Baillie y DeGennaro (1990), Ryan y Worthington (2004), Amigo y Rodríguez (2007) o García Blandón (2008).

El modelo propuesto presenta características muy similares a los empleados por Elyasiani y Mansur (1998) y Ryan y Worthington (2004). La utilización de estos modelos como referencia obedece a diversas razones. Por un lado, permiten examinar

conjuntamente el impacto de los cambios de los tipos de interés y de la volatilidad de tipos sobre la distribución de rendimientos de las acciones bancarias en el marco de un proceso GARCH(1,1) univariante, con las consiguientes ventajas sobre los modelos multivariantes en términos de sencillez operativa. Por otro, el uso de una especificación GARCH “en media” permite incorporar el efecto de la volatilidad bancaria como un determinante adicional del rendimiento de las acciones capturando, por tanto, el posible efecto de retroalimentación entre riesgo y rendimiento esperado consistente con modelos de valoración de activos como el CAPM o el APT.

Como se puede apreciar, la ecuación de la media condicional del modelo formulado, recogida en (1.2), incluye como variable explicativa adicional, junto al rendimiento de la cartera de mercado y los cambios de los tipos de interés ya utilizados por Stone, la varianza del rendimiento de la acción bancaria en cuestión. En relación a esta última, su especificación en forma logarítmica sigue el planteamiento de Engle et al. (1987), para quienes el logaritmo de la varianza es una mejor representación del riesgo que la propia varianza o la desviación típica. A su vez, el parámetro γ_i conecta explícitamente la varianza condicional con la media condicional del rendimiento del activo en cuestión y es usualmente interpretado como el coeficiente de aversión relativa al riesgo.

En lo tocante a la ecuación de la varianza condicional, recogida en (1.3), la estructura típica de los procesos GARCH ha sido ampliada al modelizar la varianza condicional del rendimiento de las acciones bancarias como función de la volatilidad de los tipos de interés retardada un período. Así, el parámetro δ_i determina la significatividad de la volatilidad de los tipos de interés.

En este contexto, si bien hasta el momento la literatura se ha centrado en el impacto de las variaciones de los tipos de interés, con un nivel de atención muy superior

al otorgado a la incidencia de la volatilidad de los tipos de interés, debe tenerse en cuenta que el efecto de la volatilidad de tipos sobre la distribución de los rendimientos de las acciones bancarias también constituye un aspecto de indudable relevancia. En concreto, su estudio va a permitir alcanzar un mayor grado de comprensión del comportamiento de las entidades financieras en respuesta a las fluctuaciones de los tipos de interés.

Específicamente, tal y como señalan Elyasiani y Mansur (1998) la incorporación del impacto de la volatilidad de tipos en el modelo resulta importante desde varias perspectivas. Por un lado, desde un punto de vista macroeconómico la volatilidad de los tipos de interés contiene información esencial sobre el nivel de volatilidad global en los mercados financieros, ya que esta variable refleja la incertidumbre existente sobre la política monetaria y la efectividad de la autoridad supervisora en la consecución de sus objetivos. Por otro, la volatilidad de tipos también influye sobre la volatilidad del rendimiento de las acciones bancarias a nivel microeconómico. A este respecto, Deshmukh et al. (1983) demostraron que, ante un incremento de la incertidumbre relativa a los tipos de interés, las entidades bancarias intentan protegerse reduciendo su nivel de exposición a dicho riesgo, lo que acaba traduciéndose en una volatilidad más baja del rendimiento de sus acciones. Este efecto se ve reforzado por un posible problema de agencia con los gestores bancarios, quienes, preocupados por mantener su puesto de trabajo, tienen un claro incentivo a reducir los riesgos financieros para contrarrestar el aumento de la incertidumbre sobre los tipos de interés.

Junto a todo lo anterior, existen varios aspectos relevantes concernientes a la estimación del modelo que merecen ser comentados. Una primera cuestión atañe a la posible colinealidad entre las series de variaciones de los tipos de interés y rendimiento de la cartera de mercado, derivada de una fuerte correlación entre ambas que puede

provocar serios problemas en la estimación. Dada la significativa correlación negativa típicamente observada en el caso español entre ambas variables, se ha considerado conveniente eliminar dicha correlación mediante la aplicación de un procedimiento de ortogonalización. Dado que el objetivo central del trabajo es el análisis del efecto del riesgo de interés sobre las entidades financieras, se ha optado por ortogonalizar el rendimiento del mercado siguiendo un esquema idéntico al empleado por Lyngé y Zumwalt (1980), Flannery y James (1984) y Czaja et al. (2009).

Un segundo aspecto a destacar concierne a la elección de la variable de tipo de interés concreta a emplear en el análisis empírico. Al respecto, los tipos de interés a largo plazo, y en particular el tipo a diez años, constituyen la variable más frecuentemente usada en la literatura.³ Ello se debe a que los tipos a largo plazo son los que incorporan en mayor medida las expectativas de los agentes sobre el futuro y los que determinan en la práctica el coste de la financiación, convirtiéndose, por tanto, en los que ejercen una mayor influencia sobre las decisiones de inversión empresarial y la evolución de la actividad económica. No obstante, y con el objeto de dotar de una mayor robustez a los resultados, los tipos de interés a corto plazo y el margen o *spread* entre los tipos a largo y a corto plazo han sido también empleados. En relación a los tipos de interés a corto plazo, se ha escogido un tipo del mercado interbancario dado que durante los últimos años este mercado se ha convertido en una referencia esencial para las entidades financieras españolas debido tanto al espectacular incremento de las operaciones de activo y pasivo referenciadas a tipos interbancarios como a que dicho mercado ha sido utilizado con profusión por las entidades para financiar sus operaciones de activo, principalmente del segmento hipotecario, en el marco del boom de la

³ Como ejemplos de utilización de los tipos a diez años pueden verse, entre otros, los trabajos de Sweeney y Warga (1986), Elyasiani y Mansur (1998), Tai (2000), Ryan y Worthington (2004) o Faff et al. (2005).

vivienda en España. A su vez, el margen entre tipos refleja la pendiente de la curva de tipos, pudiendo actuar como un indicador de la evolución del ciclo económico.

Una última cuestión hace referencia a la estimación de la volatilidad de los tipos de interés. Tal y como señalan Poon y Granger (2003), una gran cantidad de trabajos han usado modelos de la familia GARCH para estimar la volatilidad de los tipos de interés, obteniendo generalmente evidencia de persistencia en la volatilidad. En este contexto, siguiendo a Elyasiani y Mansur (1998) y Ryan y Worthington (2004) la volatilidad de cada tipo de interés ha sido estimada por separado a través de la varianza condicional de dicho tipo generada con un proceso GARCH y después incorporada a la ecuación de la varianza condicional.

4. Datos empleados

El período de análisis se extiende desde enero de 1993 hasta diciembre de 2005, abarcando un intervalo temporal en el que los tipos de interés han variado sustancialmente dentro de una marcada tendencia general a la baja. La base de datos utilizada está compuesta por series históricas de frecuencia mensual de precios bursátiles y de tipos de interés.

El empleo de datos mensuales permite trabajar de una forma más manejable con períodos muestrales de considerable amplitud, tendiendo a reflejar adecuadamente los movimientos a largo plazo en la volatilidad. Además, los datos de frecuencia más alta (por ejemplo diaria) contienen una mayor cantidad de ruido atribuible a factores de tipo idiosincrásico, lo que reduce la eficiencia de las estimaciones y dificulta la obtención de una relación significativa entre riesgo de interés y rendimientos bancarios. De hecho, numerosos trabajos en este contexto como los de Song (1994), Elyasiani y Mansur (1998), Faff y Howard (1999), y Faff et al. (2005), han usado también datos mensuales.

En relación a los datos bursátiles, se han utilizado las series de precios de cierre mensuales, ajustados por ampliaciones de capital, splits y dividendos, de las acciones de todos los bancos negociados en el Sistema de Interconexión Bursátil Español (SIBE) durante el período muestral (23 entidades en total). El rendimiento mensual de cada acción bancaria ha sido calculado como la variación relativa de su valor de cierre a final de mes entre dos observaciones consecutivas. Estos datos incluyen el conjunto de bancos negociados en el SIBE durante, al menos, un período anual y no sólo los cotizados durante todo el período de estudio, apareciendo así bancos que han sido excluidos del mercado por varias razones (compra, absorción, etc.) y otros que han sido creados (fusión) a lo largo del período muestral. Este procedimiento de selección muestral permite utilizar todos los datos disponibles en cada período anual, minimizando el posible sesgo de supervivencia y maximizando el tamaño de la muestra con objeto de mejorar la eficiencia de la estimación. La Tabla 1.2 contiene el listado de bancos considerados, mostrando para cada uno su ticker bursátil junto con el volumen total de activos medio durante el período de estudio y el número de observaciones disponible.

A su vez, la cartera de mercado utilizada constituye una versión modificada del Índice General de la Bolsa de Madrid (IGBM). Específicamente, se ha empleado un índice de mercado alternativo del que no forman parte los bancos con la finalidad de obtener una serie de rendimientos de la cartera de mercado lo más exógena posible a los rendimientos de las carteras bancarias, dado el gran peso del sector bancario dentro del IGBM.⁴ Todos los datos bursátiles necesarios para confeccionar el índice de mercado alternativo proceden de Sociedad de Bolsas, S.A.

⁴ A pesar de la no consideración de los bancos en el índice de mercado modificado, la correlación de este índice con respecto al IGBM original durante el periodo de estudio considerado es 0,95.

Por otro lado, el tanto interno de rendimiento medio mensual de las obligaciones del Estado a diez años negociadas en el mercado secundario de deuda pública anotada y la media mensual del tipo de interés a tres meses del mercado interbancario han sido tomados como variables representativas de los tipos a largo y a corto plazo, respectivamente. Por su parte, el *spread* de tipos ha sido calculado como la diferencia entre los tipos de interés a diez años y a tres meses. Estos datos han sido obtenidos de las series históricas de mercados financieros publicadas por el Banco de España.

Como se ha comentado antes, la volatilidad de los tipos de interés ha sido medida a través de su varianza condicional modelizada mediante un proceso de tipo GARCH. En particular, tras convertir cada una de las variables de tipos de interés en una serie estacionaria e incorporar en la ecuación de la media condicional el número de términos autorregresivos necesario para garantizar la ausencia de autocorrelación, se ha comprobado que el modelo más apropiado para la ecuación de la varianza condicional de los tipos de interés es siempre un GARCH (1,1). El gráfico 1.1 muestra la evolución temporal de las distintas series de tipos de interés en niveles.

En sintonía con la práctica habitual en la literatura y a fin de comprobar si existe algún tipo de relación sistemática entre el tamaño de las entidades financieras y su grado de exposición al riesgo de interés, el estudio se ha llevado a cabo a nivel de carteras de acciones bancarias construidas según criterios de tamaño en lugar de trabajar con títulos individuales. De esta forma, los bancos de la muestra han sido clasificados en tres carteras en función de su volumen total de activos medio. Así, se ha creado una cartera de bancos grandes (cartera *G* en lo sucesivo), una cartera de bancos medianos (cartera *M*) y una cartera de bancos pequeños (cartera *P*), cuya composición, recogida en la Tabla 1.2, se ha mantenido inalterada durante el periodo de estudio. En concreto, la cartera *G* está compuesta por aquellas entidades con un volumen total de activos

superior a 50.000 millones de euros, propiciando la inclusión en la misma de los dos grandes conglomerados bancarios españoles (Grupos Banco Santander y BBVA). A su vez, la cartera M está formada por aquellas entidades con un volumen de activos comprendido entre 5.000 y 50.000 millones de euros. Un total de siete entidades, representativas de la banca mediana española (Banesto, Banco Popular, Banco Sabadell, Bankinter, etc.) integran esta categoría. Por último, la cartera P , constituida por los bancos con activos totales por debajo de 5.000 millones de euros, se nutre de los doce restantes bancos de menor dimensión.

La serie de rendimientos mensuales de cada cartera bancaria ha sido obtenida como la media aritmética ponderada de los rendimientos mensuales de las acciones integrantes de la cartera en cuestión. Como factor de ponderación se ha empleado el porcentaje que representa la capitalización bursátil de cada banco respecto de la capitalización bursátil total de la cartera al final de cada periodo. El gráfico 1.2 muestra la evolución temporal de los rendimientos mensuales de las carteras G , M y P en comparación con el rendimiento mensual de la cartera de mercado.

La formación de carteras proporciona una manera eficiente de resumir una gran cantidad de información sobre el comportamiento de las acciones, con la ventaja añadida de suavizar el ruido presente en los datos, debido principalmente a shocks transitorios en las compañías individuales. En contraposición, el empleo de carteras puede enmascarar las diferencias existentes entre empresas individuales. No obstante, para el tipo de análisis aquí efectuado las ventajas asociadas a la construcción de carteras parecen superar el inconveniente señalado y buena prueba de ello es la proliferación de trabajos basados en el empleo de carteras bancarias [véase, por

ejemplo, Song (1994), Elyasiani y Mansur (1998 y 2004), Faff et al. (2005) o Joseph y Vezos (2006)].⁵

5. Resultados empíricos

5.1 Propiedades de los datos

De forma preliminar, con el propósito de comprobar la idoneidad de la metodología GARCH en el presente estudio se ha examinado las propiedades de normalidad, ruido blanco, asimetría y curtosis de las series de rendimientos de las carteras de acciones bancarias. Los resultados obtenidos aparecen en la Tabla 1.3.

El aspecto más destacable es la presencia de asimetría y curtosis significativas en los rendimientos de las carteras bancarias, sugiriendo que estas series no siguen una distribución normal, evidencia reforzada por el claro rechazo de la hipótesis de normalidad con el test de Jarque-Bera. Además, los estadísticos del contraste de Ljung-Box sobre las series de rendimientos al cuadrado son estadísticamente significativos para las tres carteras bancarias, si bien en menor grado para la cartera *P*. Este resultado de dependencia no lineal es típicamente asociado a la presencia de heterocedasticidad condicional. Así pues, la evidencia obtenida sugiere que el enfoque GARCH puede ser un marco apropiado para analizar el riesgo de interés de las acciones bancarias.

Adicionalmente, a fin de determinar si las diferentes series son estacionarias, se han aplicado los contrastes de raíces unitarias Dickey-Fuller aumentado y Phillips-Perron. Los resultados indican que todas las series de rendimientos son estacionarias en niveles, al igual que el spread entre tipos de interés, mientras que las series de tipos de

⁵ No obstante, se ha estimado también un modelo GARCH para cada una de las acciones bancarias, comprobándose que los resultados son análogos a los obtenidos con carteras. Esta evidencia no ha sido incluida por motivos de espacio, pero se encuentra disponible para cualquier lector interesado.

interés a diez años y a tres meses en niveles presentan una raíz unitaria, lo que justifica el uso de sus primeras diferencias.⁶

5.2. Interpretación de los resultados

Los resultados de la estimación del modelo propuesto para cada una de las carteras de acciones bancarias utilizando las diferentes variables alternativas de tipos de interés aparecen en la Tabla 1.4. En este sentido, debe tenerse en cuenta que la escasa variabilidad de los rendimientos de la cartera P , unida a los ya de por sí más débiles indicios de heterocedasticidad condicional hallados en la misma, provocan que la inclusión de la varianza condicional de los tipos de interés genere problemas en la estimación del modelo propuesto para el caso de la cartera P . Por esta razón, se ha optado por excluir la volatilidad de los tipos de interés de la ecuación de la varianza condicional en el modelo finalmente estimado para la cartera P .

En línea con lo esperado, la estimación del modelo para las tres carteras de acciones bancarias permite constatar cómo el parámetro λ_i , representativo de la sensibilidad del rendimiento de la cartera bancaria en cuestión ante los movimientos generales del mercado, es positivo y significativo a un nivel del 1% en todos los casos y con independencia de la variable de tipos de interés considerada. Dicho parámetro adopta siempre valores inferiores a la unidad y su cuantía desciende conforme disminuye el tamaño de la cartera. Así pues, este resultado indica que el riesgo de mercado o sistemático constituye un factor explicativo relevante del comportamiento de las acciones bancarias.

Asimismo, en el sector bancario español parece existir una relación directa entre el tamaño de las entidades y su nivel de riesgo de mercado. Este resultado no se ve en

⁶ Estos resultados no se han incluido en el trabajo por cuestiones de espacio si bien pueden ser solicitados a los autores.

absoluto influenciado por el peso que puedan tener las acciones bancarias dentro del mercado bursátil en su conjunto, puesto que éstas han sido expresamente excluidas del índice alternativo de mercado utilizado. Una explicación plausible de esta vinculación positiva apunta a que los bancos más grandes tienen mayores oportunidades para diversificar sus carteras de activos, operando generalmente en un amplio rango de zonas y sectores económicos, y además participan más activamente en operaciones fuera de balance arriesgadas (por ejemplo, mediante posiciones en derivados). Por ello, su comportamiento está más correlacionado con los shocks que afectan al mercado en general. Frente a esto, los bancos de dimensión más reducida suelen presentar una menor diversificación geográfica y de productos y un comportamiento bursátil más regido por factores de tipo idiosincrásico, lo que se traduce en una menor conexión con las fluctuaciones del mercado. A su vez, el hecho de que λ_i sea menor que la unidad parece sugerir que las carteras bancarias presentan, independientemente del tamaño institucional, un nivel de riesgo sistemático inferior al del mercado de acciones en su conjunto.

En relación al impacto de los cambios en el nivel de los tipos de interés, el parámetro θ_i es negativo prácticamente siempre, si bien sólo resulta significativo a los niveles usuales para las tres carteras al utilizar las variaciones de los tipos a diez años. Además, los movimientos de los tipos de interés a largo plazo son los que ejercen una influencia más fuerte sobre las acciones bancarias en términos de magnitud y significatividad estadística, de forma consistente con los resultados de la mayor parte de la literatura centrada en el riesgo de interés del sector bancario [véanse, por ejemplo, los trabajos de Madura y Zarruk (1995), Elyasiani y Mansur (1998 y 2004) y Bartram (2002)]. Frente a esto, las variaciones de los tipos de interés a corto plazo y el spread de

tipos no tienen un efecto significativo sobre el rendimiento de las tres carteras bancarias, exceptuando el spread en el caso de la cartera P .

Asimismo, también parece existir una relación directa entre el grado de sensibilidad ante los cambios de los tipos de interés y el tamaño de las entidades bancarias. Una posible explicación puede ser atribuida al hecho de que, durante los últimos años y en un intento de incrementar su cuota de mercado dentro de un entorno de creciente competencia, los bancos más grandes han desarrollado políticas de fijación de precios de sus productos, sobre todo por el lado del activo, más agresivas y caracterizadas por un alto grado de vinculación a los tipos de mercado (prueba de ello es el extraordinario crecimiento de los préstamos indexados). El uso ampliamente extendido de derivados sobre tipos de interés por parte de los bancos de mayor dimensión, favorecido por la presencia de economías de escala, puede haber jugado también un papel destacado en este sentido. Todo ello ha desembocado en unas cuentas de resultados y un comportamiento bursátil de los bancos grandes más influenciados por la evolución de las condiciones de mercado. En contraste, la combinación de políticas comerciales menos agresivas, la menor diversificación geográfica y de productos, el uso menos difundido de instrumentos derivados y una trayectoria bursátil ampliamente condicionada por factores de riesgo idiosincrásicos (rumores de posibles operaciones corporativas), pueden estar detrás de la menor vulnerabilidad de los bancos pequeños al riesgo de interés.

Por su parte, el parámetro γ_i , asociado a la varianza condicional del rendimiento de las carteras bancarias, ha sido normalmente interpretado como la compensación requerida por los agentes aversos al riesgo por invertir en activos arriesgados. Según esto, un incremento de la volatilidad del rendimiento debería ir acompañado de un mayor rendimiento esperado, con lo cual cabría pensar en un principio que este

parámetro debe tomar valores positivos. Sin embargo, dado que el riesgo capturado por la varianza condicional no es el riesgo sistemático no diversificable, sino el riesgo total, el signo del parámetro γ_i no tiene por qué ser necesariamente positivo, ya que en estas circunstancias un aumento del riesgo total no ha de traducirse forzosamente en un rendimiento más elevado. De hecho, si las fluctuaciones de la volatilidad tienen su origen principalmente en shocks de riesgo no sistemático, γ_i podría adoptar cualquier signo.⁷

En este caso, los valores estimados de γ_i difieren en términos de signo y magnitud entre las tres carteras bancarias, siendo positivo y significativo para las carteras G y M , y negativo y significativo para la cartera P . Esta divergencia podría ser consecuencia de la naturaleza heterogénea de las expectativas de los inversores sobre el comportamiento futuro de las carteras G , M y P , poniéndose de nuevo de manifiesto el carácter más exógeno de los bancos de menor tamaño. La ausencia de un resultado concluyente con respecto a este parámetro está en línea con la falta de consenso encontrada en la literatura. Así, French et al. (1987) y Campbell y Hentschel (1992) detectaron una vinculación positiva entre riesgo y rendimiento, mientras que Glosten et al. (1993), Elyasiani y Mansur (1998) o Faff et al. (2005) hallaron una relación negativa ($\gamma_i < 0$). Finalmente, Baillie y DeGennaro (1990) y Ryan y Worthington (2004) obtuvieron un γ_i no significativo.

⁷ En este sentido, Engle et al. (1987) mostraron que el signo y la magnitud de este parámetro dependen de las funciones de utilidad de los agentes y de las condiciones de oferta de los activos, de forma que su signo no está predeterminado. A su vez, Glosten et al. (1993) sugirieron diversas razones por las que la relación entre riesgo y rendimiento puede llegar a ser negativa. Finalmente, Elyasiani y Mansur (1998) propusieron una explicación alternativa de un coeficiente de aversión relativa al riesgo negativo en el contexto específico del sector financiero. En particular, si los bancos son menos afectados que otros sectores por los shocks económicos entonces los inversores incrementarán sus posiciones en acciones bancarias huyendo de sectores más perjudicados, lo que desembocará en una prima de riesgo más baja para las acciones bancarias.

En relación a los parámetros de la ecuación de la varianza condicional, el término constante de dicha ecuación, α_0 , es positivo, significativo y con un valor muy pequeño en todos los casos, lo que implica que el proceso generador de rendimientos de las acciones bancarias tiene un componente de volatilidad invariante en el tiempo de magnitud muy reducida. Los parámetros representativos de los efectos ARCH y GARCH, α_1 y β , respectivamente, son positivos y significativos a los niveles usuales para las tres carteras, satisfaciendo el requisito de no negatividad y sugiriendo que el comportamiento heteroscedástico del rendimiento de las acciones bancarias puede ser adecuadamente caracterizado por un modelo GARCH(1,1). Para las tres carteras el parámetro α_1 , representativo del impacto del shock ocurrido en el último período, adopta siempre una cuantía sustancialmente más baja que el de la varianza condicional retardada, β , indicativo del efecto de las sorpresas previas. Este resultado, idéntico al obtenido por Elyasiani y Mansur (1998) y Ryan y Worthington (2004) para otros mercados, implica que el comportamiento bursátil del sector bancario tiene una memoria superior a un período y que la volatilidad es más sensible a sus propios valores retardados que a las nuevas sorpresas en el mercado.

Asimismo, la suma de los parámetros ARCH y GARCH, $\alpha_1 + \beta$, representativa del grado de persistencia de la volatilidad, es inferior a la unidad para las tres carteras independientemente de la variable de tipo de interés considerada, cumpliendo las condiciones de estacionariedad de segundo orden requeridas por los modelos GARCH. El elevado valor de la medida de persistencia de la volatilidad, cuyos valores oscilan entre 0,81 y 0,93, muestra que los shocks del sector bancario tienen efectos altamente persistentes y que la función de respuesta de la volatilidad decrece a un ritmo relativamente lento. Estos resultados sugieren que el empleo de un modelo tradicional

de volatilidad constante para modelizar el rendimiento de las acciones bancarias del mercado español sería inapropiado.

A su vez, el parámetro δ_i , que mide el efecto de la volatilidad de los tipos de interés sobre la volatilidad del rendimiento de las carteras bancarias, resulta negativo y significativo para las dos carteras que incorporan la volatilidad de tipos en el modelo estimado (G y M) con independencia de la variable de tipos de interés usada. Además, de forma análoga al resultado obtenido con los movimientos de los tipos de interés, parece existir una relación positiva entre el valor absoluto de este parámetro, el tamaño de las entidades y el plazo hasta el vencimiento del tipo de interés utilizado. Así, la volatilidad de los tipos de interés tiene un impacto negativo más fuerte en términos de magnitud sobre la volatilidad del rendimiento de la cartera cuanto mayor es el tamaño de los bancos integrantes de la cartera y, además, dicha volatilidad incide en mayor medida en el caso de los tipos de interés a largo plazo.

Este resultado indica que ante un aumento de la volatilidad de los tipos de interés la volatilidad del rendimiento de las acciones bancarias tiende a estabilizarse en el siguiente período. Una posible explicación apunta a que en respuesta a un incremento de la volatilidad de tipos los bancos grandes y medianos buscan protegerse del riesgo de interés y son capaces de conseguir, al menos parcialmente, su objetivo en el plazo de un mes mediante, por ejemplo, la contratación de productos derivados o la reducción del gap de duraciones entre activos y pasivos bancarios, de tal forma que se produce una disminución de la volatilidad del rendimiento de sus acciones en el siguiente período mensual.

La consideración conjunta de este último resultado y el concerniente al impacto de los cambios de los tipos de interés pone de relieve que para las carteras G y M existe un efecto global de los tipos de interés estadísticamente significativo con independencia

de la variable de tipos de interés empleada. En consecuencia, puede afirmarse que el sector bancario español presenta una significativa exposición al riesgo de interés, especialmente al utilizar los cambios de los tipos a largo plazo como proxy de las variaciones de los tipos de interés.

Para comprobar la idoneidad del modelo formulado, se han realizado varios contrastes finales.⁸ En primer lugar, se ha contrastado si el proceso generador de rendimientos de las carteras bancarias sigue una especificación ARCH ($H_0: \beta = \delta_i = \gamma_i = 0$), GARCH ($H_0: \delta_i = \gamma_i = 0$), o ARCH-M ($H_0: \beta = \delta_i = 0$), rechazándose estas hipótesis nulas en todos los casos a un nivel del 1%, lo que parece indicar que la especificación GARCH-M constituye una forma funcional bastante apropiada para modelizar el comportamiento de los rendimientos de las acciones bancarias.⁹ En segundo lugar, el contraste de signos de Engle y Ng (1993) ha sido aplicado para detectar posibles especificaciones incorrectas relacionadas con la existencia de efectos asimétricos en las carteras bancarias. Los resultados obtenidos sugieren la ausencia de asimetrías, lo que contribuye a reforzar la idoneidad del modelo simétrico planteado.

5.3 Importancia relativa del riesgo de mercado y del riesgo de interés

Con el objeto de alcanzar una visión más clara de la importancia relativa del riesgo de mercado y del riesgo de interés, se ha realizado un análisis complementario dirigido a determinar la capacidad explicativa individual de cada uno de estos factores sobre el rendimiento de las carteras. Para ello, se ha partido del clásico modelo bifactorial de Stone y, dado que el rendimiento de la cartera de mercado y los cambios

⁸ Los resultados correspondientes a estos contrastes tampoco aparecen por motivos de espacio, aunque pueden ser solicitados a los autores.

⁹ En el caso de la cartera P las hipótesis contrastadas no incluyen, lógicamente, el parámetro δ_i .

de los tipos de interés son independientes debido a la ortogonalización efectuada, la varianza total del rendimiento de una cartera bancaria cualquiera, $Var(R_{it})$, se puede expresar como:

$$Var(R_{it}) = \lambda_i^2 Var(R_{mt}) + \theta_i^2 Var(\Delta I_t) + Var(\varepsilon_{it}) \quad (1.5)$$

Para realizar una comparación adecuada entre ambos factores se ha dividido la ecuación anterior por $Var(R_{it})$. De esta manera, el porcentaje de contribución de cada factor individual a la varianza total del rendimiento de la cartera vendrá dado por el producto de su correspondiente coeficiente al cuadrado por el cociente entre su varianza y la varianza total del rendimiento de la cartera en cuestión. La Tabla 1.5 permite constatar que, para las tres carteras bancarias y con independencia del tipo de interés utilizado, los resultados son análogos. Así, se observa que el riesgo de mercado es el determinante más relevante de la variabilidad del rendimiento de cada cartera, mientras que el riesgo de interés tiene una importancia relativa considerablemente inferior, si bien los tipos a largo plazo se revelan nuevamente como los que ejercen una mayor incidencia. Además, se aprecia que la capacidad explicativa de ambos factores disminuye conforme se reduce el tamaño de la cartera, confirmando que las carteras de menor dimensión presentan un comportamiento bursátil más guiado por factores idiosincrásicos.

5.4 Análisis por subperiodos

En este epígrafe el modelo GARCH(1,1)-M propuesto en las ecuaciones (1.2) a (1.4) ha sido extendido con el propósito de dilucidar si el impacto del riesgo de interés sobre las acciones bancarias se ha mantenido constante a lo largo de todo el período de estudio. Específicamente, se ha examinado si la introducción del euro como moneda

única en el marco de la Unión Monetaria Europea a partir del 1 de enero de 1999 ha alterado significativamente el grado de exposición al riesgo de interés de las entidades financieras españolas, distinguiendo para ello entre dos subperiodos, esto es, desde enero de 1993 a diciembre de 1998 por un lado y desde enero de 1999 a diciembre de 2005 por otro.

Dado que el elevado número de parámetros a estimar en los modelos GARCH requiere un considerable tamaño muestral, se ha optado por emplear un procedimiento de variables ficticias en lugar de realizar estimaciones por separado para cada uno de los subperiodos. En este sentido, se ha introducido una variable ficticia, D_t , que actúa de manera individual y multiplicando a la serie de cambios de los tipos de interés. Esta variable dicotómica toma un valor 1 desde enero de 1993 hasta diciembre de 1998 y 0 en el resto del período muestral. Tal y como ha sido definida esta variable, su coeficiente asociado, η_i , recoge el efecto *diferencial* en términos de exposición al riesgo de interés que se produce durante el primer subperiodo muestral. Así, la obtención de un parámetro η_i negativo y significativo puede ser interpretada como evidencia de que el efecto del riesgo de interés es sustancialmente más elevado –en valor absoluto– durante el primer subperiodo.

Los resultados de la estimación del modelo extendido con variables ficticias aparecen en la Tabla 1.6. El parámetro η_i resulta negativo y significativo en la gran mayoría de los casos al emplear los cambios de los tipos a largo y a corto plazo, si bien los resultados no son tan concluyentes al considerar el spread de tipos. Esta evidencia es consistente con la literatura previa [véase, por ejemplo, Akella y Chen (1990); Kwan, (1991); Faff y Howard (1999); o Brewer et al. (2007)], sugiriendo que la sensibilidad de

las acciones bancarias ante los movimientos de los tipos de interés se ha debilitado considerablemente a partir de la entrada en funcionamiento del euro.

Esta reducción del riesgo de interés en el sector bancario durante los últimos años puede ser básicamente atribuida al hecho de que, en respuesta a la mayor volatilidad de las condiciones financieras derivada de la creciente interdependencia entre mercados, las entidades bancarias han adoptado un papel más activo en la gestión de activos y pasivos, desarrollando sistemas más efectivos de medición y gestión del riesgo de interés. Asimismo, el uso recientemente extendido de instrumentos derivados con fines de cobertura también puede haber jugado un papel relevante.

6. Conclusiones

La incidencia del riesgo de interés sobre el valor de las entidades bancarias se ha convertido en una cuestión de indudable trascendencia como resultado de la combinación de factores tales como el sustancial incremento de la volatilidad de los tipos de interés en los últimos años y la nueva regulación sobre requerimientos mínimos de capital para la cobertura de los riesgos bancarios, junto al habitual efecto directo de las variaciones de los tipos de interés sobre los ingresos y costes financieros de las entidades de crédito. En particular, el conocimiento del impacto de los movimientos de los tipos de interés sobre las acciones bancarias resulta de gran relevancia para gestores bancarios, inversores, autoridades supervisoras e incluso académicos de cara al diseño de estrategias de cobertura del riesgo de interés, a las decisiones de asignación de activos o a la evaluación del efecto de las medidas de política monetaria.

En este trabajo se examina la exposición del sector bancario español al riesgo de interés mediante un análisis a nivel de carteras construidas según criterios de tamaño y utilizando diferentes variables alternativas de tipos de interés. A diferencia de la

literatura clásica sobre riesgo de interés de las acciones bancarias, centrada básicamente en el impacto de los cambios en el nivel de los tipos de interés, aquí también se presta atención destacada al efecto de la volatilidad de los tipos de interés sobre la distribución de los rendimientos de las carteras bancarias. Con tal fin, una versión extendida de un modelo GARCH-M univariante es empleada como marco de análisis.

La evidencia empírica obtenida confirma la percepción ampliamente extendida de que el riesgo de interés constituye un importante factor explicativo del proceso generador de rendimientos de las acciones bancarias españolas, si bien es cierto que, como era de prever, desempeña un papel secundario con respecto al riesgo de mercado. En línea con el grueso de la literatura, se pone de relieve que las variaciones de los tipos de interés tienen un efecto negativo sobre el rendimiento de las diferentes carteras bancarias, siendo los tipos a largo plazo los que ejercen una influencia más significativa.

Esta conexión inversa puede ser explicada en base a las siguientes razones. Primero, el planteamiento más común apunta al tradicional desequilibrio de plazos en los balances bancarios, en virtud del cual los activos tienden a presentar un plazo de vencimiento medio superior al de los pasivos, como el principal factor responsable. Segundo, al igual que ocurre con los títulos de renta fija, las acciones bancarias exhiben una correlación negativa con los tipos de interés, estrechamente ligada a su consideración de activos sustitutivos de los bonos. A estos dos argumentos de índole más general, puede añadirse un tercer motivo, vinculado al ciclo económico alcista experimentado por la economía española desde mediados de los años 90. Específicamente, los resultados del sector bancario español han experimentado un crecimiento espectacular durante los últimos años, con el consiguiente efecto positivo sobre las cotizaciones bursátiles, en un contexto de tipos de interés históricamente bajos.

En esencia, se ha tratado de un crecimiento impulsado principalmente por el extraordinario aumento del número de operaciones activas contratadas, sobre todo en el segmento hipotecario, en el marco del boom inmobiliario español.

Además, parece existir una relación directa entre el tamaño de las entidades y su grado de sensibilidad ante los movimientos de los tipos de interés. Esta divergencia podría ser el resultado de diferencias sustanciales entre bancos de distinto tamaño en términos de política de fijación de precios de las operaciones bancarias, sobre todo por el lado del activo, del grado de utilización de derivados sobre tipos de interés y otras innovaciones financieras, del nivel de diversificación geográfica y de productos, etc. Así, los bancos de mayor dimensión tienen un comportamiento bursátil ampliamente influenciado por las condiciones de mercado, mientras que los bancos más pequeños son afectados en mayor medida por factores de tipo idiosincrásico.

De manera adicional, se aprecia una conexión significativa entre el riesgo y el rendimiento de las diferentes carteras bancarias, si bien el signo de la misma resulta ambiguo dependiendo de la cartera concreta. En consecuencia, este resultado no contribuye a aclarar la controversia existente en la literatura con respecto a esta cuestión.

Finalmente, la volatilidad de los tipos de interés se configura asimismo como un determinante significativo del comportamiento de las acciones bancarias, constatándose un efecto negativo sobre la volatilidad del rendimiento de las carteras. En este caso también parece haber una relación entre la magnitud –en valor absoluto– del impacto de la volatilidad de tipos y el tamaño institucional, de tal forma que los bancos más grandes son los que parecen en mejores condiciones de ajustar sus estrategias para protegerse ante un incremento del riesgo de interés asociado a una mayor volatilidad de tipos.

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Anexo: Tablas y Gráficos

Tabla 1.1
Medición del Riesgo de Interés en el Sector Bancario
 Metodología Tipo GARCH (1994-2006)

Trabajos	Metodología	Periodo muestral	Ámbito de estudio	Variables empleadas	Resultados obtenidos
Song (1994)	ARCH univariante	1977-1987	Mercado estadounidense	Cartera de mercado Tipo de interés	Los riesgos de mercado y de interés tienen un impacto significativo aunque pequeño en el periodo 1979-1981 y a partir de 1982 estos valores se ven incrementados, siendo el riesgo de mercado la variable más volátil.
Elyasiani y Mansur (1998)	GARCH-M univariante	1970-1992	Mercado estadounidense	Tipo de interés Volatilidad del tipo de interés	Ambas variables tienen un impacto significativo sobre la distribución de los rendimientos de las carteras de acciones bancarias.
Tai (2000)	GARCH-M multivariante	1987-1998	Mercado estadounidense	Cartera de mercado Tipo de interés Tipo de cambio	Presta especial atención a la variabilidad del valor de las primas de riesgo a lo largo de la muestra. Las variables son significativas utilizando tres procedimientos de estimación diferentes, siendo la variable tipo de interés el factor más valorado.
Elyasiani y Mansur (2004)	GARCH multivariante	1988-2000	Mercado estadounidense	Cartera de mercado Tipo de interés (CP y LP) Volatilidad del tipo de interés	Tanto las variaciones de los tipos de interés como sus volatilidades ejercen una significativa influencia sobre los rendimientos de las carteras bancarias, siendo el efecto de los tipos a largo plazo el más importante.
Faff et al. (2005)	GARCH-M multivariante	1978-1998	Mercado australiano	Tipo de interés (CP y LP) Volatilidad del tipo de interés	El efecto de las variaciones de los tipos de interés sobre los rendimientos de diferentes carteras bancarias prevalece sobre el de la volatilidad y la repercusión del riesgo del interés sobre el sector financiero viene condicionada por el proceso de desregulación financiera.
Joseph y Vezos (2006)	EGARCH univariante	1990-2000	Mercado estadounidense	Cartera de mercado Tipo de interés Tipo de cambio	Investiga el impacto de dichas variables a nivel individual y de carteras. Destaca el predominio del riesgo de mercado sobre los otros dos factores de riesgo, así como la débil incidencia del riesgo de interés.

Tabla 1.2
Listado de bancos y composición de las carteras

Carteras	Ticker	Volumen Activo (miles €)	Obs.		Ticker	Volumen Activo (miles €)	Obs.
Cartera G							
Banco Santander Central Hispano	BSCH	369.124.995	81	Banco Bilbao Vizcaya	BBV	100.026.979	85
Banco Bilbao Vizcaya Argentaria	BBVA	297.433.664	71	Argentaria	ARG	69.998.972	80
Banco Santander	SAN	113.404.303	75	Banco Central Hispano	BCH	68.793.146	75
Cartera M							
Banesto	BTO	42.332.585	156	Bankinter	BKT	15.656.910	156
Banco Exterior	EXT	32.130.967	51	Banco Pastor	PAS	8.789.945	156
Banco Popular Español	POP	29.548.620	156	Banco Atlántico	ATL	7.591.378	138
Banco Sabadell	SAB	26.686.670	56				
Cartera P							
Banco Zaragozano	ZRG	4.597.099	130	Banco Galicia	GAL	1.726.563	156
Banco Valencia	BVA	4.213.420	156	Banco de Vasconia	VAS	1.330.458	156
Banco Guipuzcoano	GUI	4.082.463	156	Banco de Vitoria	VIT	875.974	62
Banco Andalucía	AND	3.521.838	156	Banco Crédito Balear	CBL	854.972	156
Banco Herrero	HRR	2.624.824	95	Banco Alicante	ALI	835.576	64
Banco de Castilla	CAS	2.151.742	156	Banco Simeón	SIM	686.451	67

Esta tabla muestra la lista de bancos considerados y su distribución en carteras grande (*G*), mediana (*M*) y pequeña (*P*) según un criterio de tamaño (volumen total de activos).

Tabla 1.3
Principales estadísticos descriptivos de las series de rendimientos de las
carteras bancarias

Carteras Bancarias Ponderadas			
	Cartera G	Cartera M	Cartera P
Observaciones	156	156	156
Media	0,0165	0,0116	0,0130
Varianza muestral	0,0064	0,0029	0,0014
Mínimo	-0,2926	-0,1711	-0,0701
Máximo	0,2611	0,1982	0,2435
Asimetría	-0,4465**	-0,0028	2,2059***
Curtosis	5,1566***	5,3475***	13,4299***
JB	35,4181***	35,8218***	833,6212***
Q(12)	9,6344	9,8951	29,2857***
Q(24)	12,5575	19,5186	35,6335*
Q(36)	24,3749	27,1294	50,6139*
Q ² (12)	49,5900***	95,9229***	25,9366**
Q ² (24)	61,6832***	109,5708***	28,3502
Q ² (36)	100,7131***	145,1550***	32,6492

JB es el estadístico Jarque-Bera que contrasta la hipótesis nula de normalidad de los rendimientos de las carteras bancarias. $Q(n)$ es el estadístico Ljung-Box para n retardos que contrasta la presencia de correlación serial de orden n . Finalmente, ***, ** y * denotan significatividad a los niveles del 1%, 5% y 10%, respectivamente.

Tabla 1.4
Estimación del modelo GARCH (1,1)-M ampliado por máxima verosimilitud

	Cartera <i>G</i>			Cartera <i>M</i>			Cartera <i>P</i>			
	3 meses	10 años	Spread	3 meses	10 años	Spread	3 meses	10 años	Spread	
Ecuación de la Media	ω	-0,01*** (4,99)	0,03*** (9,08)	0,13*** (3,24)	0,02*** (11,04)	0,04*** (14,29)	0,05*** (18,84)	-0,15*** (-53,73)	-0,11*** (-42,01)	-0,18*** (-66,93)
	λ	0,96*** (17,60)	0,89*** (15,38)	0,95*** (15,82)	0,50*** (10,16)	0,48*** (8,82)	0,51*** (9,71)	0,27*** (5,12)	0,25*** (4,26)	0,26*** (5,20)
	θ	-1,12 (-0,94)	-6,80*** (-7,25)	-0,32 (-0,90)	-1,31 (-1,17)	-3,19*** (-3,04)	0,03 (0,18)	-1,31 (-1,17)	-3,28*** (-3,37)	-0,61*** (-3,23)
	γ	0,004*** (9,47)	0,003*** (6,41)	0,018*** (3,10)	0,002*** (8,87)	0,005*** (12,18)	0,007*** (16,78)	-0,02*** (-58,56)	-0,01*** (-46,50)	-0,03*** (-75,23)
Ecuación de la Varianza	α_0	0,0003*** (10,22)	0,0004*** (11,04)	0,0003*** (2,17)	0,0004*** (18,63)	0,0003*** (19,48)	0,0001*** (12,45)	0,00009*** (12,89)	0,00009*** (13,17)	0,00008*** (12,67)
	α_1	0,09*** (5,67)	0,14*** (6,65)	0,10** (2,08)	0,15*** (4,74)	0,11*** (5,19)	0,08*** (5,39)	0,03*** (6,33)	0,04*** (6,80)	0,02*** (5,90)
	β	0,82*** (54,94)	0,79*** (43,33)	0,80*** (11,16)	0,66*** (27,83)	0,78*** (48,76)	0,83*** (66,60)	0,89*** (148,20)	0,87*** (138,17)	0,89*** (155,75)
	δ	-15,04*** (-8,56)	-45,34*** (-8,97)	-10,00*** (-3,79)	-13,88*** (-12,98)	-30,49*** (-10,36)	-9,10*** (-5,40)	-	-	-

Esta tabla muestra los parámetros estimados del modelo GARCH (1,1)-M ampliado univariante aplicado para las diferentes carteras bancarias y variables alternativas de tipos de interés consideradas. El modelo estimado es el siguiente:

Carteras <i>G</i> y <i>M</i>	Cartera <i>P</i>
$R_{it} = \omega_i + \lambda_i R_{mt} + \theta_i \Delta I_t + \gamma_i \log h_{it} + \varepsilon_{it}$	$R_{it} = \omega_i + \lambda_i R_{mt} + \theta_i \Delta I_t + \gamma_i \log h_{it} + \varepsilon_{it}$
$h_{it} = \alpha_0 + \alpha_1 \varepsilon_{it-1}^2 + \beta h_{it-1} + \delta_i CVI_{t-1}$	$h_{it} = \alpha_0 + \alpha_1 \varepsilon_{it-1}^2 + \beta h_{it-1}$
$\varepsilon_{it} \Omega_{t-1} \sim N(0, h_t)$	$\varepsilon_{it} \Omega_{t-1} \sim N(0, h_t)$

Los valores del estadístico *t* se recogen entre paréntesis y ***, **, y * denotan significatividad estadística a los niveles del 1%, 5% y 10%, respectivamente.

Tabla 1.5
Importancia relativa de los factores de riesgo
Valores obtenidos de R²

		Tipos de Interés								
		3 meses			10 años			Spread		
		ΔI_t	R_{mt}	Total	ΔI_t	R_{mt}	Total	ΔI_t	R_{mt}	Total
Cartera G	R^2 (%)	0,85	53,84	54,69	2,81	51,77	54,58	1,22	53,47	54,69
Cartera M	R^2 (%)	1,30	34,21	35,52	2,74	32,78	35,52	1,19	34,83	36,02
Cartera P	R^2 (%)	1,24	15,19	16,42	5,59	12,40	17,99	1,08	15,35	16,43

Esta tabla muestra el porcentaje de contribución de los riesgos de mercado y de interés, medidos a través del R² factorial obtenido en base a la expresión (1.5), a la explicación de la varianza total del rendimiento de cada una de las carteras bancarias.

Tabla 1.6
Estimación del modelo GARCH (1,1)-M extendido con variable ficticia

	Cartera G			Cartera M			Cartera P		
	3 meses	10 años	Spread	3 meses	10 años	Spread	3 meses	10 años	Spread
θ	1,94 (0,69)	-3,44 (-1,60)	-1,88*** (-7,63)	2,42 (1,42)	2,59 (1,62)	-0,73*** (-4,40)	-1,69 (-1,59)	-0,67 (-0,81)	-0,17 (-0,92)
η	-6,52** (-2,09)	-4,69** (-1,97)	1,52*** (4,67)	-4,57*** (-4,42)	-6,53*** (-3,33)	0,95*** (5,06)	0,13 (0,11)	-3,43*** (-3,86)	-0,61** (-2,11)

Esta tabla muestra los parámetros estimados del modelo GARCH (1,1)-M univariante extendido que afectan a la serie de variaciones de los tipos de interés. El modelo se ha aplicado a las diferentes carteras bancarias y variables alternativas de tipos de interés consideradas e incluye una variable ficticia, D_t , que permite diferenciar el impacto del riesgo de interés sobre las entidades bancarias en dos subperiodos muestrales (antes y después de la introducción del euro en enero de 1999). El modelo estimado es:

Carteras G y M:

$$R_{it} = \omega_i + \lambda_i R_{mt} + \theta_i \Delta I_t + \alpha_i D_t + \eta_i D_t \Delta I_{it} + \gamma_i \log h_{it} + \varepsilon_{it}$$

$$h_{it} = \alpha_0 + \alpha_1 \varepsilon_{it-1}^2 + \beta h_{it-1} + \delta_i CVI_{t-1}$$

$$\varepsilon_{it} | \Omega_{t-1} \sim N(0, h_{it})$$

Cartera P:

$$R_{it} = \omega_i + \lambda_i R_{mt} + \theta_i \Delta I_t + \alpha_i D_t + \eta_i D_t \Delta I_{it} + \gamma_i \log h_{it} + \varepsilon_{it}$$

$$h_{it} = \alpha_0 + \alpha_1 \varepsilon_{it-1}^2 + \beta h_{it-1}$$

$$\varepsilon_{it} | \Omega_{t-1} \sim N(0, h_{it})$$

donde $D_t = \begin{cases} 1 & \text{si } t \leq \text{Enero 1999} \\ 0 & \text{si } t > \text{Enero 1999} \end{cases}$

Gráfico 1.1
Evolución de los diferentes tipos de interés

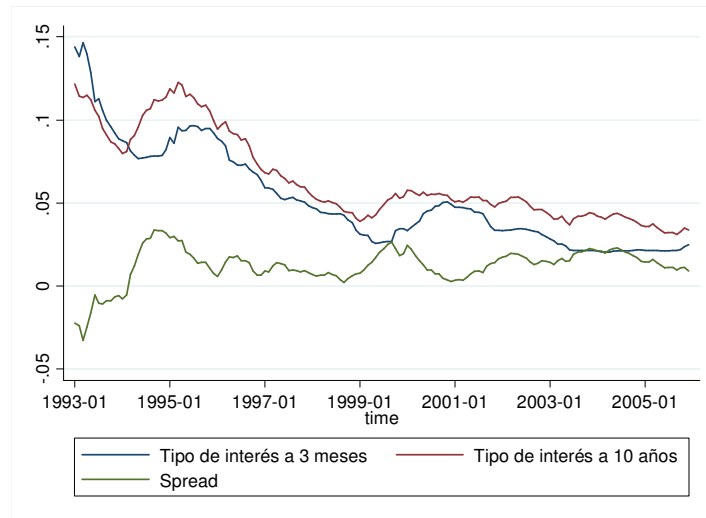
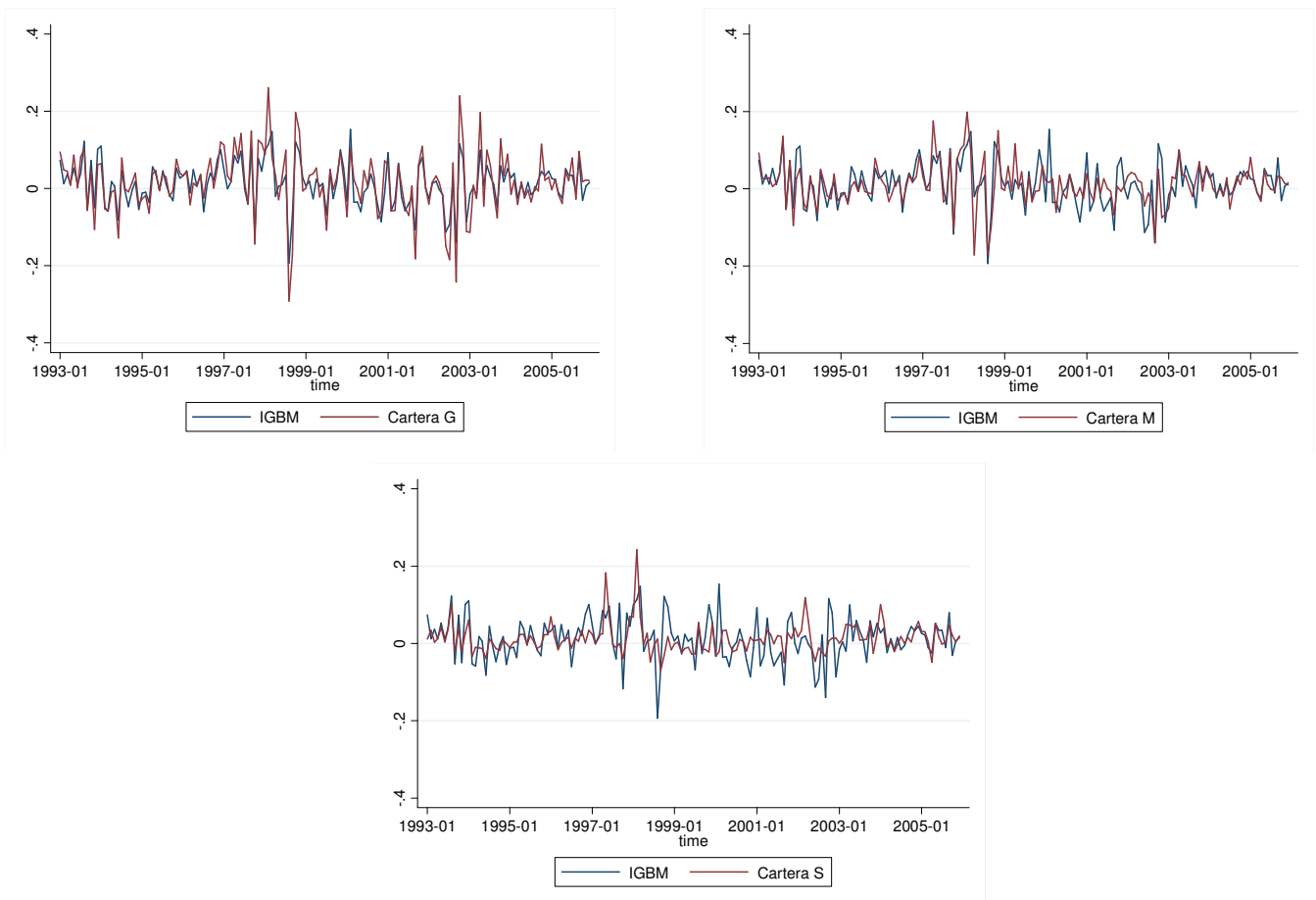


Gráfico 1.2
Rendimientos mensuales de las carteras G, M y P VS rendimiento de la cartera de mercado



Chapter 2

Linear and Nonlinear Interest Rate Sensitivity of Bank Stock Returns in Spain

1. Introduction

Interest rate risk (IRR, hereafter) is broadly acknowledged as one of the most important financial risks faced by companies. This is due to the fact that changes in interest rates affect both the firm's expected future cash flows and the discount rates used to value these cash flows. Moreover, the high volatility in interest rates and financial market conditions in recent years along with the significant degree of financial leverage for most of the companies have also contributed to the growing importance of interest rate exposure.

As stated in the first chapter of this dissertation, much of the research on corporate exposure to IRR has been concentrated on financial institutions because of the particularly interest rate sensitive nature of the banking business. Specifically, financial assets and liabilities represent a substantial portion of the total assets of financial firms and it is generally admitted that there exists a maturity mismatch between banks' assets and liabilities. The most common approach consists of measuring interest rate exposure as the sensitivity of bank stock returns to movements in interest rates using traditional linear regression models (e.g., Flannery and James, 1984; Madura and Zarruk, 1995; Faff and Howard, 1999; Fraser et al., 2002; or Au Yong and Faff, 2008).

There are, however, several reasons to suspect that the relationship between interest rates and market value of banks may be of nonlinear nature. On the one hand, since bank stock prices depend on interest rates through the discount factor and through the impact of interest rate changes on expected cash flows, it seems reasonable to assume that the link between interest rates and bank equity values may not be strictly linear. On the other hand, the risk management policy followed by banks may also play a major role in explaining the presence of nonlinearity in interest rate exposure. In addition, the response of bank stock returns to interest rate shocks may depend upon the

sign or the magnitude of the shock, thus generating an asymmetric exposure to IRR. Specifically, interest rate rises and falls may affect bank value differently (*sign asymmetry*). Similarly, larger interest rate fluctuations may have a differential effect on bank value than smaller interest rate changes (*size or magnitude asymmetry*). Lastly, it is also possible that the relationship between interest rates and stock prices does not follow a time invariant functional form. Obviously, should these cases exist the conventional linear model would not be appropriate for estimating interest rate exposure of banks.

This study aims to provide a comprehensive analysis of the interest rate exposure of the Spanish banking industry both at the portfolio and firm level. To this end, the degree of interest rate exposure is assessed not only by employing the standard linear model used in most studies, but examining the possible existence of nonlinear exposure through alternative nonlinear parametric and nonparametric approaches as well. The primary contribution of the paper lies in the fact that it represents, to the best of our knowledge, the first attempt to estimate interest rate exposure using nonparametric regression methods. This new perspective helps to improve the understanding of the effect of IRR on banking firms and how it can be measured, which is an essential prerequisite for effective hedging decisions.

Nonparametric estimation techniques provide a flexible approach to model the relationship between interest rates and stock prices. Unlike parametric regression analysis, this method allows estimating a different functional form for each firm and also permits this function to vary over time. The comparison of the results of the alternative empirical techniques allows us to assess the extent to which the assumptions regarding the functional relationship between interest rates and bank stock prices may influence the conclusions over the level of interest rate exposure.

The Spanish banking sector provides an excellent context to investigate whether the introduction of the euro as a common currency in January 1999, with its implications in terms of greater financial stability and deepening and broadening of capital markets, has significantly affected the nature and magnitude of interest rate exposure of Spanish banks.

The empirical evidence in this study reveals some interesting points. In general, the Spanish banking system is characterized by a remarkable exposure to IRR during the sample period. It must be noted, however, that the extent of IRR faced by Spanish banks has noticeably decreased after the adoption of the euro. Furthermore, a distinctive feature of the Spanish case is that a pattern of positive interest rate exposure seems to emerge during the post-euro period, reflecting a sharp change in the nature of the impact of IRR on bank stocks. A significant nonlinear component is also detected in the link between interest rates and bank stock prices, confirming the importance of nonlinearity. This implies that using only the conventional linear model to measure interest rate exposure may underestimate the true degree of exposure.

The evidence of a lower exposure to interest rate changes in the more stable environment associated to the European Monetary Union can be relevant results for other countries which are currently involved in a process of rapid development and deep transformations just like the one occurred in Spain over the past two decades. This is the case, for example, of the Central and Eastern European countries which have joined the European Union and have adopted the Euro recently or are expected to do so in the following years.

The knowledge of the impact of interest rate fluctuations on the value of banking firms is essential not only for purposes of IRR management, but also for other areas of

finance such as asset allocation, portfolio management, implementation of monetary policy, and banking regulation.

The rest of the paper is organized as follows. Section 2 offers a brief survey of previous literature regarding banks' exposure to interest rate risk. Section 3 describes the data used. Section 4 discusses the model specifications employed in the analysis. Section 5 reports the major empirical results. Finally, Section 6 provides some concluding remarks.

2. Literature review

A large number of empirical studies have examined the impact of IRR on the value of firms since the early 1980s. Most of this research has adopted a stock market approach within the framework of the two-index linear regression model developed by Stone (1974), which includes an interest rate change factor in addition to the traditional market index for explaining stock returns of firms. This literature is primarily focused on financial institutions because of the special nature of the business of financial intermediation (e.g., Flannery and James, 1984; Elyasiani and Mansur, 1998; Fraser et al., 2002; or Czaja et al, 2009 and 2010).¹⁰ Further, prior studies investigating the exposure of banks to IRR have limited to a few developed countries, principally the US, and only more recently Japan, the UK, Germany, or Australia. Three main results emerge from this line of work. First, a significant negative effect of movements in interest rates on the stock returns of financial firms is generally documented, which has commonly been attributed to the maturity mismatch between banks' assets and liabilities. Since banks tend to borrow short and lend long, the average maturity of the assets is usually longer than the average maturity of the liabilities. Thus, a rise in

¹⁰ For a survey of the literature on bank interest rate exposure see Staikouras (2003 and 2006).

interest rates not only adversely affects a bank's net worth (the value of its assets falls more than the value of its liabilities), but also bank profits are reduced (the cost of its liabilities increases more rapidly than the yield on its assets). Second, bank stock returns typically exhibit more sensitivity to changes in long-term interest rates than to changes in short-term rates (e.g., Akella and Chen, 1990; Faff and Howard, 1999; Bartram, 2002; Saporoschenko, 2002; or Czaja et al., 2009). Third, as pointed out by Faff and Howard (1999), Benink and Wolff (2000), Ryan and Worthington (2004), and Joseph and Vezos (2006), among others, the interest rate sensitivity of stock returns of financial institutions has declined over time, possibly as a result of the increasing availability of more advanced tools and techniques for measuring and managing IRR.

Moreover, it is worth mentioning that the implicit assumption underlying almost all the literature on corporate exposure to IRR is that interest rate exposure is linear. Much less attention has been paid, however, to other possible interest rate risk profiles. In fact, the vast majority of studies of exposure to macroeconomic risks (such as exchange rate, interest rate, or inflation risk) that investigate the presence of nonlinear or asymmetric exposure components focus on exchange rate risk (e.g., Di Iorio and Faff, 2000; Koutmos and Martin, 2003; Bartram, 2004; Tai, 2005; and Priestley and Odegaard; 2007).

One critical reason why the standard approach based on a linear exposure pattern has been subject to persistent criticism is that using the same functional form for all the firms can be too restrictive, leading to understate the level of interest rate exposure. In this regard, it is widely accepted that the degree of exposure depends on firm and industry characteristics such as leverage, profitability, size, liquidity or risk management strategy. These characteristics not only determine the degree of exposure, but also have important implications for the functional relationship between changes in

interest rates and the value of the firm. In addition, the relationship between interest rates and stock prices does not have to follow a time invariant functional form. Interest rate exposure may vary over time as firm and industry characteristics, and market conditions change. Hence, the assumption of a time invariant function implicit in the traditional approach to measuring the impact of IRR can lead to the erroneous conclusion that exposure is insignificant.

There exist, however, a few empirical papers that explore the possibility of a profile of exposure to IRR more complex than the linear one. The seminal work in this field was done by Chen and Chan (1989), who investigate for potential asymmetry of interest rate sensitivity of U.S. financial institutions around different interest rate cycles. Their results reveal a significant interest rate asymmetry during up and down cycles of interest rates, suggesting that the sensitivities of bank stock returns are highly sample-dependent. Similarly, Hallerbach (1994) shows that the sensitivity of the Dutch stock market to changes in interest rates is not constant over time and finds a clear pattern of asymmetry to interest rate fluctuations of different sign. He argues that the specification of a nonlinear model could partly explain the asymmetry between sensitivities for interest rate rises and falls.

In a very influential paper, Bartram (2002) investigates the impact of IRR on a large sample of German nonfinancial corporations at the industry level. Bartram presents empirical evidence for the existence of significant linear and nonlinear exposures with regard to various interest rate factors. In another empirical study, Verma and Jackson (2008) use a multivariate EGARCH (exponential generalized autoregressive conditional heteroskedastic) model to examine the presence of spillover effects and asymmetries between short- and long-term interest rates and portfolios of US banks. Their results provide evidence of response asymmetries for the portfolios of

money center and other large banks, indicating that these banks are more sensitive to negative than positive interest rate changes.

In a more recent paper, Ferrer et al. (2010) conduct a comprehensive study of the influence of IRR on Spanish companies at the industry level. It is reported that interest rate exposure differs largely across sectors. In particular, highly leveraged, regulated, and banking are the most interest rate sensitive industries, although the introduction of the euro seems to have weakened the degree of interest rate exposure. It is also documented that the standard linear exposure profile is economically more important than the nonlinear or asymmetric exposure patterns.

Nevertheless, it should be noted that, to our best knowledge, the estimation of interest rate exposure using nonparametric regression techniques has not been addressed until now. As a matter of fact, the only two studies that have employed a nonparametric approach in the context of corporate exposure to risk have focused on exchange rate exposure (e.g., Guo and Wu, 1998; and Aysun and Guldi, 2009).

3. Data

The sample consists of all Spanish commercial banks listed on the Spanish Stock Exchange during the period of study (a total number of 23 banking firms). Thus, the sample size varies over time because the number of publicly traded banks changes over time. The rationale for this sample selection procedure is to use all the firms' data available in each period, hence minimizing the survivor bias, and to maximize the membership in the sample in order to improve estimator efficiency. The sample period runs from January 1993 to December 2008, covering a time interval in which interest rates have varied considerably within a framework of clear downward trend.

The period of study allows us to investigate whether the introduction of the Euro in January 1999 has caused a significant change in the magnitude and pattern of interest rate exposure of Spanish commercial banks. To this end, the total sample period is split into two sub-samples, namely January 1993 to December 1998 (pre-Euro period), and January 1999 to December 2007 (post-Euro period).

The adoption of the euro as a common European currency is a major historical event in international financial markets with a potentially significant impact on the degree of IRR. The euro may affect bank interest rate exposure through two principal channels. First, since the launch of the euro, Eurozone interest rates are set by the European Central Bank (ECB) at the expense of national central banks. The ECB is responsible for monetary policy within the Eurozone, so its decisions are taken from a euro area-wide perspective, without any national bias. Therefore, the greater financial stability and transparency induced by the single monetary policy should have theoretically led to a reduction in the degree of IRR faced by European financial institutions. Second, the broadening and deepening of European financial markets since the introduction of the euro may have also contributed to improved interest rate risk management by banks.

Weekly stock prices and interest rate data are used in the empirical analysis. Weekly stock returns are computed using Wednesday closing prices of bank stocks. All stock prices have been adjusted for dividends, splits and capital gains.

With the aim of checking whether there exists a relationship between the size of banking institutions and the level of interest rate exposure, the analysis is conducted using bank stock portfolios constructed according to size (amount of total assets). This procedure is consistent with earlier studies on bank IRR (e.g., Song, 1994; Elyasiani and Mansur, 1998; Faff et al., 2005; Joseph and Vezos, 2006; or Verma and Jackson, 2008).

Thus, Spanish commercial banks are categorized into three portfolios: large banks portfolio, medium banks portfolio, and small banks portfolio. Table 2.1 lists the individual banks included in the sample and their allocation among the three bank portfolios, along with the corresponding stock ticker symbol, number of observations, and average amount of total assets during the sample period. Summary descriptive statistics for each individual bank and portfolio are also reported. The portfolio returns employed are market value-weighted figures.¹¹

In particular, the large banks portfolio (portfolio *L*, hereafter) consists of those banks with total assets exceeding €60 billion, leading to the inclusion therein of the two Spanish banking conglomerates (Banco Santander and BBVA). The medium banks portfolio (portfolio *M*) is composed of those entities whose total assets range from €7 billion to €60 billion. A total of seven banking firms, representative of the traditional Spanish mid-size banks, comprise this category. Lastly, the small banks portfolio (portfolio *S*) consists of the twelve smallest banks of the sample (amount of total assets below €7 billion). Note that the classification of Spanish banks into the three groups stated above is the same than the one indicated in Chapter one.

The summary statistics suggest that the series of individual bank and portfolio returns are skewed and leptokurtic relative to the normal distribution. Consequently, the null hypothesis of normality of returns is clearly rejected at conventional levels of significance in all cases.

Analogously to the first Chapter, the series of weekly returns on each portfolio are calculated as the weighted arithmetic average of weekly returns on individual stocks included in each portfolio. The factor weight for each individual bank stock in the

¹¹ The composition of the three bank stock portfolios remains fixed for the whole sample period.

portfolio is the ratio of its stock market capitalization at the end of fiscal year over the market capitalization of the whole portfolio.

The proxy used for the market portfolio is the *Indice General de la Bolsa de Madrid*, the widest Spanish value-weighted market index. Equity market data are obtained from the Bolsa de Madrid Spanish Stock Exchange database. The average yield on 10-year Spanish Government bonds and the one-year and three-month average rates of the Spanish interbank market are employed as proxies for market interest rates. Weekly interest rate data are collected from the Bank of Spain historical database.

Table 2.2 presents the descriptive statistics of the levels and first differences of the interest rate series used in the study. As expected, for both the whole sample period and the two sub-periods the mean value of the series of 10-year government bond yields in levels is higher than that series of 1-year and 3-month interbank rates in levels, which in turn have similar mean value and very high correlation (0.98). For the series in first differences, the mean is almost zero in all the cases. With regard to the standard deviation, the 3-month rate series appears as the one with higher variability, followed by 1-year and 10-year rate series, with the exception of the post-euro period. Graph 2.1 displays the time evolution of the returns of large-, medium- and small-bank portfolios and the return on the market portfolio. The time evolution of the levels of the series of interest rates is also shown. It can be seen how comparatively the large and medium bank portfolios have much higher correlation with the market portfolio return (0.69 and 0.53, respectively) than the small banks portfolio (0.26). In turn, the series of interest rates exhibit a decreasing trend over the sample period.

4. Methodology

In this section, we briefly describe the different models used to estimate interest rate exposure both at the portfolio and individual bank level. We begin with the linear model traditionally employed in the exposure literature. Parametric nonlinear, asymmetric and nonparametric models are then discussed.

4.1. Parametric models

4.1.1. Linear Model

Following the standard practice in the literature, the classical two-index linear regression model postulated by Stone (1974) is used as the starting point to quantify interest rate exposure. This model has the following form:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \delta_i \Delta I_t + \varepsilon_{it} \quad (2.1)$$

where R_{it} denotes the return on bank i 's stock in period t , R_{mt} the return on the market portfolio in period t , ΔI_t the change in the interest rate used as reference in period t , and ε_{it} is an error term for period t .

The coefficient on the return of the market portfolio β_i reflects the sensitivity of the return on i th bank stock or portfolio to general market fluctuations. The inclusion of a market index permits to control for general macroeconomic effects and reduces omitted variable bias. In turn, the coefficient on the interest rate term δ_i measures the sensitivity of i th bank stock or portfolio returns to movements in interest rates controlling for changes in the return on the market. Hence, it can be interpreted as a measure of the average linear interest rate exposure of i th bank over the estimation

period. Note that a negative interest rate exposure coefficient corresponds to the traditional view of banks as borrowing short-term and lending long-term.

This model is estimated for each bank stock and portfolio return in the sample using OLS. To avoid possible multicollinearity problems, the market portfolio return is orthogonalized with respect to the interest rate change variable. Thus, the original market portfolio return series in Eq. (2.1) is replaced by the residuals from a regression of the market return variable on a constant and the interest rate change variable. This orthogonalization procedure has been used by, among others, Lyngne and Zumwalt (1980), Hirtle (1997), Fraser et al. (2002) and Czaja et al. (2009). After orthogonalization, the coefficient β_i captures the pure sensitivity to general market movements. In turn, the coefficient δ_i represents a total measure of interest rate exposure as it reflects both the direct effect of interest rate changes on bank equity returns and the indirect effect through changes in the return on the market. It should be noted that the same orthogonalization approach is followed in all the other models described below.

4.1.2. Nonlinear Model

Early empirical studies of corporate exposure to IRR have focused almost exclusively on linear exposure. Nevertheless, as Bartram (2002) states, the value of a firm, defined as the present value of all its expected future cash flows, could depend in a very complex way on movements in interest rates. Since changes in interest rates affect both expectations about future cash flows and discount rates, it may occur that the relationship between firm value and interest rates is not strictly linear. Furthermore, companies primarily use instruments with linear payoff profiles (e.g., forward rate agreements, futures or swaps) to reduce their linear IRR. In contrast, nonlinear

exposures are taken into account by firms to a much lesser extent when designing their hedging strategies with derivatives.¹² Hence, it is possible to empirically find a significant nonlinear exposure in certain cases, which could be hedged using instruments with nonlinear payoff structures such as interest rate options.

Nonetheless, it could be very restrictive to impose *a priori* a particular functional form to be used for measuring nonlinear interest rate exposure since the shape of the exposure may not be uniform across firms. Specifically, the exact form of nonlinearity may be a complex function of several firm characteristics such as financial leverage ratio, profitability, size, liquidity or risk management strategy. Given that this study can be viewed as a first attempt for assessing nonlinear interest rate exposure for Spanish banks (basis of comparison), a simple approach is taken assuming that some standard nonlinear functions may be sufficient to capture the possible nonlinearities. Thus, a regression equation with a generic nonlinear component is written as:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \delta_i f(\Delta I_t) + \varepsilon_{it} \quad (2.2)$$

where $f(\cdot)$ denotes a nonlinear function of the changes in interest rates and the parameter δ_i measures the effect of nonlinear movements in interest rates on the stock returns of bank i .

Various types of nonlinear functions may be appropriate for our purposes. One of the simplest ways to capture nonlinearity is by using a polynomial function of the third degree specified as $f(x) = a + b \cdot x + c \cdot x^2 + d \cdot x^3$, where the quadratic and cubic terms allow this function to take different shapes depending on the sign and magnitude of the parameters c and d . Another possible choice could be using the hyperbolic sine and inverse hyperbolic sine functions. The hyperbolic sine function,

¹² See Stultz (2005).

$f(x) = \sinh(x) = (e^x - e^{-x})/2$, is characterized by a positive slope in the origin. Further, it is a convex function for positive values of the variable x , whereas it is a concave function for negative values of x . This feature can help to reflect a comparatively more aggressive response of bank stock returns to larger interest rate fluctuations. In turn, the inverse hyperbolic sine function, defined as $f(x) = \operatorname{invsinh}(x) = \ln(x + \sqrt{x^2 + 1})$, has the opposite behaviour.

Therefore, the polynomial and the hyperbolic sine functions can be suitable to capture a nonlinear relationship between interest rate fluctuations and stock returns. Specifically, they accommodate the idea of inefficiencies in capital markets in the sense that whereas small interest rate movements are possibly dominated by other price relevant information and, thus, are less reflected in returns or even neglected, large interest rate fluctuations may have a greater impact on banks' stocks returns. Further, they allow distinguishing the effects of interest rate rises from the effects of interest rate falls.

Unfortunately, the last two specifications have proven not to be suitable for our purposes since the values of the independent variable (the series of interest rate changes) are not large enough to generate significant differences in the values of both nonlinear functions. Thus, the image set of the function is practically the same as the original series of changes in interest rates. Therefore, a third degree polynomial function is applied in the empirical analysis.

4.1.3. Asymmetric Sign and Size Model

An alternative way of detecting a nonlinear exposure is to examine the existence of an asymmetric response of bank stock returns to changes in interest rates of different sign and/or size. Note that bank stock returns may react differently to interest rate rises

and falls (*sign asymmetry*). Besides, stock returns can be affected differently by large and small interest rate changes (*size or magnitude asymmetry*). In order to allow for these asymmetries, the basic model in Eq. (2.1) has been extended.

In particular, the sign asymmetry can be tested using the following equation:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \delta_i \Delta I_t + \gamma_i D_t^{sign} + \eta_i D_t^{sign} \Delta I_t + \varepsilon_{it} \quad (2.3)$$

where a dummy variable, D_t^{sign} , is included to capture the potential sign asymmetry. In particular, $D_t^{sign} = 1$ if $\Delta I_t > 0$, and zero otherwise. Thus, for a given value of the market portfolio return, the response of bank stock returns to interest rate changes

$\left(\frac{\partial R_{it}}{\partial \Delta I_t} \right)$ will be equal to δ_i when $\Delta I_t < 0$, and it will be $\delta_i + \eta_i$ for $\Delta I_t > 0$.

Analogously, the size or magnitude asymmetry can be analyzed through the following equation:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \delta_i \Delta I_t + \gamma_i D_t^{mag} + \eta_i D_t^{mag} \Delta I_t + \varepsilon_{it} \quad (2.4)$$

In this case, the dummy variable, D_t^{mag} , reflects the potential size asymmetry. Thus, $D_t^{mag} = 1$ if $\Delta I_t \geq z_U$ or $\Delta I_t < z_L$ where z_U and z_L indicate the upper and lower threshold levels, respectively, that discriminate between small and large interest rate changes, and $D_t^{mag} = 0$ otherwise. The threshold values z_L are calculated as $\overline{\Delta I_t} + 2\sigma_{\Delta I_t}$ and $\overline{\Delta I_t} - 2\sigma_{\Delta I_t}$, respectively.¹³ As in the previous case, the response of bank stock

returns to interest rate changes $\left(\frac{\partial R_{it}}{\partial \Delta I_t} \right)$ will be equal to δ_i when $\Delta I_t \geq z_U$ or $\Delta I_t < z_L$,

and $\delta_i + \eta_i$ in the remaining cases.

¹³ Thus, if the series of interest rate changes follow a Gaussian distribution, the dummy variable will take the value 1 only in the 5% of the cases.

Additionally, notice that for the models (2.3) and (2.4) the value of the standard error associated with the sum of the estimated coefficients δ_i and η_i to be used in calculating their statistical significance, is calculated as follows:

$$\hat{\sigma}_{\frac{\partial R_{it}}{\partial \Delta I_t}} = \sqrt{Var(\hat{\delta}_i) + D_t^2 Var(\hat{\eta}_i) + 2D_t Cov(\hat{\delta}_i, \hat{\eta}_i)} \quad (2.5)$$

4.2. Nonparametric Model

All four model specifications presented above (linear, nonlinear, sign asymmetry and size asymmetry) require a specific functional form and assume that this functional form does not change during the period of study. Moreover, these methodologies rule out the possibility of different functions for different firms. In order to tackle these issues, we also estimate the relationship between movements in interest rates and bank stock returns without adhering to any specific parametric functional form using a non-parametric regression method. In particular, the local linear regression method developed by Stone (1977) is employed in order to avoid the typical specification problems inherent to traditional parametric approaches. This approach is chosen because it has a higher asymptotic efficiency and allows for faster convergence at boundary points compared to other nonparametric methods.¹⁴

As a first step the following linear regression is estimated for each individual bank stock and portfolio:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it} \quad (2.6)$$

where R_{mt} is the orthogonalized market portfolio return.

¹⁴ See Fan and Gijbels (1992) and Pagan and Ullah (1999) for a more detailed discussion of these properties.

From (2.6) the parameter $\hat{\beta}_i$ is obtained for each bank stock and portfolio. Then, the excess return on bank i 's stock, \hat{R}_{it}^e , is calculated as follows:

$$\hat{R}_{it}^e = R_{it} - \hat{\beta}_i R_{mt} \quad (2.7)$$

Finally, for each bank stock and portfolio return the following expression is estimated:

$$\hat{R}_{it}^e = f(\Delta I_t) + \varepsilon_{it} \quad (2.8)$$

Although the exact form for $f(\Delta I_t)$ is not known, the local linear estimation methodology approximates the relationship between ΔI_t and \hat{R}_{it}^e by making use of the Taylor's series expansion around each observation of interest rate changes such that

$$f(\Delta I_t) \approx f(\Delta I_j) + f'(\Delta I_j)(\Delta I_t - \Delta I_j) = a_j + b_j(\Delta I_t - \Delta I_j) \quad \forall j \quad (2.9)$$

Next, it fits a line for each observation of ΔI_j by minimizing the following expression:

$$\text{Min} \sum_{t=1}^N \left\{ \hat{R}_{it}^e - [a_j + b_j(\Delta I_t - \Delta I_j)] \right\}^2 / K_j \quad (2.10)$$

where $K_j = \frac{K(\Delta I_t - \Delta I_j)}{h}$ is a function that weights the distance or gap between each ΔI_t with ΔI_j and depends on a normal kernel and h denotes the regression smoother bandwidth. Following the standard practice, we set h equal to $h = \sigma_{\Delta I_t} / N^5$, where $\sigma_{\Delta I_t}$ is the standard error of the interest rate change series and N the number of observations. Notice that only observations close to ΔI_j are included in the minimization problem so that the coefficients a and b are functions of ΔI_j .

After estimating b_j for every point in the sample, the mean of the estimator is calculated as:

$$\bar{\hat{b}}_i = \sum_{j=1}^N \hat{b}_j / N \quad (2.11)$$

to quantify the relationship between the interest rate and the bank's excess stock return.

Similarly, the variance of b_i is measured as

$$\sigma^2(b_i) = \sum_{j=1}^N (\hat{b}_j - \bar{\hat{b}}_i)^2 / N - 1 \quad (2.12)$$

Rilstone (1991) shows that this estimator is consistent and asymptotically normal. Furthermore, its standard errors are comparable to those obtained from a conventional parametric estimation.

5. Empirical results

Table 2.3 summarizes the results of the estimation of the interest rate exposure coefficients at the portfolio level for the three proxies of market interest rates under consideration. Columns (1) to (4) correspond to the different parametric models used, whereas column (5) presents the results of the nonparametric estimation. Panel A reports the exposure estimates for the entire sample period, and Panels B and C refer to the pre-euro and post-euro sub-periods, respectively.

Linear interest rate exposure

Regarding the linear effect of interest rate movements on bank portfolio returns, the exposure coefficients obtained from estimating the two-index model of Stone (1974) outlined in Eq. (2.1) are always negative for the entire sample period, although they are only statistically significant at conventional levels for the three portfolios when 10-year

and 3-month interest rate changes are used. This implies that Spanish bank stock returns are, on average, adversely impacted by rises in interest rates. This negative relationship between movements in interest rates and bank stock returns is consistent with the typical bank balance sheet maturity structure, where long-term assets are funded with short-term liabilities (positive duration gap). The negative link also agrees with most of the empirical literature on interest rate exposure of the banking industry (e.g., Flannery and James, 1984; Madura and Zarruk, 1995; Elyasiani and Mansur, 1998; and Czaja et al., 2009 and 2010).

However, the different series of interest rate changes have not a homogeneous effect on the three bank portfolios. Thus, whereas changes in 10-year government bond yields have greater impact on the medium banks and small banks portfolios, fluctuations in 3-month interbank rates primarily affect to the large banks portfolio. In contrast, changes in 1-year interbank rates appear by far as those that exert a lower linear influence on bank portfolio returns. Additionally, the small banks portfolio seems to be the less vulnerable one to linear IRR (in absolute terms) during the total sample period regardless of the proxy of interest rates used.

Nonlinear interest rate exposure

As shown in column (2) of Table 2.3, the cubic function of changes in interest rates permits to identify a level of nonlinear exposure to IRR during the entire sample period even higher than that found for the linear specification. In particular, all the estimated nonlinear exposure coefficients are statistically significant at the 1% level regardless of the bank portfolio and proxy of market interest rates used. The sign of the nonlinear coefficients is always negative, indicating that, on average, Spanish banks take advantage of decreases in interest rates from a nonlinear perspective, thus supporting the widespread view that banks tend to maintain a positive mismatch

between the maturity of their assets and liabilities. Similarly to the linear approach, the estimated exposure coefficients are larger (in absolute terms) when changes in 10-year government bond yields are used, and the large banks portfolio appears as the one with higher nonlinear exposure irrespective of the proxy of interest rates considered.

Since the independent variables in the linear and nonlinear specifications are different, in order to compare the economic importance of both kinds of exposure the product of the exposure coefficient with one standard deviation of the proxy for market interest rates is computed for all bank portfolios exhibiting both significant linear and nonlinear exposure. As Bartram (2002) notes, this procedure makes the coefficients comparable as it standardizes the variables across regression specifications.

As shown in Table 2.4, for almost all the portfolios regardless of the proxy for interest rates and the sample period considered, the absolute values obtained for the nonlinear exposure coefficients are larger than those corresponding to the linear exposure. This result means that, in general, the nonlinear interest rate exposure of Spanish banking firms is economically more important than the linear exposure.

Analysis of asymmetries

The asymmetric sign model, consistently with the linear model, shows negative coefficients on the interest rate changes, but in this case the independent variables are statistically significant only in 50% of the cases (see Table 2.3). Bank stock returns are especially sensitive to 10-year and 3-month rate changes. Again, the larger the banks included in the portfolio, the greater the interest rate exposure.

Accordingly with the above result, when interest rates decrease, bank stock returns increase; this relationship is shown to be particularly important for the larger banks, regardless of the interest rate proxy considered. However, for interest rate rises,

there seems not to be such a clearly negative effect on the bank stock returns, especially for larger banks, since none of the interest rate proxies is statistically significant in that case.

However, this idea of asymmetries in the in the sensitivity of bank stock returns to interest rate positive and negative variations which could be suggested by the above results is not supported by the Wald test carried out to identify them. As it can be seen in Table 2.5, the parameter η_i is not statistically different from zero in most of the cases, so no asymmetric sign effect is detected for the bank interest rate exposure.

With respect to the size or magnitude asymmetry, it should be pointed out that firstly it has been necessary to set both the upper and lower threshold in order to separate small from large interest rate fluctuations. For each proxy of interest rate changes, the upper threshold is computed as its sample mean plus two standard deviations whereas that the lower threshold is calculated as the sample mean of the interest rate change series minus two standard deviations.

Analogously to the sign asymmetry, the results of Table 2.3 could suggest that the size asymmetry is basically manifested when short-term (3-month) interest rates are used. In that case portfolios L and M show a negative relationship with the interest rate changes. These interest rate changes are significant if they are large enough to exceed the thresholds but they are not otherwise. Additionally, the coefficients are larger when the 3-month interest rate changes are outside the bounds. For the case of the other two interest rate proxies, consistently with the results for the symmetric linear model, the 1-year interest rate changes do not seem to exert any influence on the bank stock returns, regardless the magnitude of the changes and independent of the size of the portfolio considered; in turn, the 10-year interest rate changes are always significant.

The above statements, however, should be reconsidered according to the results obtained with the Wald test, which are shown in Table 2.5. As it can be seen, for the entire sample period there are no size asymmetries detected at 5% level for any bank portfolio.

Non Parametric model

Analogously to the previous models, regardless the portfolio and the interest rate proxy considered, all the estimated durations show negative sign when estimated through the non parametric model.

As expected, the estimated exposure coefficients are very close to the values obtained in the linear parametric model. However, the standard deviations of the estimators are much lower when using the nonparametric specification. This helps to provide greater reliability relative to the statistic significance of the estimated coefficients. The idea of the stability of the parameter can be observed in Graph 2.2, where it can be seen that the range of values for the estimated coefficient \hat{b} is really small, even though the scale of the graph could suggest just the opposite.

Sub-period analysis

The sub-period analysis reveals a substantial reduction of the degree of interest rate exposure for all the specifications considered. This seems to indicate that the importance of interest rate risk in explaining bank stock return variability has declined following the introduction of the euro. A possible explanation for this finding is related to the greater stability and lower levels of interest rates, and the development of better interest rate risk management tools in recent years. In this regard, financial institutions may have taken advantage of the increased depth and completeness of corporate bond

markets with the advent of the euro to implement a more effective management of interest rate risk.

In the pre-euro period (1993-1998) all the significant exposure coefficients have negative sign for the different specifications employed regardless of the bank portfolio and proxy of interest rates under consideration. There may be also a size effect, so larger banks exhibit a higher interest rate exposure. In turn, long-term interest rates seem to be the ones that exert a greater influence (in absolute value) on bank portfolio returns. Additionally, the absolute values of the exposure coefficients are always greater than those obtained for the entire sample period.

The post-euro period (1999-2008), however, shows a completely different pattern of results. The number of significant interest rate exposure coefficients is considerably lower than that obtained in the pre-euro period regardless of the bank portfolio, proxy of interest rates, and model specification used. Moreover, a large part of the significant exposure coefficients take positive values. This implies that Spanish banks benefit from rising interest rates during the post-euro era, which is opposite to the evidence obtained for the entire sample and pre-euro periods. This finding is also in conflict with the significant negative relationship between bank stock returns and interest rate fluctuations typically documented in the literature (e.g., Flannery and James, 1984; Madura and Zarruk, 1995; Elyasiani and Mansur, 1998; or Czaja et al., 2009).

Two major reasons may help to explain the positive exposure of Spanish banking firms to interest rate risk. First, the dramatic reduction of the traditional maturity mismatch (borrowing short and lending long) in recent years due to the combined effect of several new trends in banking. On the one hand, the massive use of adjustable-rate banking products tied to short-term interbank rates since the mid-1990s.

Specifically, interbank market rates have become the usual reference in the price setting of bank retail operations, mainly in the mortgage segment. On the other hand, the unprecedented growth of asset securitization transactions in Spain, mostly remarkable in the residential mortgages area, along with the increased use of interest rate derivatives may also have played an outstanding role in this context.¹⁵ Second, the positive impact of interest rate risk may reflect the serious difficulties of banks to maintain their margins at reasonable levels in a falling interest rate scenario. Thus, when interest rates are very low banking firms face to a narrowing of the lending-deposit rate spread since a positive interest on their deposit accounts is required. This argument is consistent with the evidence of gradual compression in bank margins within an environment of pronounced decline of interest rates and intense competitiveness as the occurred in the Spanish banking industry over the last decade.

It should be pointed out that the values of the standard deviations of the estimators obtained for this sub-period in the parametric models are substantially higher than the ones corresponding to the pre-euro and the entire sample period. Therefore, a more caution in the interpretation of the findings obtained in the post-euro period is required. In fact, the results for this period do not show a clear pattern for the different portfolios or interest proxies used. This finding is especially evident in the case of the non-parametric model, which shows results that diverge from the corresponding to the parametric models. This result can be suggesting that, whereas for the pre-euro period the parametric and nonparametric models capture adequately the interest rate exposure for the portfolios and the individual stocks, the post-euro period requires a different

¹⁵ According to the European Securitisation Forum Data Report 2008:Q2, since 2006 Spain constitutes the second largest country, only behind the U.K., in terms of issuance volumes in the European securitised debt markets.

functional form for each bank that can vary along the time, which is the main feature of the nonparametric specification. Thus, for the post-euro period the parametric models, which show estimators with greater standard deviations in comparison to the nonparametric model, may not be appropriate to adequately capture a common interest rate exposure for the banks included in the same portfolio.

The idea of that the results are less consistent in the post-euro period is supported by the results shown in the Table 2.6, corresponding to the measures of fit obtained with each model for the different portfolios, interest proxies, and sample periods used in the analysis. It can be seen that the adjusted R^2 statistic shows systematically higher values for the pre-euro period, so indicating better model fit. This result is valid for any model specification and interest proxy used, regardless of the portfolio considered.

With regard to the existence of sign or size asymmetries in any of the two sub-periods of study, whereas the Wald test does not permit to detect evidence of sign asymmetries, some size asymmetries are detected (see Table 2.5). Specifically, the returns of the L portfolio show different sensitivity to small and large interest variations during the pre-euro period, regardless of the interest rate proxy considered. This result obeys to the fact that both the level and variability of the interest rates is much higher during the pre-euro period (see Table 2.2). Thus, it is more likely that there exists an asymmetric behaviour in the sensitivity of bank stock returns. In contrast, during the post-euro period, due to the convergence process of interest rates, their range is much smaller so it is the chance to find size asymmetries.

The analysis carried out at the portfolio level is complemented with an analysis of the banks working on an individual basis. The results obtained in this complementary study are shown in Table 2.7. Specifically, this table shows the percentages of banking

firms with significant interest rate exposure for the different models and interest proxies used. As usual, Panels A, B and C show the results for the entire sample period, pre- and post-euro sub-periods, respectively.

The findings support the idea that the negative empirical durations obtained for the whole sample period are due to the results corresponding to the pre-euro sub-period. Thus, taking the standard symmetric linear model as the reference, in the entire period all the empirical duration coefficients are negative for the statistically significant 1-year and 3-month interest rate changes, and only 2 out of 23 firms show a positive empirical duration coefficient when the proxy considered is the long-term interest rate changes. The results for the remaining models are in the same line.

In the pre-euro period this negative relationship between stock returns and interest rate changes is accentuated. No positive empirical durations are detected in the symmetric linear model regardless the interest rate proxy used, and only one banking firm shows a positive coefficient when the nonlinear model is used to capture the interest rate risk.

The results, however, are drastically different in the post-euro period, especially when the 1-year interest rate changes are used in the context of a symmetric linear model. Now the prior negative empirical durations turn into positive values in most cases, indicating that banks benefit from rising interest rates. This finding is in conflict with the significant and negative relationship between bank stock returns and interest rate fluctuations typically documented in the literature (see e.g. Flannery and James, 1984; Madura and Zarruk, 1995; Elyasiani and Mansur, 1998; or Czaja et al., 2009). However, it should be pointed out the existence of some differences among the results corresponding to the 1-year interest rate and the results obtained for the other two

interest rate proxies, which could suggest a different pattern of exposure depending on the interest rate considered as relevant for the banking firms during the post-euro period.

Residual Analysis

In addition to using a measure of overall adjustment amongst the models, to properly compare them it is necessary to analyze the series of each model's residuals. The idea is to observe the adjustment with each particular observation, in the sense that it could be possible that global adjustment measures were very similar, as it actually happens in the case of portfolios, without implying that the different models perform the data equally. With illustrative purposes, Graph 2.3 shows the actual and fitted portfolio series and residuals for all the estimated models for the whole period.

Tables 2.8 and 2.9 show the descriptive statistics of residuals series obtained in parametric models and the correlation matrix between these residuals and the dependent variable, respectively.¹⁶ The results in both tables correspond to the analysis at the portfolio level and, as usual, they are disaggregated for the three portfolios, interest rate proxies and sample periods. Those results will be jointly commented on below.

With regard to the descriptive statistics, for all portfolios the series of residuals obtained with the different models are quite similar. Thus, there are no significant differences in mean, standard deviation, maximum, and minimum values. This idea is supported by the fact that the correlation coefficients amongst the residuals of the different models for the entire sample period are greater than 0.99. The null hypothesis of normality is clearly rejected for each residuals series, due basically to the excess of kurtosis of those series.

In the comparison among different models, notice that the lower the standard deviation of the residuals and the correlation of those residuals with the dependent

¹⁶ Notice that the nonparametric estimation has no residuals.

variable, the greater the model explanatory power. According to this criterion, the model with greater explanatory power is the asymmetric size model in most cases regardless the portfolio and the interest rate proxy considered.

Regarding the correlation between the residuals and the bank portfolios returns should be noted that in all cases portfolio *L* exhibits the lowest value in all sample periods, so confirming that usually models have a better adjustment for the portfolio of large banks.

Analyzing the differences between sample periods, it can be seen that regardless of the model considered, the standard deviation of its residuals and the correlation between those residuals and the portfolio returns are higher in post-euro period. These results confirm that the fit of the model is better in the pre-euro sample period.

To complement the above results, the Wilcoxon signed-rank test for residuals¹⁷ has been carried out (see Table 2.10). It constitutes a non-parametric statistical hypothesis test for the case of two related samples or repeated measurements on a single sample and it can be used as an alternative to the paired Student's t-test when the population cannot be assumed to be normally distributed, as it happens in our case. Its null hypothesis is that the median difference between pairs of observations is zero.¹⁸

It can be seen that most of *p*-values in Table 2.10 are less than 0.05, so indicating that according to this test, the series of residuals of the parametric models considered are different. This result suggests that even though the correlation coefficients amongst the series of residuals are exceptionally high, the explanatory

¹⁷ Wilcoxon (1945).

¹⁸ Note that this hypothesis is different from the null hypothesis of the paired t-test, which is that the mean difference between pairs is zero, or the null hypothesis of the sign test, which is that the number of differences in each direction is equal.

variables considered in the four parametric models have not the same information content about the variability of bank portfolio returns.

6. Conclusions

This paper provides a comprehensive analysis of the impact of interest rate risk on the Spanish banking sector using both parametric and non-parametric models. In particular, the traditional linear interest rate exposure approach is extended to allow for the possibility of a nonlinear component as well as the presence of asymmetric behaviour in the exposure pattern. The main contribution of this study is to use for the first time a non-parametric regression method that avoids the assumption of a specific functional form to measure the degree of bank interest rate exposure.

The study shows some interesting results. In general, the Spanish banking industry presents a remarkable exposure to interest rate risk during the sample period. It must be noted, however, that the extent of interest rate risk borne by Spanish banks has noticeably decreased after the adoption of the euro. This lower interest rate sensitivity is possibly due to the higher monetary stability, the low levels of interest rates derived from the European convergence process, and the increasing availability of better tools for managing interest rate risk in recent years. Furthermore, a pattern of positive interest rate exposure seems to emerge during the post-euro period, reflecting a sharp change in the nature of the impact of interest rate risk on bank stocks. This distinctive feature of the Spanish banking system can be attributed to two main reasons. First, the substantial reduction of the maturity mismatch due to the conjunction of various recent trends in the Spanish banking industry such as the prevalence of adjustable rate products, the spectacular growth of asset securitization or the widespread use of financial derivatives. Second, the positive exposure may also reflect the strong pressure on bank margins in a

scenario of strong downward trend in interest rates and intense competition in force over the last years.

It is also documented that the nonlinear exposure profile is economically more important than the linear one, whereas very scant evidence of sign and size asymmetries is found. The key role played by nonlinear interest rate exposure has important practical implications in terms of interest rate risk management. Thus, the standard linear models should be augmented to capture the nonlinear component of risk in order to gain a better insight into the effect of interest rate risk on banking firms.

With respect to asymmetric models is tested that no asymmetric sign and size effect are detected for the bank interest rate exposure for the entire sample period. In the two sub-periods of study some size asymmetries are detected, specifically, the returns of the *L* portfolio show different sensitivity to small and large interest variations during the pre-euro period, regardless of the interest rate proxy considered. This result obeys to the fact that both the level and variability of the interest rates is much higher during the pre-euro period. Thus, it is more likely that there exists an asymmetric behaviour in the sensitivity of bank stock returns. In contrast, during the post-euro period, due to the convergence process of interest rates, their range is much smaller so it is the chance to find size asymmetries.

Using the nonparametric specification the estimated exposure coefficients are very close to the values obtained in the linear parametric model, however, the standard deviations of the estimators are much lower. This helps to provide greater reliability relative to the statistic significance of the estimated coefficients.

Comparing the series of residuals obtained in the parametric models, the model with greater explanatory power is the asymmetric size model in most cases regardless the portfolio and the interest rate proxy considered.

Analyzing the differences between sample periods, it can be seen that regardless of the model considered, the standard deviation of its residuals and the correlation between those residuals and the portfolio returns are higher in post-euro period. These results confirm that the fit of the model is better in the pre-euro sample period.

Analyzing the residuals series obtained in the parametric models, the result is that this series are different. This result suggests that even though the correlation coefficients amongst the series of residuals are exceptionally high, the explanatory variables considered in the four parametric models have not the same information content about the variability of bank portfolio returns.

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Annex: Tables and Graphs

Table 2.1
List of Banks, Composition of Bank Portfolios and Descriptive Statistics of Bank and Market Weekly Returns

Bank	Ticker	Obs.	Asset Volume (€ x 10 ³)	Mean	Std. Deviation	Minimum	Maximum	Skewness	Kurtosis (excess)	JB
Portfolio L		811		0.0017	0.0413	-0.2024	0.1881	-0.3945***	4.0181***	566.6283***
Banco Santander Central Hispano	BSCH	493	527.699.133	-0.0004	0.0440	-0.2139	0.2083	-0.4093***	3.4977***	265.0774***
Banco Bilbao Vizcaya Argentaria	BBVA	453	346.037.438	0.0003	0.0469	-0.1856	0.2340	0.2726**	4.0452***	314.4888***
Banco Bilbao Vizcaya	BBV	358	178.232.614	0.0052	0.0434	-0.2340	0.1780	-0.7377***	6.0490***	578.2846***
Banco Santander	SAN	318	138.205.050	0.0041	0.0476	-0.2550	0.1947	-0.8727***	5.6107***	457.4783***
Banco Central Hispano	BCH	318	71.668.583	0.0041	0.0413	-0.1769	0.1989	0.4152***	3.6253***	183.8544***
Argentaria	ARG	341	71.360.857	0.0032	0.0390	-0.1606	0.1515	-0.0740	1.4619***	30.6810***
Portfolio M		811		0.0010	0.0270	-0.1468	0.1403	0.0065	4.1839***	591.5475***
Banesto	BTO	811	54.805.640	0.0006	0.0395	-0.2477	0.2856	-0.0111***	10.8877***	4005.7982***
Banco Popular Español	POP	811	43.308.947	0.0017	0.0374	-0.1651	0.2009	0.2947***	3.6503***	462.0225***
Banco Exterior	EXT	217	34.941.640	-0.0014	0.0172	-0.0583	0.1310	2.3881***	17.9776***	3128.5090***
Banco Sabadell	SAB	391	28.529.393	-0.0001	0.0311	-0.1711	0.1029	-1.1476***	5.8192***	637.5175***
Bankinter	BKT	811	22.133.367	0.0019	0.0432	-0.1442	0.3048	0.7053***	5.4133***	1057.5052***
Banco Pastor	PAS	811	12.177.073	0.0020	0.0315	-0.1078	0.1901	0.6390***	4.0906***	620.6553***
Banco Atlántico	ATL	581	7.807.936	0.0024	0.0263	-0.1625	0.3412	4.6393***	60.9188***	91923.92***
Portfolio S		811		0.0013	0.0166	-0.0798	0.1294	0.6883***	9.1546***	2896.067***
Banco Valencia	BVA	811	6.713.193	0.0033	0.0305	-0.1397	0.2353	1.0020***	7.5072***	2040.2043***
Banco Guipuzcoano	GUI	811	5.123.700	0.0017	0.0278	-0.1143	0.1814	1.1666***	7.9904***	2341.4559***
Banco Andalucía	AND	811	5.097.787	0.0009	0.0282	-0.1695	0.3001	1.4331***	20.0062***	13802.69***
Banco Zaragozano	ZRG	553	4.713.960	0.0043	0.0332	-0.0971	0.2366	1.8118***	9.5679***	2411.8961***
Banco Herrero	HRR	404	2.944.989	0.0000	0.0376	-0.2513	0.2809	0.5917***	18.2621***	5637.5732***

Chapter 2: Linear and Nonlinear Interest Rate Sensitivity of Bank Stock Returns in Spain

Banco de Castilla	CAS	811	2.709.587	0.0004	0.0282	-0.1842	0.2580	1.3998***	17.7088***	10862.05***
Banco Galicia	GAL	811	2.233.393	0.0014	0.0308	-0.1890	0.2979	2.2172***	25.5837***	22782.03***
Banco de Vasconia	VAS	811	1.846.067	0.0003	0.0319	-0.2231	0.3036	0.8099***	17.3193***	10224.78***
Banco de Vitoria	VIT	271	1.271.736	-0.0003	0.0391	-0.2000	0.2727	1.9468***	17.5775***	3659.9822***
Banco Crédito Balear	CBL	811	1.098.787	0.0014	0.0348	-0.2000	0.2518	1.8374***	13.2345***	6375.03***
Banco Alicante	ALI	271	872.386	-0.0015	0.0153	-0.0622	0.1473	3.4386***	35.7005***	14925.64***
Banco Simeón	SIM	284	836.763	-0.0026	0.0455	-0.3263	0.2792	-1.4332***	19.0991***	4413.7671***
Market Portfolio (IGBM)		811		0.0022	0.0275	-0.1138	0.1261	-0.3145***	1.7203***	113.3831***

This table displays the list of Spanish commercial banks considered and their distribution in portfolios according to size criteria (portfolios *L*, *M* and *S*). JB is the Jarque-Bera test for normality of returns. This statistic is distributed as chi-squared with two degrees of freedom. ***, ** and * represent significance at the 1%, 5% and 10%, respectively.

Table 2.2
Descriptive Statistics of Level and First Differences of Interest Rates

	Mean	Std. Deviation	Minimum	Maximum
Entire sample period (1993-2008)				
TIR10	0.0597	0.0255	0.0305	0.1244
Δ TIR10	-0.0001	0.0013	-0.0062	0.0070
TIR1	0.0506	0.0268	0.0195	0.1426
Δ TIR1	-0.0001	0.0014	-0.0228	0.0089
TIR3	0.0499	0.0276	0.0198	0.1542
Δ TIR3	-0.0001	0.0020	-0.0362	0.0209
<i>Corr(TIR10, TIR1) = 0.94</i>				
<i>Corr(TIR10, TIR3) = 0.91</i>				
<i>Corr(TIR1, TIR3) = 0.98</i>				
Pre-euro period (1993-1998)				
TIR10	0.0855	0.0245	0.0399	0.1244
Δ TIR10	-0.0003	0.0019	-0.0062	0.0070
TIR1	0.0763	0.0262	0.0317	0.1426
Δ TIR1	-0.0004	0.0021	-0.0229	0.0090
TIR3	0.0768	0.0264	0.0328	0.1542
Δ TIR3	-0.0004	0.0032	-0.0362	0.0209
Post-euro period (1999-2008)				
TIR10	0.0444	0.0068	0.0305	0.0586
Δ TIR10	0.0000	0.0009	-0.0029	0.0036
TIR1	0.0352	0.0102	0.0196	0.0551
Δ TIR1	0.0000	0.0008	-0.0035	0.0031
TIR3	0.0334	0.0100	0.0198	0.0540
Δ TIR3	0.0000	0.0008	-0.0054	0.0051

Table 2.3
Exposure of Bank Portfolios to Interest Rate

Panel A: Entire sample period (1993-2008)							
	Linear Model (2.1)	Nonlinear Model (2.2)	Asymmetric Sign Model (2.3)		Asymmetric Size Model (2.4)		Nonparametric Model (2.10)
	δ_i	δ_i	δ_i	$(\delta_i + \eta_i)$	δ_i	$(\delta_i + \eta_i)$	\hat{b}_i
10-year interest rate							
Portfolio <i>L</i>	-2.3047** (0.9054)	-102670.30*** (31031.77)	-3.7050** (1.7064)	-1.9823 (1.4188)	-1.7887 (1.3568)	-2.8417*** (0.9349)	-2.3061*** (0.0032)
Portfolio <i>M</i>	-3.0899*** (0.6284)	-97596.83*** (22497.26)	-2.7278** (1.1077)	-3.0427** (1.0938)	-3.5093*** (0.9123)	-2.6565*** (0.7177)	-3.0908*** (0.0024)
Portfolio <i>S</i>	-1.6396*** (0.4052)	-62855.17*** (14172.32)	-0.7382 (0.8134)	-2.3058** (0.7484)	-1.4478** (0.6122)	-1.8099*** (0.4928)	-1.6410*** (0.0028)
1-year interest rate							
Portfolio <i>L</i>	-0.2708 (0.8026)	-2495.47*** (316.951)	-1.1377 (1.0110)	-0.8771 (1.1699)	2.4059 (1.6674)	-1.5139 (0.9751)	-0.2710*** (0.0008)
Portfolio <i>M</i>	-0.6906 (0.4911)	-682.83*** (253.59)	-0.7960 (0.7257)	-1.2041 (0.8548)	0.2241 (1.0082)	-0.9891 (0.7868)	-0.6915*** (0.0013)
Portfolio <i>S</i>	-0.2739 (0.3059)	-804.96*** (128.70)	-0.1734 (0.4291)	-1.7216* (0.6779)	0.6566 (0.6866)	-0.7216* (0.3763)	-0.2743*** (0.0008)
3-month interest rate							
Portfolio <i>L</i>	-1.5899*** (0.4879)	-1285.64*** (141.48)	-1.8446*** (0.6748)	-1.3156 (0.4602)	0.4036 (1.7259)	-1.7494*** (0.4096)	-1.5905*** (0.0017)
Portfolio <i>M</i>	-1.0733*** (0.3766)	-514.66*** (124.10)	-1.1784** (0.5825)	-0.4482 (0.2761)	-0.5321 (1.0498)	-0.9633** (0.4026)	-1.0752*** (0.0026)
Portfolio <i>S</i>	-0.4122** (0.2047)	-358.04*** (110.26)	-0.4585* (0.2649)	-0.2741 (0.4018)	0.3950 (0.7542)	-0.5020 (0.2125)	-0.4132*** (0.0009)
Panel B: Pre Euro period (1993-1998)							
10-year interest rate							
Portfolio <i>L</i>	-6.0372*** (0.5402)	-231892.29*** (30679.40)	-7.4335*** (1.1255)	-7.9702*** (1.02483)	-5.2875*** (0.8130)	-7.1679*** (0.5894)	-6.0390*** (0.0057)
Portfolio <i>M</i>	-4.9635*** (0.5085)	-155293.58*** (24062.26)	-5.8355*** (1.0330)	-3.7873*** (1.1286)	-5.1632*** (0.6975)	-4.8898*** (0.6585)	-4.9662*** (0.0061)
Portfolio <i>S</i>	-1.9041*** (0.3297)	-73900.75*** (12159.82)	-1.6036* (0.8885)	-2.3527** (0.6837)	-1.5765*** (0.4867)	-2.3896*** (0.4408)	-1.9059*** (0.0031)
1-year interest rate							
Portfolio <i>L</i>	-2.4275*** (0.6249)	-7227.11*** (309.21)	-3.2923*** (0.5263)	-2.7008* (0.9637)	-0.7203 (0.7252)	-3.3556*** (0.1530)	-2.4283*** (0.0013)
Portfolio <i>M</i>	-2.0932*** (0.3542)	-3568.56*** (267.16)	-2.2046*** (0.52952)	-1.4219 (1.0440)	-2.1110** (0.6084)	-1.8986*** (0.3824)	-2.0943*** (0.0016)
Portfolio <i>S</i>	-0.7191*** (0.2189)	-1737.38*** (123.97)	-0.9190*** (0.2751)	-1.6833 (0.7983)	-1.7775 (0.4337)	-2.6324* (0.2559)	-0.7199*** (0.0016)
3-month interest rate							
Portfolio <i>L</i>	-1.6473*** (0.2682)	-1730.74*** (192.01)	-1.9515*** (0.2595)	-1.9520*** (0.2340)	0.5164 (1.0543)	-2.0458*** (0.1107)	-1.6492*** (0.0021)
Portfolio <i>M</i>	-1.2503*** (0.2511)	-857.64*** (172.16)	-1.1700*** (0.3522)	-0.6551 (0.3011)	-0.4878 (0.7412)	-1.3328*** (0.3741)	-1.2519*** (0.0020)
Portfolio <i>S</i>	-0.5483*** (0.1499)	-474.05*** (131.46)	-0.6733*** (0.2004)	-0.5038 (0.4077)	-0.1160 (0.5398)	-0.6059* (0.2034)	-0.5497*** (0.0013)

Panel C: Post Euro period (1999-2008)

10-year interest rate							
Portfolio <i>L</i>	7.0858** (2.8734)	1039059.19 (909703.63)	1.3094 (7.8710)	11.0115*** (4.6589)	8.6238*** (2.1637)	3.3521 (7.7489)	1.0000 (0.0009)
Portfolio <i>M</i>	1.6552 (1.8276)	16315.34 (573103.60)	3.3275 (4.6523)	-0.9299 (3.2989)	2.9724** (1.4842)	-0.5684 (4.9926)	-0.7062 (0.0019)
Portfolio <i>S</i>	-0.9497 (1.1322)	-459916.06 (343701.65)	0.6197 (3.0016)	-3.1730* (2.2884)	0.0450 (0.8374)	-2.3570* (2.9074)	1.0000 (0.0009)
1-year interest rate							
Portfolio <i>L</i>	9.0641** (3.6070)	187006.33 (1711796.8)	6.4021 (9.5915)	7.1958* (4.2429)	9.5608*** (2.5080)	8.3099*** (6.7621)	2.7048 (0.0030)
Portfolio <i>M</i>	5.4656*** (1.9520)	232532.54 (932149.54)	6.6603 (5.3414)	3.3442 (2.1279)	6.1921*** (1.7163)	3.5063* (3.5242)	1.0000 (0.0008)
Portfolio <i>S</i>	1.7239 (1.3217)	55083.41 (493051.61)	4.4846 (3.5321)	-1.9054 (1.5176)	1.3561 (1.1567)	1.0503 (2.2343)	1.0000 (0.0008)
3-month interest rate							
Portfolio <i>L</i>	-1.4429 (4.8956)	-450821.42 (492240.63)	-4.5516 (7.8907)	1.1340 (6.5157)	1.1977 (4.3447)	-3.5346 (6.5964)	6.4294 (0.0158)
Portfolio <i>M</i>	0.8345 (2.7061)	-191386.31 (263543.46)	0.0021 (4.5842)	0.9088 (1.8300)	3.1917 (2.8810)	-1.0028 (3.3890)	5.8632 (0.0038)
Portfolio <i>S</i>	1.0558 (1.7621)	-13032.67 (161982.82)	2.1306 (3.1889)	0.1295 (2.0120)	-1.4456 (2.0916)	1.7622 (2.3048)	4.0778 (0.0023)

This table reports the coefficients of the interest rate exposure for the five estimated models with the three different interest rate proxies and the three portfolios for the entire sample, pre-euro and post-euro period. OLS is used to estimate equation (1) to (4). Cubic function is used in the non linear model. Nonparametric model (5) is estimated with local linear regression method developed by Stone (1977). Estimated standard deviations in parenthesis. ***, ** and * represent significance at 1%, 5% and 10% level, respectively.

(1) $R_{it} = \alpha_i + \beta_i R_{mt} + \delta_i \Delta I_t + \varepsilon_{it}$	(3) $R_{it} = \alpha_i + \beta_i R_{mt} + \delta_i \Delta I_t + \gamma_i D_t^{sign} + \eta_i D_t^{sign} \Delta I_t + \varepsilon_{it}$ $D_t^{sign} = 1; \Delta I_t > 0; D_t^{sign} = 0; \Delta I_t < 0$
(2) $R_{it} = \alpha_i + \beta_i R_{mt} + \delta_i f(\Delta I_t) + \varepsilon_{it}$	(4) $R_{it} = \alpha_i + \beta_i R_{mt} + \delta_i \Delta I_t + \gamma_i D_t^{mag} + \eta_i D_t^{mag} \Delta I_t + \varepsilon_{it}$ $D_t^{mag} = 1; \Delta I_t \geq z_U \text{ and } \Delta I_t < z_L; D_t^{mag} = 0 \text{ otherwise}$
(5) $Min \sum_{t=1}^N \left\{ \hat{R}_{it}^e - [a_j + b_j (\Delta I_t - \Delta I_j)] \right\}^2 / K_j; K_j = \frac{K(\Delta I_t - \Delta I_j)}{h}; h = \sigma_{\Delta I_t} / N^5$	

Table 2.4
Economic significance of linear and nonlinear exposures

	Linear Model (2.1)			Nonlinear Model (2.2)		
	10-year interest rate	1-year interest rate	3-month interest rate	10-year interest rate	1-year interest rate	3-month interest rate
Panel A: Entire sample period (1993-2008)						
Portfolio <i>L</i>	-0.0028	-0.0011	-0.0022	-0.0032	-0.0004	-0.0033
Portfolio <i>M</i>	-0.0026	-0.0003	-0.0009	-0.0043	-0.0010	-0.0022
Portfolio <i>S</i>	-0.0017	-0.0003	-0.0006	-0.0023	-0.0004	-0.0009
Panel B: Pre-euro period (1993-1998)						
Portfolio <i>L</i>	-0.0102	-0.0050	-0.0048	-0.0115	-0.0050	-0.0053
Portfolio <i>M</i>	-0.0068	-0.0025	-0.0024	-0.0095	-0.0043	-0.0041
Portfolio <i>S</i>	-0.0032	-0.0012	-0.0013	-0.0036	-0.0015	-0.0018
Panel C: Post-euro period (1999-2008)						
Portfolio <i>L</i>	0.0042	0.0007	-0.0053	0.0066	0.0071	-0.0011
Portfolio <i>M</i>	0.0001	0.0008	-0.0023	0.0016	0.0043	0.0006
Portfolio <i>S</i>	-0.0018	0.0002	-0.0002	-0.0009	0.0013	0.0008

Table 2.5
Asymmetry in Interest Rate Exposure

	Asymmetric Sign Model			Asymmetric Size Model		
	10-year interest rate	1-year interest rate	3-month interest rate	10-year interest rate	1-year interest rate	3-month interest rate
Panel A: Entire sample period (1993-2008)						
Portfolio <i>L</i>	1.7227 (2.0520)	0.2606 (1.4137)	0.5290 (0.8262)	-1.0530 (1.4917)	-3.9198* (2.2299)	-2.1530 (1.8489)
Portfolio <i>M</i>	-0.3149 (1.4332)	-0.4081 (1.0714)	0.7302 (0.6289)	0.8528 (1.0788)	-1.2132 (1.4075)	-0.4312 (1.1476)
Portfolio <i>S</i>	-1.5676 (1.0538)	-1.5482* (0.7988)	0.1844 (0.4896)	-0.3621 (0.7627)	-1.3782* (0.8246)	-0.8970 (0.7904)
Panel B: Pre-euro period (1993-1998)						
Portfolio <i>L</i>	-0.2367 (1.5959)	0.5915 (0.9099)	-0.0005 (0.3219)	-1.8804* (0.9954)	-2.6353*** (0.7429)	-2.5622** (1.0878)
Portfolio <i>M</i>	2.0482 (1.5489)	0.7827 (0.9623)	0.5149 (0.4364)	0.2734 (0.9497)	0.2124 (0.7029)	-0.8450 (0.8439)
Portfolio <i>S</i>	-0.7491 (1.1848)	-0.7643 (0.8862)	0.1695 (0.4526)	-0.8131 (0.6550)	-0.8548* (0.5081)	-0.4899 (0.5926)
Panel C: Post-euro period (1999-2008)						
Portfolio <i>L</i>	9.7021 (8.7141)	0.7937 (10.3602)	5.6856 (9.8519)	-5.2717 (7.9781)	-1.2509 (7.1661)	-4.7323 (7.5855)
Portfolio <i>M</i>	-4.2574 (5.2197)	-3.3161 (5.6627)	0.9067 (4.8001)	-3.5408 (5.2753)	-2.6858 (3.9849)	-4.1945 (4.3822)
Portfolio <i>S</i>	-3.7927 (3.6083)	-6.3900* (3.7992)	-2.0011 (3.7961)	-2.4420 (2.9494)	-0.3058 (2.4931)	3.2078 (3.2576)

This table shows the estimated coefficient η_i and their respective standard deviation (in parenthesis) testing the null hypothesis that both estimated coefficient of interest rate exposure in asymmetric models (2.3) and (2.4) are the same.

Table 2.6
Adjustment Measures: Adjusted R^2 and Sum of Squared Residuals

	Linear Model (2.1)		Nonlinear Model (2.2)		Asymmetric Sign Model (2.3)		Asymmetric Size Model (2.4)	
	R^2 Adj.	SSR	R^2 Adj.	SSR	R^2 Adj.	SSR	R^2 Adj.	SSR
Panel A: Entire sample period (1993-2008)								
10-year interest rate								
Portfolio <i>L</i>	47.66	0.7214	47.51	0.7235	47.61	0.7203	47.56	0.7210
Portfolio <i>M</i>	28.03	0.4257	26.46	0.4350	27.86	0.4256	27.90	0.4254
Portfolio <i>S</i>	7.60	0.2076	6.77	0.2095	7.60	0.2071	7.86	0.2065
1-year interest rate								
Portfolio <i>L</i>	47.77	0.7199	47.83	0.7191	47.81	0.7176	48.41	0.7094
Portfolio <i>M</i>	27.23	0.4305	27.11	0.4312	27.08	0.4303	27.60	0.4272
Portfolio <i>S</i>	6.55	0.2100	6.54	0.2100	6.67	0.2092	6.83	0.2088
3-month interest rate								
Portfolio <i>L</i>	47.64	0.7217	47.28	0.7267	47.54	0.7214	48.11	0.7135
Portfolio <i>M</i>	27.28	0.4301	26.70	0.4336	27.21	0.4295	27.73	0.4265
Portfolio <i>S</i>	6.66	0.2099	6.47	0.2102	6.38	0.2099	6.82	0.2089
Panel B: Pre-euro period (1993-1998)								
10-year interest rate								
Portfolio <i>L</i>	72.19	0.1069	69.91	0.1156	72.59	0.1046	72.26	0.1059
Portfolio <i>M</i>	56.73	0.1070	51.46	0.1200	56.67	0.1064	56.78	0.1062
Portfolio <i>S</i>	17.51	0.0751	16.63	0.0759	17.04	0.0750	17.15	0.0749
1-year interest rate								
Portfolio <i>L</i>	74.58	0.1073	72.07	0.1073	72.33	0.1056	72.82	0.1038
Portfolio <i>M</i>	58.83	0.1066	55.38	0.1103	56.65	0.1065	56.84	0.1060
Portfolio <i>S</i>	6.01	0.0750	17.37	0.0752	17.59	0.0745	17.41	0.0747
3-month interest rate								
Portfolio <i>L</i>	74.17	0.1095	71.09	0.1111	71.69	0.1081	72.14	0.1064
Portfolio <i>M</i>	58.33	0.1069	55.44	0.1108	56.87	0.1059	57.25	0.1050
Portfolio <i>S</i>	5.88	0.0751	17.04	0.0755	17.07	0.0750	17.38	0.0747
Panel C: Post-euro period (1999-2008)								
10-year interest rate								
Portfolio <i>L</i>	38.46	0.5841	37.03	0.5976	38.66	0.5799	38.79	0.5786
Portfolio <i>M</i>	14.14	0.2880	13.78	0.2892	14.05	0.2872	14.28	0.2864
Portfolio <i>S</i>	2.98	0.1276	3.98	0.1273	3.10	0.1270	3.72	0.1262
1-year interest rate								
Portfolio <i>L</i>	38.49	0.5837	35.87	0.6086	38.41	0.5822	38.26	0.5836
Portfolio <i>M</i>	14.64	0.2863	12.02	0.2951	14.42	0.2859	14.83	0.2846
Portfolio <i>S</i>	2.26	0.1286	1.59	0.1295	3.00	0.1271	3.18	0.1269
3-month interest rate								
Portfolio <i>L</i>	39.28	0.5763	40.72	0.5626	39.33	0.5735	39.44	0.5724
Portfolio <i>M</i>	14.03	0.2884	14.73	0.2860	13.76	0.2881	14.56	0.2855
Portfolio <i>S</i>	2.15	0.1287	1.91	0.1290	2.01	0.1284	2.38	0.1279

Table 2.7
Percentage of individual banks with significant interest rate exposure (*)

	Linear Model (2.1)	Nonlinear Model (2.2)	Asymmetric Sign Model (2.3)		Asymmetric Size Model (2.4)		Nonparametric Model (2.10)
	δ_i	δ_i	δ_i	$(\delta_i + \eta_i)$	δ_i	$(\delta_i + \eta_i)$	\hat{b}_i
Panel A: Entire sample period (1993-2008)							
10-year interest rate							
Positive	13.04%	17.39%	26.09%	13.04%	30.43%	17.39%	13.04%
% significant	66.67%	25.00%	16.67%	0.00%	14.29%	25.00%	100.00%
Negative	86.96%	82.61%	73.91%	86.96%	69.57%	82.61%	86.96%
% significant	65.00%	52.63%	41.18%	45.00%	50.00%	63.16%	100.00%
1-year interest rate							
Positive	43.48%	26.09%	21.74%	21.74%	65.22%	30.43%	43.48%
% significant	0.00%	66.67%	0.00%	0.00%	13.33%	0.00%	100.00%
Negative	56.52%	73.91%	78.26%	78.26%	34.78%	69.57%	56.52%
% significant	100.00%	82.35%	16.67%	16.67%	0.00%	25.00%	100.00%
3-month interest rate							
Positive	13.04%	13.04%	13.04%	30.43%	56.52%	13.04%	13.04%
% significant	0.00%	33.33%	66.67%	28.57%	7.69%	0.00%	100.00%
Negative	86.96%	86.96%	86.96%	69.57%	43.48%	86.96%	86.96%
% significant	45.00%	90.00%	50.00%	50.00%	0.00%	45.00%	100.00%
Panel B: Pre-euro period (1993-1998)							
10-year interest rate							
Positive	8.70%	4.35%	13.04%	13.04%	17.39%	4.35%	8.70%
% significant	0.00%	0.00%	0.00%	0.00%	25.00%	100.00%	100.00%
Negative	86.96%	91.30%	82.61%	82.61%	78.26%	91.30%	86.96%
% significant	85.00%	80.95%	52.63%	63.16%	83.33%	85.71%	100.00%
1-year interest rate							
Positive	13.04%	8.70%	4.35%	21.74%	26.09%	8.70%	13.04%
% significant	0.00%	50.00%	0.00%	40.00%	0.00%	0.00%	100.00%
Negative	82.61%	86.96%	91.30%	73.91%	69.57%	86.96%	82.61%
% significant	50.00%	90.00%	61.90%	70.59%	31.25%	75.00%	100.00%
3-month interest rate							
Positive	8.70%	13.04%	8.70%	13.04%	34.78%	8.70%	8.70%
% significant	0.00%	0.00%	50.00%	33.33%	0.00%	0.00%	100.00%
Negative	86.96%	82.61%	86.96%	82.61%	60.87%	86.96%	86.96%
% significant	70.00%	94.74%	75.00%	78.95%	21.43%	75.00%	100.00%
Panel C: Post-euro period (1999-2008)							
10-year interest rate							
Positive	56.52%	39.13%	56.52%	34.78%	60.87%	39.13%	39.13%
% significant	23.08%	0.00%	23.08%	25.00%	50.00%	11.11%	100.00%
Negative	26.09%	43.48%	26.09%	47.83%	21.74%	43.48%	43.48%
% significant	16.67%	10.00%	0.00%	27.27%	0.00%	30.00%	100.00%
1-year interest rate							
Positive	73.91%	60.87%	73.91%	43.48%	69.57%	60.87%	73.91%
% significant	70.59%	28.57%	35.29%	10.00%	50.00%	57.14%	100.00%
Negative	8.70%	21.74%	8.70%	39.13%	13.04%	21.74%	8.70%
% significant	0.00%	0.00%	0.00%	33.33%	0.00%	20.00%	100.00%
3-month interest rate							
Positive	52.17%	39.13%	52.17%	47.83%	34.78%	56.52%	73.91%
% significant	25.00%	22.22%	41.67%	36.36%	12.50%	15.38%	100.00%
Negative	30.43%	43.48%	30.43%	34.78%	47.83%	26.09%	8.70%
% significant	0.00%	10.00%	0.00%	12.50%	0.00%	16.67%	100.00%

(*) The significance level used to consider a firm as exposed to interest rate risk has been 5%.

Table 2.8
Descriptive Statistics of Residuals

	Mean	Std. Deviation	Minimum	Maximum	Skewness	Kurtosis (excess)	JB
Panel A: Entire sample period (1993-2008)							
Portfolio L							
10-year interest rate							
R1	0.0000	0.0299	-0.2181	0.2981	-0.1034	22.2705***	16740.73***
R2	0.0000	0.0299	-0.2187	0.3009	-0.0471	22.6131***	17258.45***
R3	0.0000	0.0298	-0.2182	0.2959	-0.1381	22.0242***	16373.60***
R4	0.0000	0.0299	-0.2181	0.2991	-0.0750	22.4317***	16983.17***
1-year interest rate							
R1	0.0000	0.0298	-0.2159	0.3007	-0.04350	22.5931***	17228.01***
R2	0.0000	0.0298	-0.2153	0.3014	-0.0238	22.6983***	17388.65***
R3	0.0000	0.0298	-0.2147	0.2991	-0.0514	22.4108***	16951.12***
R4	0.0000	0.0296	-0.2098	0.2845	-0.1293	20.0873***	13620.41***
3-month interest rate							
R1	0.0000	0.0299	-0.2173	0.2964	-0.1293	21.9197***	16218.06***
R2	0.0000	0.0300	-0.2148	0.3047	0.0160	22.7306***	17438.12**
R3	0.0000	0.0299	-0.2171	0.2956	-0.1330	21.8193***	16070.17***
R4	0.0000	0.0297	-0.2145	0.2802	-0.2811***	19.7238**	13140.39***
Portfolio M							
10-year interest rate							
R1	0.0000	0.0229	-0.1188	0.1577	0.1228	9.3020***	2922.36***
R2	0.0000	0.0232	-0.1251	0.1626	0.1856**	9.5882***	3107.47***
R3	0.0000	0.0229	-0.1188	0.1583	0.1307	9.3232***	2935.97***
R4	0.0000	0.0229	-0.1205	0.1570	0.1003	9.2968***	2918.39***
1-year interest rate							
R1	0.0000	0.0231	-0.1247	0.1635	0.1730**	9.7970***	3243.42***
R2	0.0000	0.0231	-0.1252	0.1658	0.2028**	9.8927***	3308.57***
R3	0.0000	0.0231	-0.1250	0.1633	0.1671*	9.7780***	3230.59***
R4	0.0000	0.0230	-0.1249	0.1536	0.1375	9.2012***	2859.93***
3-month interest rate							
R1	0.0000	0.0231	-0.1245	0.1617	0.1552*	9.6786***	3164.85***
R2	0.0000	0.0232	-0.1249	0.1673	0.2226***	9.9011***	3315.30***
R3	0.0000	0.0230	-0.1236	0.1607	0.1427*	9.5950***	3109.92***
R4	0.0000	0.0230	-0.1245	0.1494	0.0941	9.0540***	2767.85***
Portfolio S							
10-year interest rate							
R1	0.0000	0.0160	-0.0840	0.1260	0.7328***	10.0236***	3109.92***
R2	0.0000	0.0161	-0.0870	0.1259	0.7711***	10.1519***	3558.65***
R3	0.0000	0.0160	-0.0825	0.1250	0.7332***	9.8965***	3378.13***
R4	0.0000	0.0160	-0.0788	0.1257	0.7521***	9.8968***	3382.09***
1-year interest rate							
R1	0.0000	0.0161	-0.0881	0.1257	0.7547***	10.1168***	3558.65***
R2	0.0000	0.0161	-0.0883	0.1258	0.7676***	10.1387***	3448.88***
R3	0.0000	0.0161	-0.0885	0.1262	0.7519***	10.1894***	3580.40***
R4	0.0000	0.0161	-0.0885	0.1261	0.7826***	10.1050***	3529.01***
3-month interest rate							
R1	0.0000	0.0161	-0.0880	0.1255	0.7473***	10.0829***	3448.88***
R2	0.0000	0.0161	-0.0882	0.1261	0.7753***	10.1713***	3572.77***
R3	0.0000	0.0161	-0.0879	0.1254	0.7449***	10.0685***	3496.31***

Chapter 2: Linear and Nonlinear Interest Rate Sensitivity of Bank Stock Returns in Spain

R4	0.0000	0.0161	-0.0883	0.1268	0.7742***	10.1687***	3570.78***
	Mean	Std. Deviation	Minimum	Maximum	Skewness	Kurtosis (excess)	JB
Panel B: Pre Euro period (1993-1998)							
Portfolio L							
10-year interest rate							
R1	0.0000	0.0188	-0.0819	0.0769	-0.4401**	3.3153***	148.55***
R2	0.0000	0.0196	-0.0777	0.0633	-0.3376**	1.8757***	50.17***
R3	0.0000	0.0186	-0.0798	0.0771	-0.3193**	3.0601***	123.37***
R4	0.0000	0.0187	-0.0813	0.0739	-0.4566***	3.1809***	138.27***
1-year interest rate							
R1	0.0000	0.0189	-0.0832	0.0873	-0.3970***	4.0080***	210.77***
R2	0.0000	0.0189	-0.0823	0.0879	-0.3032**	3.5993***	168.20***
R3	0.0000	0.0187	-0.0810	0.0893	-0.3333**	3.9694***	204.53***
R4	0.0000	0.0185	-0.0823	0.0878	-0.3507**	3.9982***	208.02***
3-month interest rate							
R1	0.0000	0.0190	-0.0832	0.0866	-0.4069***	3.9789***	208.24***
R2	0.0000	0.0192	-0.0821	0.0839	-0.2914**	3.3058***	142.26***
R3	0.0000	0.0189	-0.0814	0.0838	-0.3636**	3.5892***	169.32***
R4	0.0000	0.0188	-0.0817	0.0824	-0.3144**	3.4829***	158.14***
Portfolio M							
10-year interest rate							
R1	0.0000	0.0188	-0.0899	0.0978	-0.0823	5.5579***	390.33***
R2	0.0000	0.0199	-0.0932	0.0947	-0.1551	4.8149***	293.91***
R3	0.0000	0.0188	-0.0880	0.0990	-0.0288	5.5532***	389.37***
R4	0.0000	0.0188	-0.0888	0.0978	-0.0453	5.5503***	389.02***
1-year interest rate							
R1	0.0000	0.0188	-0.0900	0.0980	-0.0506	5.6415***	401.93***
R2	0.0000	0.0191	-0.0910	0.0968	0.0281	5.3581***	362.50***
R3	0.0000	0.0188	-0.0899	0.0987	-0.0290	5.6518***	403.32***
R4	0.0000	0.0187	-0.0893	0.0980	-0.0491	5.5871***	394.21***
3-month interest rate							
R1	0.0000	0.0188	-0.0908	0.0982	-0.0636	5.5977***	395.80***
R2	0.0000	0.0191	-0.0913	0.0964	-0.0054	5.2630***	349.71***
R3	0.0000	0.0187	-0.0905	0.1005	-0.0550	5.7748***	421.17***
R4	0.0000	0.0187	-0.0901	0.0971	-0.0707	5.6370***	401.42***
Portfolio S							
10-year interest rate							
R1	0.0000	0.0158	-0.0502	0.1239	2.6776***	18.0562***	4478.16***
R2	0.0000	0.0159	-0.0490	0.1233	2.6556***	17.7133***	4317.35***
R3	0.0000	0.0158	-0.0502	0.1235	2.6602***	17.9448***	4422.84***
R4	0.0000	0.0158	-0.0499	0.1238	2.6829***	18.1625***	4528.20***
1-year interest rate							
R1	0.0000	0.0158	-0.0502	0.1238	2.6747***	18.0257***	4463.45***
R2	0.0000	0.0158	-0.0499	0.1237	2.6755***	17.9261***	4418.47***
R3	0.0000	0.0157	-0.0493	0.1247	2.7112***	18.4056***	4648.14***
R4	0.0000	0.0157	-0.0500	0.1238	2.7009***	18.2299***	4564.05***
3-month interest rate							
R1	0.0000	0.0158	-0.0501	0.1238	2.6767***	18.0473***	4473.82***
R2	0.0000	0.0158	-0.0501	0.1245	2.6826***	18.0832***	4491.81***

Chapter 2: Linear and Nonlinear Interest Rate Sensitivity of Bank Stock Returns in Spain

	Mean	Std. Deviation	Minimum	Maximum	Skewness	Kurtosis (excess)	JB
R3	0.0000	0.0158	-0.0497	0.1242	2.6994***	18.2319***	4564.54***
R4	0.0000	0.0157	-0.0501	0.1245	2.7268***	18.5114***	4701.71***
Panel C: Post Euro period (1999-2008)							
Portfolio L							
10-year interest rate							
R1	0.0000	0.0340	-0.2075	0.2870	0.0262	17.3371***	6337.20***
R2	0.0000	0.0344	-0.2024	0.2877	-0.0254	16.2994***	5601.29***
R3	0.0000	0.0339	-0.2082	0.2765	-0.2462**	16.4939***	5740.78***
R4	0.0000	0.0339	-0.2083	0.2663	-0.3724***	15.6229***	5157.62***
1-year interest rate							
R1	0.0000	0.0340	-0.2046	0.2903	0.1126	17.5674***	6507.68***
R2	0.0000	0.0347	-0.2202	0.2665	-0.4237***	14.7283***	4588.58***
R3	0.0000	0.0340	-0.2067	0.2839	-0.0105	17.0494***	6128.57***
R4	0.0000	0.0340	-0.2048	0.2887	0.0931	17.4184***	6397.42***
3-month interest rate							
R1	0.0000	0.0338	-0.2182	0.2611	-0.3881***	15.5703***	5124.03***
R2	0.0000	0.0334	-0.2200	0.1995	-0.9857***	12.2888***	3265.85***
R3	-0.0001	0.0337	-0.2217	0.2473	-0.6480***	15.0222***	4783.74***
R4	0.0000	0.0337	-0.2111	0.2608	-0.2127*	15.1278***	4828.72***
Portfolio M							
10-year interest rate							
R1	0.0000	0.0239	-0.1127	0.1427	0.2052*	8.2692***	1445.23***
R2	0.0000	0.0239	-0.1083	0.1386	0.1227	7.7237***	1259.02***
R3	0.0000	0.0238	-0.1072	0.1459	0.3124***	8.4187***	1502.50***
R4	0.0000	0.0238	-0.1048	0.1391	0.2117*	7.9695***	1342.83***
1-year interest rate							
R1	0.0000	0.0238	-0.1159	0.1520	0.4047***	8.9113***	1688.06***
R2	0.0000	0.0242	-0.1126	0.1428	0.1975*	7.9994***	1352.42***
R3	0.0000	0.0238	-0.1157	0.1554	0.4468***	9.1420***	1778.90***
R4	0.0000	0.0237	-0.1167	0.1526	0.4272***	8.9657***	1710.13***
3-month interest rate							
R1	0.0000	0.0239	-0.1151	0.1420	0.2156*	8.3321***	1467.61***
R2	0.0000	0.0238	-0.1152	0.1311	-0.0811	7.0966***	1062.35***
R3	0.0000	0.0239	-0.1158	0.1384	0.1777	8.2260***	1429.33***
R4	0.0000	0.0238	-0.1161	0.1416	0.3019***	8.4208***	1502.69***
Portfolio S							
10-year interest rate							
R1	0.0000	0.0159	-0.0799	0.0790	-0.4641***	4.7621***	496.29***
R2	0.0000	0.0158	-0.0799	0.0793	-0.4830***	4.4509***	437.34***
R3	0.0000	0.0159	-0.0752	0.0798	-0.3635***	4.5799***	453.38***
R4	0.0000	0.0158	-0.0756	0.0798	-0.3501***	4.3982***	418.17***
1-year interest rate							
R1	0.0000	0.0160	-0.0844	0.0806	-0.3336***	4.9424***	524.40***
R2	0.0000	0.0160	-0.0834	0.0812	-0.4101***	4.9453***	529.80***
R3	0.0000	0.0159	-0.0838	0.0808	-0.2368**	5.1022***	553.59***
R4	0.0000	0.0159	-0.0847	0.0803	-0.2275**	5.1076***	554.38***
3-month interest rate							
R1	0.0000	0.0160	-0.0842	0.0813	-0.3363***	5.0053***	537.74***

R2	0.0000	0.0160	-0.0840	0.0808	-0.4403***	4.9184***	526.36***
R3	0.0000	0.0159	-0.0838	0.0811	-0.2545**	5.0839***	550.39***
R4	0.0000	0.0159	-0.0837	0.0797	-0.2517**	5.0343***	539.69***

R1, R2, R3 and R4 are the residuals of the linear, nonlinear, asymmetric sign and size model, respectively. JB is the Jarque-Bera test for normality of returns. This statistic is distributed as chi-squared with two degrees of freedom. ***, ** and * represent significance at the 1%, 5% and 10% levels, respectively.

Table 2.9
Correlation matrix between residuals and the dependent variable

Panel A: Entire sample period (1993-2008)												
	Portfolio L				Portfolio M				Portfolio S			
10-year interest rate												
	R1	R2	R3	R4	R1	R2	R3	R4	R1	R2	R3	R4
R2	0.9968				0.9909				0.9948			
R3	0.9992	0.9966			0.9999	0.9904			0.9988	0.9937		
R4	0.9997	0.9977	0.9993		0.9997	0.9891	0.9997		0.9974	0.9935	0.9986	
<i>Portfolio</i>	0.7225	0.7236	0.7220	0.7223	0.8473	0.8565	0.8472	0.8470	0.9600	0.9643	0.9588	0.9575
1-year interest rate												
R2	0.9996				0.9993				0.9998			
R3	0.9984	0.9987			0.9998	0.9992			0.9981	0.9978		
R4	0.9927	0.9939	0.9945		0.9962	0.9959	0.9960		0.9973	0.9977	0.9953	
<i>Portfolio</i>	0.7218	0.7214	0.7206	0.7165	0.8520	0.8527	0.8518	0.8488	0.9655	0.9655	0.9637	0.9629
3-month interest rate												
R2	0.9969				0.9972				0.9993			
R3	0.9997	0.9973			0.9993	0.9965			0.9999	0.9993		
R4	0.9943	0.9929	0.9955		0.9957	0.9933	0.9965		0.9976	0.9975	0.9978	
<i>Portfolio</i>	0.7227	0.7252	0.7225	0.7186	0.8517	0.8550	0.8510	0.8480	0.9652	0.9659	0.9652	0.9629
Panel B: Pre Euro period (1993-1998)												
10-year interest rate												
	R1	R2	R3	R4	R1	R2	R3	R4	R1	R2	R3	R4
R2	0.9249				0.9526				0.9889			
R3	0.9894	0.9410			0.9974	0.9453			0.9995	0.9898		
R4	0.9955	0.9468	0.9909		0.9961	0.9434	0.9981		0.9988	0.9931	0.9986	
<i>Portfolio</i>	0.5255	0.5466	0.5200	0.5232	0.6556	0.6944	0.6539	0.6530	0.9052	0.9100	0.9047	0.9041
1-year interest rate												
R2	0.9767				0.9856				0.9975			
R3	0.9921	0.9825			0.9995	0.9860			0.9968	0.9954		
R4	0.9833	0.9851	0.9879		0.9974	0.9842	0.9982		0.9979	0.9980	0.9964	
<i>Portfolio</i>	0.5266	0.5267	0.5225	0.5179	0.6543	0.6657	0.6540	0.6526	0.9046	0.9060	0.9017	0.9027
3-month interest rate												
R2	0.9810				0.9891				0.9971			
R3	0.9935	0.9816			0.9953	0.9832			0.9993	0.9975		
R4	0.9856	0.9816	0.9897		0.9909	0.9849	0.9861		0.9975	0.9964	0.9983	
<i>Portfolio</i>	0.5319	0.5359	0.5285	0.5243	0.6554	0.6653	0.6524	0.6495	0.9052	0.9078	0.9046	0.9029
Panel C: Post Euro period (1999-2008)												
10-year interest rate												
	R1	R2	R3	R4	R1	R2	R3	R4	R1	R2	R3	R4
R2	0.9913				0.9980				0.9965			
R3	0.9964	0.9886			0.9985	0.9965			0.9974	0.9959		
R4	0.9954	0.9835	0.9954		0.9972	0.9951	0.9977		0.9942	0.9963	0.9965	

<i>Portfolio</i>	0.7829	0.7919	0.7801	0.7793	0.9248	0.9267	0.9234	0.9222	0.9830	0.9780	0.9805	0.9773
1-year interest rate												
R2	0.9818				0.9882				0.9971			
R3	0.9987	0.9802			0.9993	0.9875			0.9943	0.9915		
R4	0.9999	0.9816	0.9989		0.9969	0.9845	0.9980		0.9933	0.9905	0.9963	
<i>Portfolio</i>	0.7827	0.7992	0.7816	0.7826	0.9221	0.9361	0.9214	0.9192	0.9866	0.9900	0.9810	0.9800
3-month interest rate												
R2	0.9908				0.9933				0.9983			
R3	0.9977	0.9918			0.9996	0.9937			0.9987	0.9969		
R4	0.9966	0.9895	0.9926		0.9949	0.9897	0.9944		0.9968	0.9949	0.9982	
<i>Portfolio</i>	0.7777	0.7684	0.7756	0.7751	0.9253	0.9215	0.9249	0.9206	0.9872	0.9884	0.9860	0.9841

R1, R2, R3 and R4 are the residuals of the linear, nonlinear, asymmetric sign and size model respectively.

Table 2.10
Wilcoxon signed-rank test for residuals

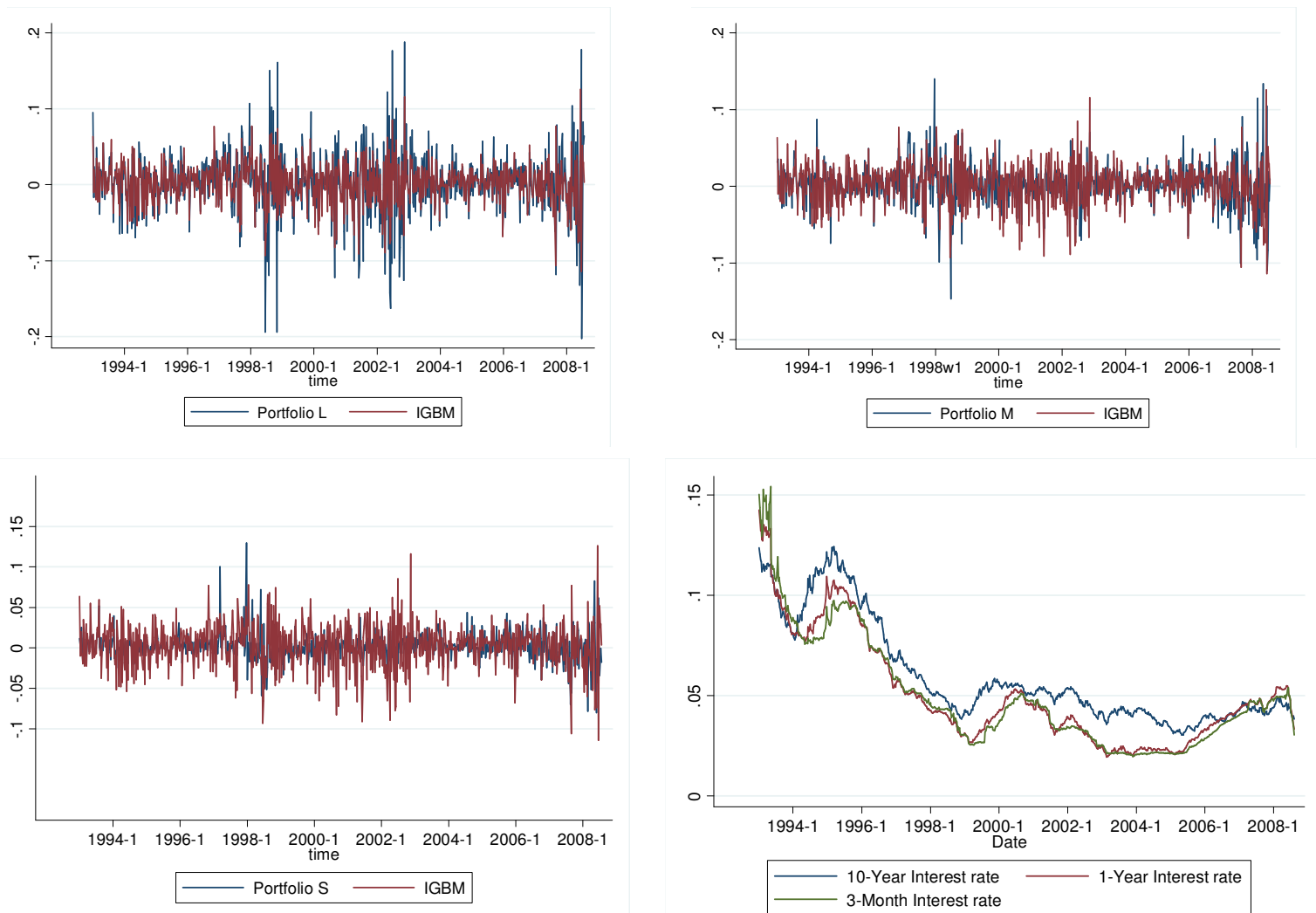
WILCOXON SIGNED-RANK TEST									
Panel A: Entire sample period (1993-2008)									
	Portfolio L			Portfolio M			Portfolio S		
	R1	R2	R3	R1	R2	R3	R1	R2	R3
10-year interest rate									
R2	0.8376			0.9948			0.9390		
R3	0.3995	0.0000		0.3141	0.7585		0.0000	0.0020	
R4	0.6927	0.7188	0.8060	0.2165	0.9241	0.0000	0.0000	0.0046	0.0213
1-year interest rate									
R2	0.0263			0.0659			0.3137		
R3	0.0703	0.3376		0.0221	0.3946		0.1067	0.2621	
R4	0.0017	0.006	0.0010	0.0000	0.0000	0.0000	0.0197	0.0000	0.0000
3-month interest rate									
R2	0.0000			0.0000			0.0000		
R3	0.0000	0.0000		0.0000	0.0000		0.0156	0.0000	
R4	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0002	0.0000	0.3372
Panel B: Pre Euro period (1993-1998)									
	R1	R2	R3	R1	R2	R3	R1	R2	R3
10-year interest rate									
R2	0.9077			0.7701			0.9072		
R3	0.8978	0.9880		0.0093	0.8478		0.0147	0.2051	
R4	0.2696	0.9995	0.9990	0.0000	0.9191	0.7993	0.5208	0.9974	0.0000
1-year interest rate									
R2	0.8509			0.7383			0.8999		
R3	0.0876	0.1568		0.8222	0.2870		0.7782	0.2300	
R4	0.0640	0.0000	0.7274	0.0000	0.0852	0.0000	0.1561	0.0000	0.2817
3-month interest rate									
R2	0.7054			0.3187			0.4162		
R3	0.0016	0.6503		0.0173	0.0471		0.1120	0.0126	
R4	0.6531	0.1644	0.4013	0.0000	0.0000	0.9379	0.0000	0.0000	0.0137
Panel C: Post Euro period (1999-2008)									
	R1	R2	R3	R1	R2	R3	R1	R2	R3
10-year interest rate									
R2	0.8502			0.8066			0.0001		
R3	0.0262	0.2817		0.0330	0.0216		0.0223	0.0091	
R4	0.0000	0.7794	0.0546	0.0004	0.8813	0.0000	0.0000	0.0000	0.0158
1-year interest rate									
R2	0.3657			0.4535			0.4006		
R3	0.6567	0.5706		0.0014	0.0163		0.0003	0.0000	

Chapter 2: Linear and Nonlinear Interest Rate Sensitivity of Bank Stock Returns in Spain

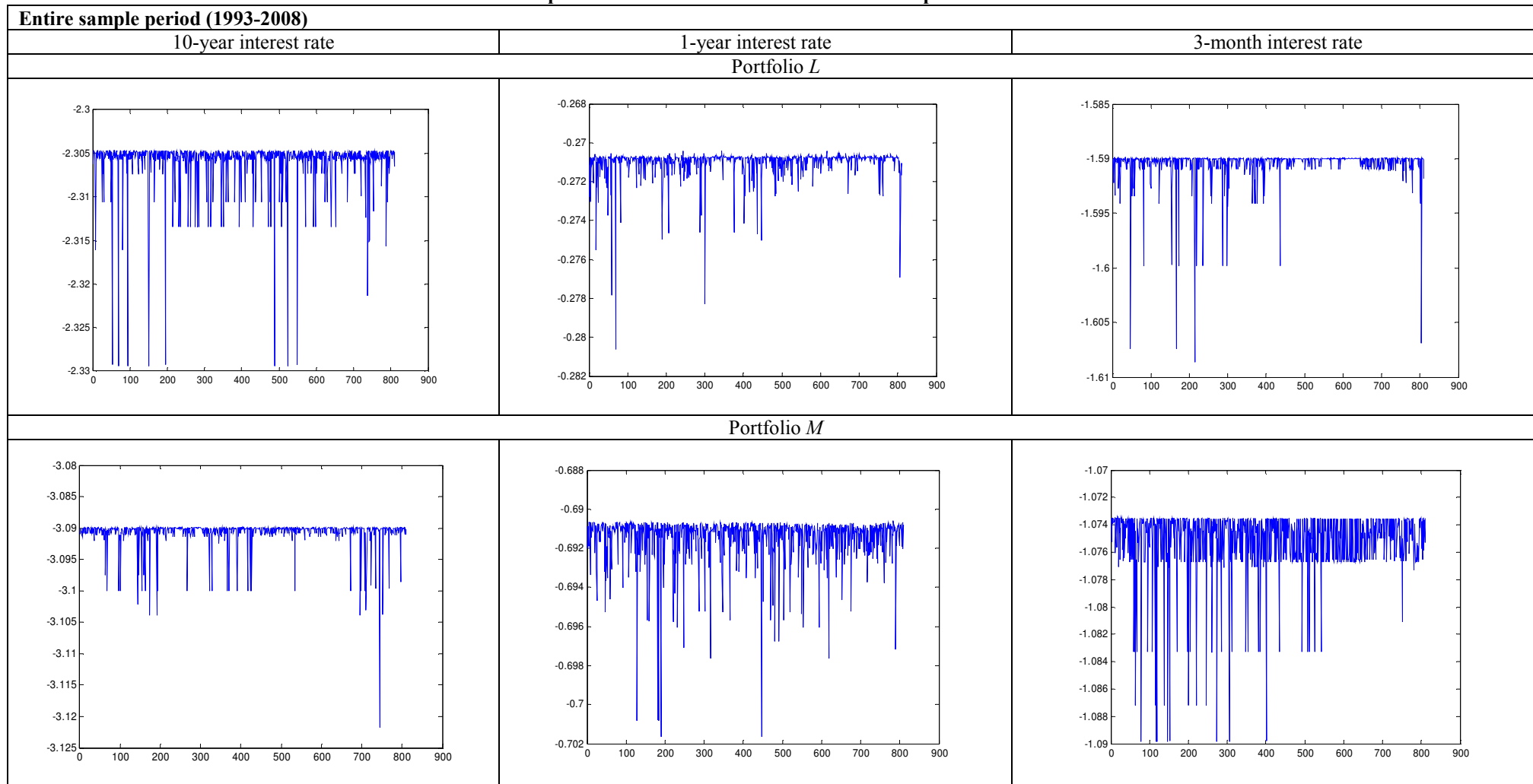
R4	0.0015	0.3763	0.9299	0.0000	0.1144	0.2838	0.0000	0.0000	0.3419
3-month interest rate									
R2	0.0000			0.0000			0.0009		
R3	0.0029	0.5937		0.0001	0.0008		0.0041	0.0000	
R4	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0500	0.0000	0.0004

This table shows the p value obtained in the non-parametric Wilcoxon signed-rank test. Its null hypothesis is that the median difference between pairs of observations is zero. R1, R2, R3 and R4 are the residuals of the linear, nonlinear, asymmetric sign and size model respectively.

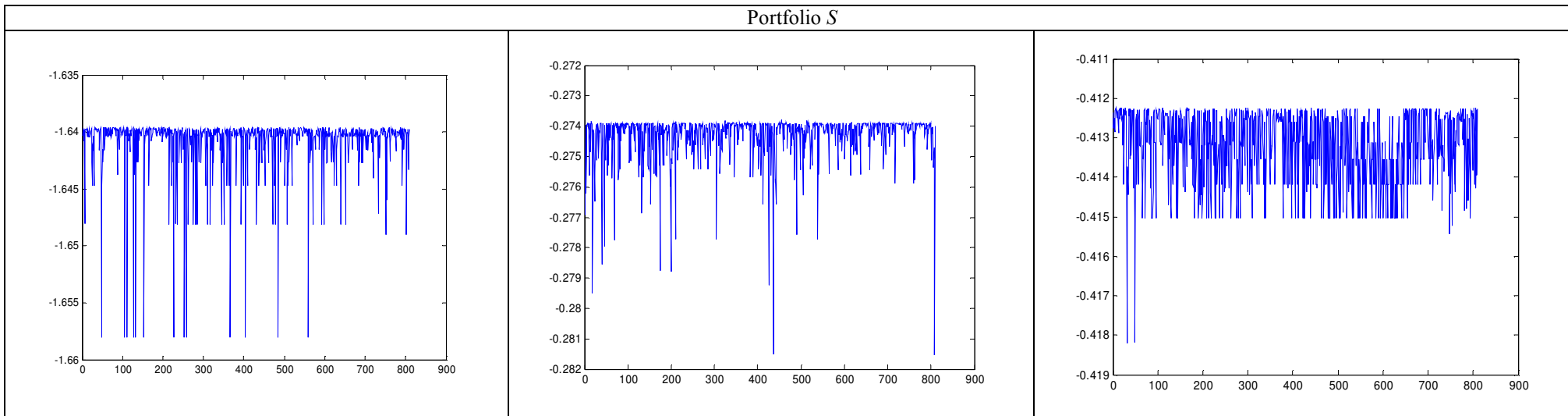
Graph 2.1
Returns on Bank and Market Portfolios and Level of Interest Rates



Graph 2.2
Nonparametric Model: Values of the estimated parameter \hat{b}

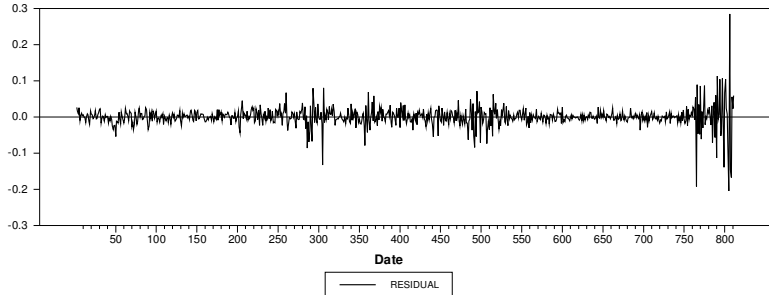
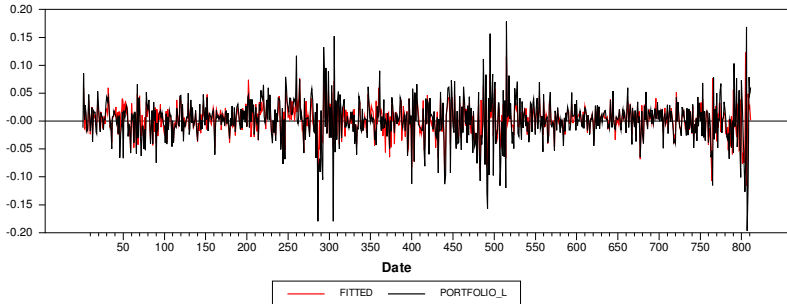


Portfolio *S*

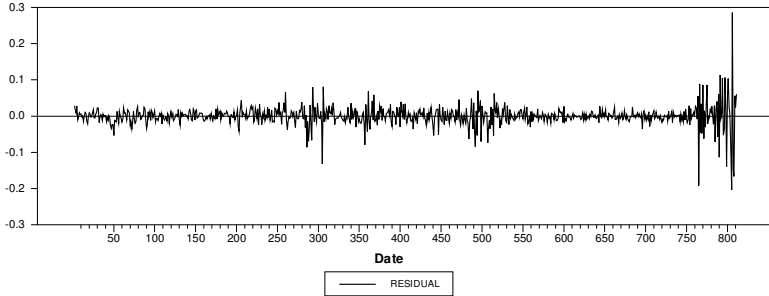
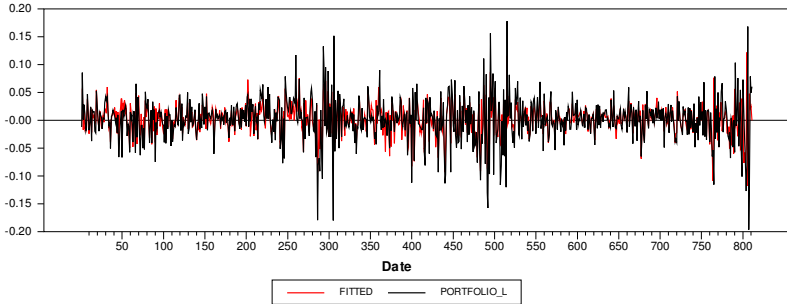


Graph 2.3
Fitted vs Actual Values and Residuals
Entire sample period (1993-2008)
Portfolio L & 1-year interest rate

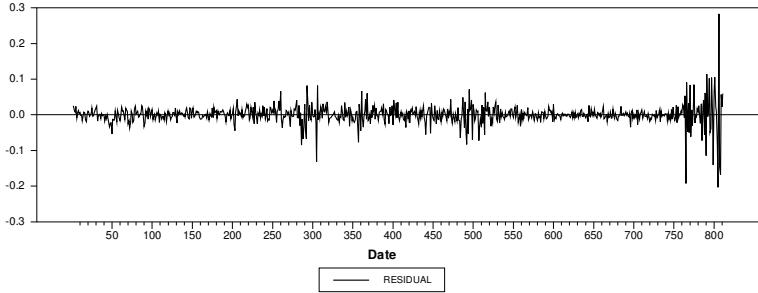
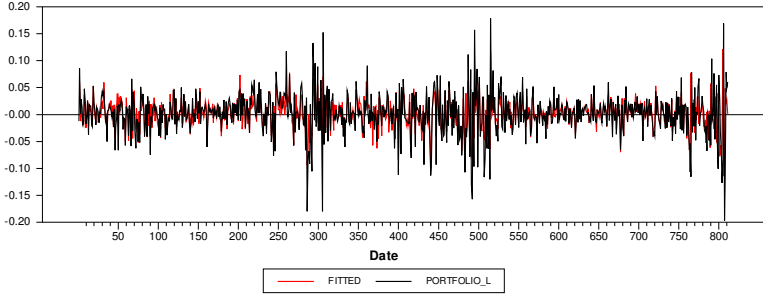
Linear Model



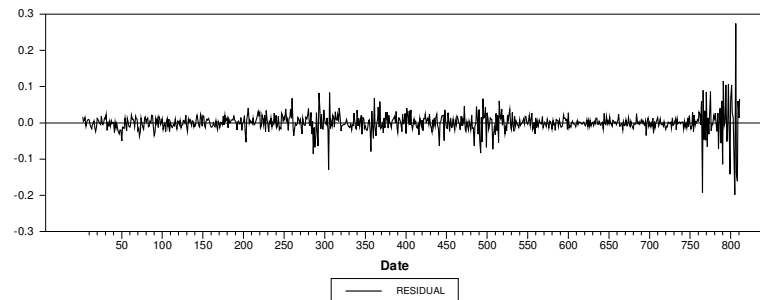
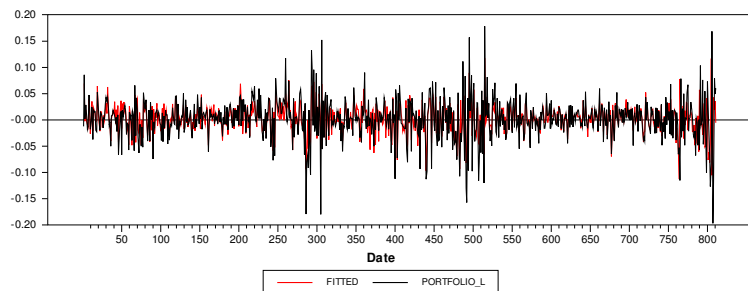
Nonlinear Model



Asymmetric Sign Model

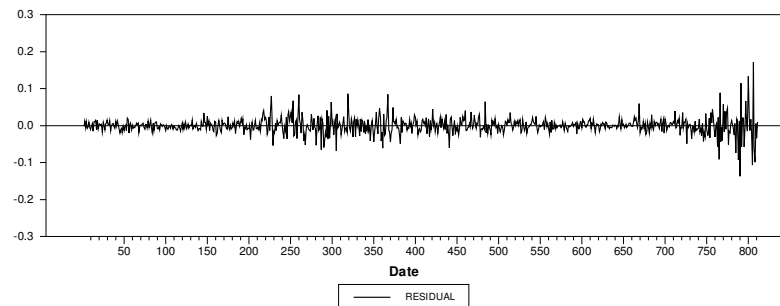
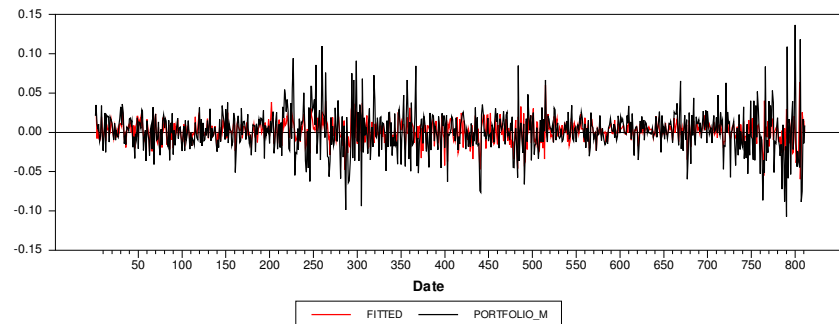


Asymmetric Size Model

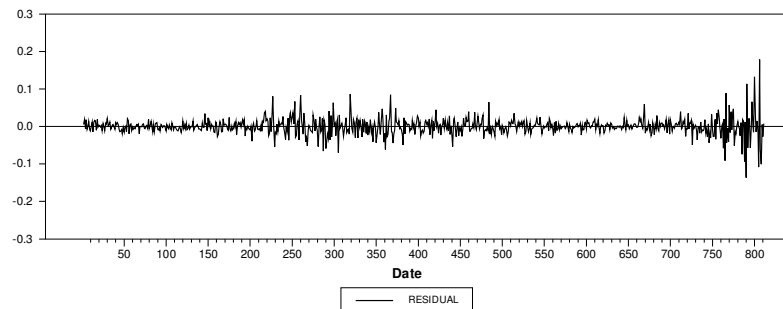
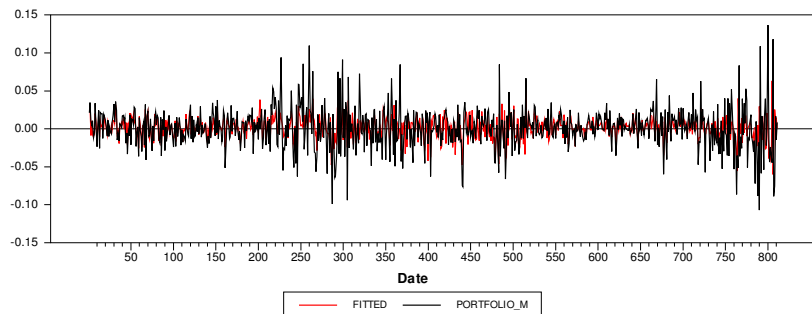


Portfolio M & 1-year interest rate

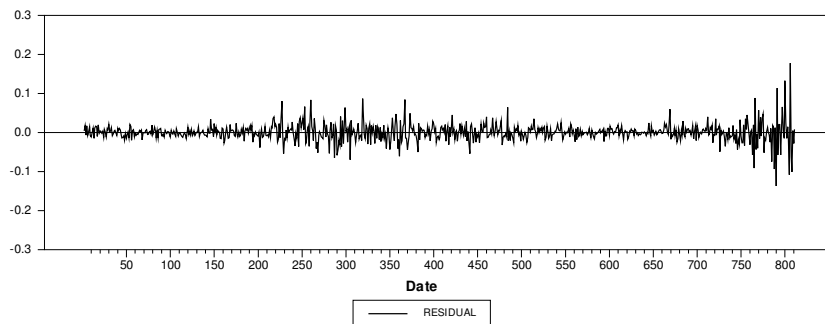
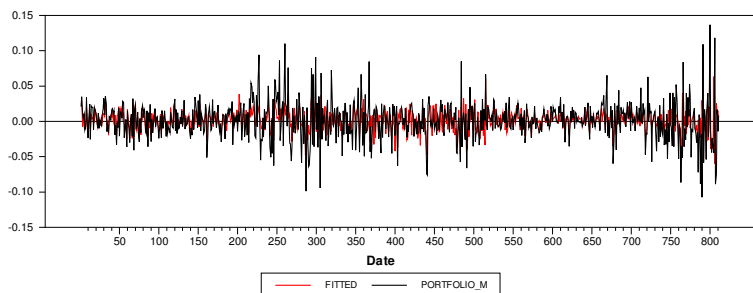
Linear Model



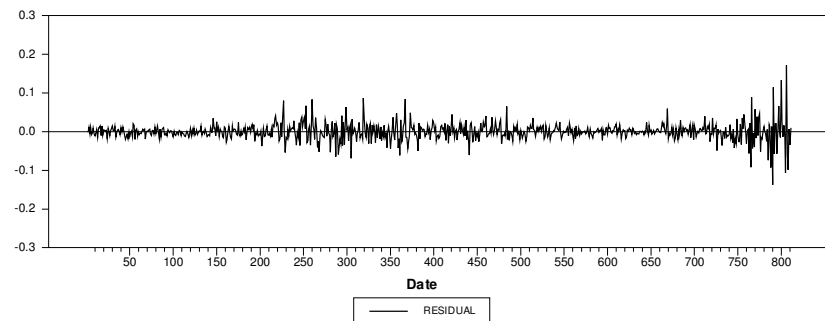
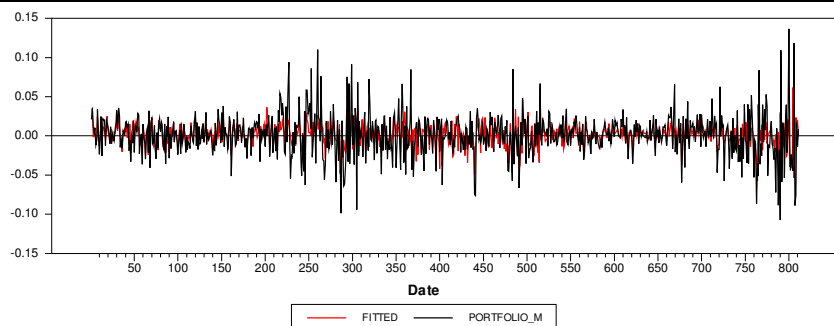
NonLinear Model



Asymmetric Sign Model

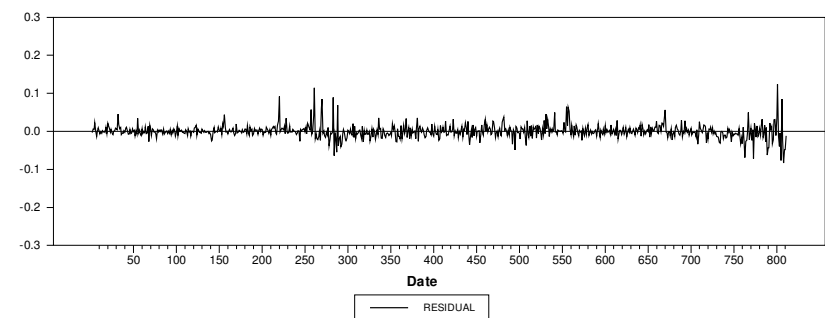
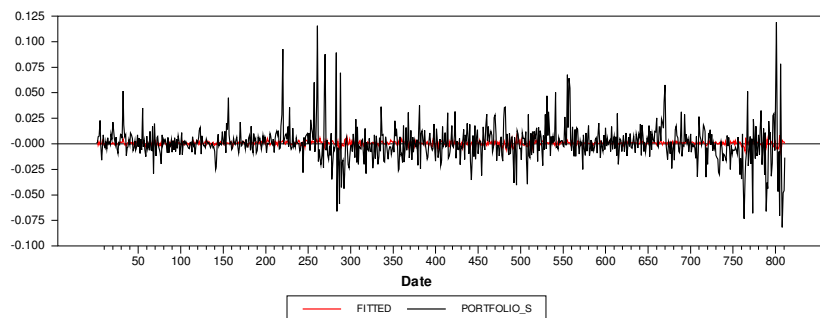


Asymmetric Size Model

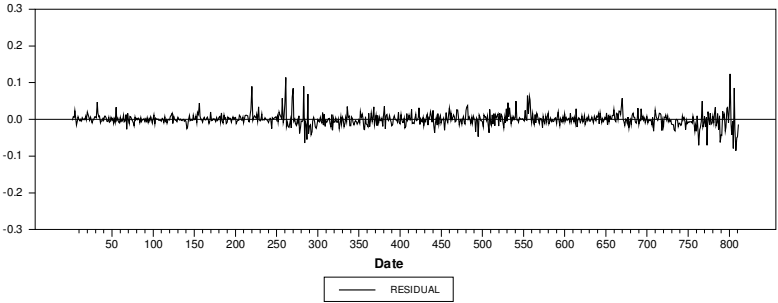
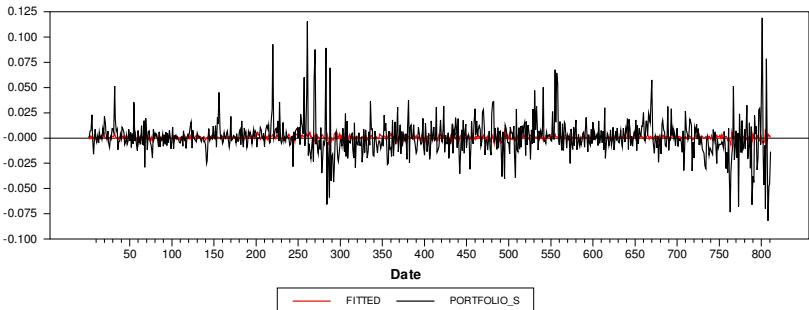


Portfolio S & 1-year interest rate

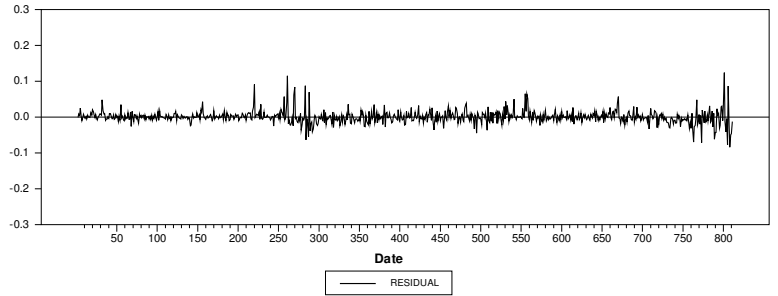
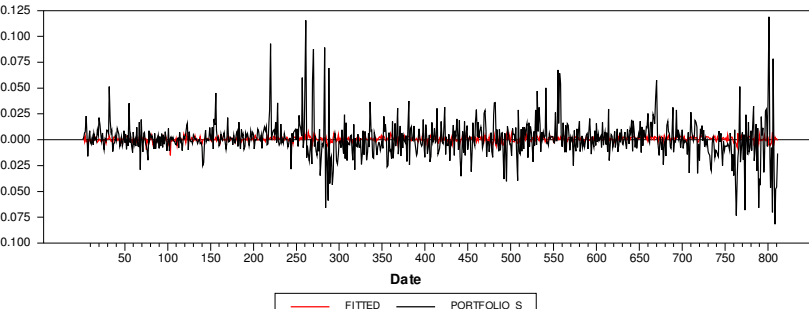
Linear Model



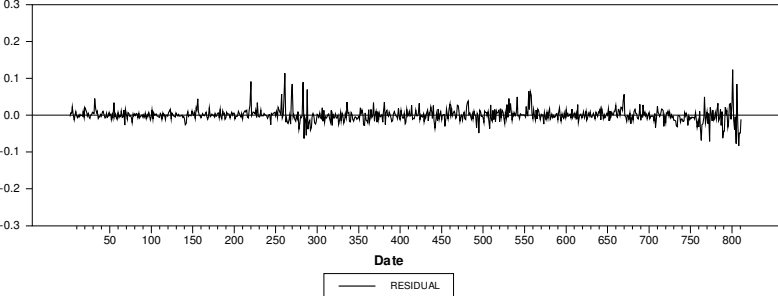
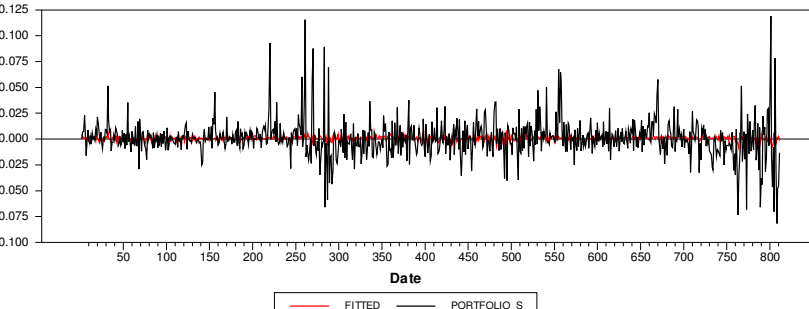
NonLinear Model



Asymmetric Sign Model



Asymmetric Size Model



Chapter 3

Determinants of Interest Rate Exposure of the Spanish Banking Industry

1. Introduction

Interest rate risk (IRR) is one of the main types of financial risk that banks face in their role as financial intermediaries. It can be defined as the risk that a bank's income and/or net worth will be adversely affected by movements in interest rates. IRR stems from the very nature of the banking business and it can be mostly attributed to two reasons. On the one hand, banks primarily hold in their balance sheets financial assets and liabilities fixed in nominal (non-inflation adjusted) terms, hence especially interest rate sensitive. On the other hand, banks traditionally perform a maturity transformation function using short-term deposits to finance long-term loans. The resulting mismatch between the maturity or repricing terms of banks' assets and liabilities can lead to volatility in income and net worth as interest rates fluctuate hence exposing banking institutions to repricing risk, which is generally viewed as the most important form of banks' IRR. Apart from repricing risk, banks are subject to other kinds of IRR. Basis risk arises due to imperfect correlation in the adjustment of the rates earned and paid on different asset and liability instruments with otherwise similar repricing characteristics. Yield curve risk is associated to unanticipated changes in the shape of the yield curve which have an adverse impact on a bank's value. Lastly, optionality risk has its origin in the options embedded in many assets, liabilities, and off-balance sheet items. As a result, the banking industry is seen as one of the sectors with higher interest rate sensitivity.

In recent years, IRR management has gained prominence in the banking system due to several reasons. First, the high levels of volatility in interest rates and financial market conditions have had a significant impact on the income streams and the cost of funds of banks. Second, the current international emphasis on the supervision and control of banks' market risks, including IRR, under the new Basel Capital Accord

(Basel II) has also contributed to an increasing concern on this issue.¹⁹ Third, the net interest income, which is heavily dependent on interest rate movements, still accounts for the largest component of total bank revenue in spite of the rising relevance of non-interest income. Fourth, the magnitude of the importance of IRR is also evidenced by the extraordinary growth of markets for interest rate derivatives.

Bank exposure to IRR has been the focus of an extensive body of research. The most common approach has been to estimate the sensitivity of changes in stock prices, normally used to denote the value of a banking firm, to movements in interest rates after controlling for general market fluctuations (e.g. Lynge and Zumwalt, 1980; Madura and Zarruk, 1995; Dinenis and Staikouras, 1998; Faff and Howard, 1999). In contrast, there exists a considerably lower amount of empirical evidence regarding the factors that explain the variation in interest rate sensitivity across banks and over time (e.g. Flannery and James, 1984; Hirtle, 1997; Fraser et al., 2002; Au Yong et al., 2009).

Initial studies investigating the determinants of bank IRR typically used asset-liability maturity gap as the key variable that drives banks' interest rate exposure. Nevertheless, this approach has severe drawbacks given the well-known limitations of static gap indicators, together with the difficulties to obtain precise and accurate year-by-year gap measures for most of banking firms. For this reason, an interesting alternative, which however has so far received little attention in the literature, is to examine the association between each bank's estimated IRR and a set of bank-specific characteristics with a potentially significant role in explaining that exposure such as bank size, equity capital, balance sheet composition or off-balance sheet activities.

¹⁹ Although the new Basel Capital Accord (Basel II) does not impose an explicit capital requirement tied to IRR under Pillar 1, the treatment of IRR in the banking book is one of the key issues addressed in Pillar 2 of Basel II. Specifically, depository institutions are required to provide qualitative and quantitative disclosures on their IRR and their policies for the management of this risk. More detailed information about the management and supervision of IRR can be found in Bank for International Settlements (2004).

The present study fills this gap in the Spanish case by undertaking a comprehensive analysis aimed at finding out the determinants of interest rate exposure of commercial banks. This analysis differs from previous studies in three ways. First, to the best of our knowledge, this is the first work to specifically tackle this issue for the Spanish banking system. In fact, the bulk of the research in this area has focused on the banking sectors of a few highly developed countries, particularly the US and only more recently Japan or Australia. The Spanish banking industry has undergone a profound transformation over the past two decades characterized by an intensive process of deregulation, liberalization, and consolidation that has led to a sharp increase in competition. A critical driving force behind these developments has been the progressive banking integration during the run-up to the European Economic and Monetary Union. Therefore the Spanish banking system provides an interesting context to explore whether the introduction of the euro as a single currency in 1999, with their implications in terms of greater financial stability induced by a common monetary policy, and deepening and expansion of financial markets, has affected the nature and magnitude of banks' exposure to IRR. Further, useful insights can be drawn from the Spanish experience for countries whose banking sectors are currently involved in a process of drastic changes in the quest for financial development and stability just like the one occurred in Spain. This is the case, for instance, of the Central and Eastern European countries which have recently joined the European Union.

Second, the analysis of the determinants of bank interest rate exposure is conducted using panel data estimation techniques rather than the standard cross-sectional regression approach. As far as we know, this is the first study in which panel data analysis is applied to examine the main factors affecting bank IRR. In particular, the system GMM estimator developed for dynamic panel data models by Arellano and

Bover (1995) and Blundell and Bond (1998) is employed. This methodology accounts for potential endogeneity, unobserved individual heterogeneity, and the persistence of the dependent variable.

Third, in an attempt to obtain a deeper understanding of the sources of bank IRR this study includes a number of bank-specific characteristics higher than usually considered in earlier works, taking into account both traditional on-balance and off-balance sheet activities.

Overall, the empirical evidence shows a considerable degree of interest rate exposure in the Spanish banking system, although the introduction of the euro has resulted in a substantial reduction of the IRR of banking institutions. An interesting distinctive feature of the Spanish case is that a pattern of positive exposure to IRR seems to emerge following the launch of the euro, which may have its origin in the dramatic transformations experienced by the banking industry in recent years. Moreover, it is found that the sensitivity of bank stock returns to changes in interest rates is systematically linked with several bank-specific attributes. Specifically, the net interest margin is, by far, the variable that has the greatest explanatory power for bank interest rate exposure, reflecting the critical role still played by the traditional interest rate-related business. Thus, banks with higher net interest margin are perceived by the stock market as less vulnerable to shocks in interest rates. In addition, credit risk, bank size, off-balance sheet activities and efficiency are also identified, although to a lesser degree, as important determinants of bank IRR. Credit risk, measured by the ratio of loan loss provisions to total loans, exhibits significant information content regarding interest rate exposure of Spanish banks, although the direction of its influence is unclear. In turn, bank size has a negative effect on IRR, indicating that larger banks benefit from economies of scale, greater diversification and easier access to capital

markets to reduce their interest rate exposure. In contrast, off-balance sheet activities appear as an IRR enhancing factor rather than an IRR reducing factor, supporting the conjecture that Spanish commercial banks primarily use financial derivatives for speculation purposes. Lastly, bank efficiency seems to have a certain positive impact on interest rate exposure, suggesting that more efficient banks tend to take greater risks in order to achieve improved efficiency.

The characterization of the profile of exposure to IRR in terms of a reduced set of bank variables measured from basic financial statement information may be of great interest for a wide audience. This information could be especially helpful for bank managers, investors, bank supervisors, and even academicians, all of them concerned about how to effectively measure, manage, and hedge interest rate exposure.

The rest of the paper is organized as follows. Section 2 reviews the existing literature examining the determinants of bank IRR. Section 3 describes the data set and methodology employed in this study. The empirical results are presented in Section 4. Finally, Section 5 draws some concluding remarks.

2. Literature review

The influence of IRR on the value of banking firms has been the subject of a large amount of literature during the last three decades. The vast majority of empirical studies have adopted a stock market approach based on the estimation of the sensitivity of bank stock returns to movements in interest rates within the framework of the two-index regression model developed by Stone (1974). This formulation is an augmented version of the simple single-index market model, where an interest rate change factor is incorporated as an additional explanatory variable to the market portfolio return in order to better explain the variability of bank stock returns.

The bulk of this research has documented a significantly negative effect of interest rate fluctuations on stock returns of banks (e.g. Lyngé and Zumwalt, 1980; Dinenis and Staikouras, 1998; Hahm, 2004; Yong and Faff, 2008; Czaja et al., 2009), which has been primarily attributed to the usual maturity mismatch between bank's assets and liabilities. In fact, banking institutions typically exhibit a positive maturity or duration gap, i.e. the average maturity or duration of their assets exceeds the average maturity or duration of their liabilities. Thus, an increase in interest rates not only adversely affects the market value of a bank net worth because the market value of its assets decreases more than the market value of its liabilities, but also the bank's income will be deteriorated whether the cost of the liabilities rises more rapidly than the yield on assets.

In comparison, although the study of determinants of bank interest rate exposure has received much less attention it is currently possible to distinguish two principal strands of literature. Early empirical research focused on the relationship between the interest rate sensitivity of bank stock returns and the maturity composition of banks' assets and liabilities. Specifically, the one-year maturity gap (the difference between assets and liabilities that mature or reprice within one year) is the variable most commonly employed to measure on-balance sheet maturity composition.²⁰ The seminal work by Flannery and James (1984) provided empirical evidence that the maturity mismatch between a bank's nominal assets and liabilities may be used to explain the cross-sectional variation in interest rate sensitivity (*maturity mismatch hypothesis*). Thus, banks that perform a greater maturity transformation have higher IRR and, consequently, their stock returns exhibit higher interest rate sensitivity. This finding has

²⁰ Maturity gap constitutes a classical method to quantify IRR based on comparing the potential changes in value of assets and liabilities in response to interest rate fluctuations over some predefined relevant intervals.

been confirmed by subsequent studies of Brickley and James (1986), Yourougou (1990), Kwan (1991), and Akella and Greenbaum (1992).

This body of work is based on the *nominal contracting hypothesis* introduced by Kessel (1956) and French et al. (1983), which postulates that a firm's holdings of nominal assets and liabilities can affect stock returns through the wealth redistribution effects caused by unanticipated inflation. Hence, stockholders of firms with more nominal liabilities than nominal assets benefit from unexpected increases in inflation because unanticipated inflation lowers the real value of nominal contracts. Under the assumption that movements in interest rates are primarily driven by changes in inflationary expectations, the nominal contracting hypothesis implies a relationship between stock returns and interest rate fluctuations (e.g. Fama, 1975 and 1976; Fama and Gibbons, 1982). The larger the asset-liability maturity mismatch, the more sensitive stock returns to interest rate changes. This hypothesis may be especially relevant for the banking industry because most of the banks' assets and liabilities are contracted in nominal terms and there generally exists a significant maturity mismatch between them. In short, the maturity mismatch hypothesis can be seen as a testable implication of the nominal contracting hypothesis within the banking framework (Flannery and James, 1984).

In an attempt to overcome the serious problems to get reliable and noise-free measures of maturity gap in most banks, and to gain better understanding of the nature of bank IRR, a second strand of research has extended the basic model of Flannery and James (1984) by analyzing the link between interest rate exposure and a set of potentially prominent bank-specific attributes (e.g. Hirtle, 1997; Drakos, 2001;

Saporoschenko, 2002; Fraser et al., 2002; Au Yong et al., 2009).²¹ The evidence obtained shows that, in general, the degree of IRR is systematically related to several bank-specific variables such as bank size, equity to total assets ratio, loans to total assets ratio, demand deposits to total deposits ratio, or non-interest income to total revenue ratio. Further, it is worth mentioning that this firm characteristic-based approach is also used in a number of studies that explore the main factors affecting the interest rate sensitivity of nonfinancial companies (e.g. O’Neal, 1998; Bartram, 2002; Soto et al., 2005; Singh, 2009).

In this context, the huge growth in derivative usage by banks over the last years has driven the development of a line of research focused on the relationship between IRR and a wide range of variables, putting a special emphasis on the impact of bank’s derivative activities on IRR. This approach has its origin in the theory of financial intermediation developed by Diamond (1984) in which banks have a comparative advantage in monitoring credits relative to individual lenders. An implication of Diamond’s model is that, in the presence of costly bank failures, banks should hedge all systematic risks in which they do not have any special monitoring advantages. Thus, in this model it is optimal for banks to hedge IRR by using derivative contracts.

The evidence from this strand of literature is mixed. For example, Choi and Elyasiani (1997) and Hirtle (1997) document that derivative usage is associated with higher interest rate sensitivity of US bank stock returns, consistent with the notion that derivatives are mainly employed to speculate. In contrast, Schrand (1997), Brewer et al. (2001), and Zhao and Moser (2006) find that derivatives are effective in reducing

²¹ It is important to note that the maturity gap analysis has several limitations. First, it excludes the effect of potential mismatches within the gap measurement period. Second, it does not consider the effect of non-parallel shifts in the yield curve. Third, it faces to serious difficulties to estimate the effective maturity of core deposits. Fourth, it does not take into account prepayment risk on loans and early withdrawal risk on deposits.

exposure of US banks to changes in interest rates. In turn, Reichert and Shyu (2003) show that not all derivatives affect bank risk uniformly. Thus, the use of interest rate options tends to increase IRR for a sample of large international dealer banks in the US, Europe and Japan, while swaps reduce risk, particularly for US banks. In the same vein, Au Yong et al. (2009) conclude that the level of derivative activities, especially interest rate derivatives, of Asia-Pacific banks is significantly and positively associated with their long-term interest rate exposure but negatively related to their short-term interest rate exposure.

With regard to the Spanish case, the evidence concerning the sources of banks' interest rate exposure is very limited. Jareño (2006 and 2008) examines the differential effect of real interest rate changes and expected inflation rate changes on the stock returns of both financial and nonfinancial firms at the industry level. Several extensions of the Stone's two-index model are proposed and the role of some common factors in explaining both real interest and inflation rate sensitivity of Spanish companies is assessed using a standard cross-sectional analysis. Nevertheless, it should be emphasized that these papers do not take into account bank-specific characteristics in their investigation of the determinants of corporate IRR.

3. Data

This study includes all Spanish commercial banks listed on the Madrid Stock Exchange over the period 1993-2007 with at least three consecutive years of data. A total of 22 domestic banking firms meet this requirement. According to the Bank of Spain, commercial banks represented approximately 56 per cent of total assets in the Spanish banking industry at the end of 2007. It should be noted that not all banks started to be quoted at the same moment and, additionally, some of them were involved in mergers and acquisitions or even their shares were delisted during the period under

review. As a result, the sample used is formed by an unbalanced panel data set with 220 annual observations. This approach eliminates any possible survivorship bias and improves the efficiency of the estimation.

The choice of this period of study allows us to examine whether the adoption of the euro in January 1999 did cause a substantial alteration in the pattern of interest rate exposure of Spanish commercial banks. With this aim, the entire sample period is split into two separated subperiods, namely January 1993 to December 1998 (pre-euro period), and January 1999 to December 2007 (post-euro period).

The introduction of the euro as a single currency within the framework of European Economic and Monetary Union represents a major historic event in international financial markets with notable implications on the banking industry. The principal effect on the European banking sector has been a reinforcement of the underlying tendency towards enhanced competition. In the context of the present study, the implantation of the euro may have had a remarkable impact on the degree of banks' IRR. There are two main channels through which the euro may affect bank interest rate exposure. First, after the euro adoption Eurozone interest rates are not longer set by the different national central banks but by the European Central Bank (ECB). The ECB implements a common monetary policy within the euro area acting from an European-wide perspective, with no national bias. The scenario of lower and more stable interest rates driven by the unification of monetary policy is likely to lead to a decline in the overall exposure to IRR. Second, the greater depth and breadth of financial markets since the launch of the euro have allowed firms in general and banks in particular to design better strategies of IRR management in an environment of growing financial innovation. Accordingly, the introduction of the euro should lead to a decrease in the interest rate exposure within the banking system.

3.1 First stage data: Equity and interest rate market data

Equity market data are obtained from the Madrid Spanish Stock Exchange database. Following a quite common practice in the literature, monthly bank stock returns are used for the estimation of interest rate exposure. The proxy for the market portfolio is the *Indice General de la Bolsa de Madrid*, the widest Spanish equity market index. Details related to the number of banks and observations for each bank together with the descriptive statistics of bank stock returns are given in Table 3.1.

Concerning to interest rate data, three alternative proxies of market interest rates are used. The monthly averages of the yield on ten-year Spanish government bonds on the one hand, and the one-year and three-month rate of the Spanish interbank market on the other hand, have been taken as the representative variables of long-term and short-term interest rates, respectively. Graph 3.1 displays the evolution over the sample period of the proxies considered.

The choice of the yield on ten-year government bonds as a proxy of long-term market interest rates has become a standard in the literature.²² This obeys to the fact that long-term interest rates are the ones which incorporate to a greater extent the expectations about the future and determine the cost of financing. Consequently, long-term rates have a meaningful influence on corporate investment decisions and on overall economic activity.

With regard to short-term interest rates, the monthly average of the three-month rate of the Spanish interbank market is employed since during the last years the interbank money market has become a key reference for Spanish banking firms mainly due to two reasons. First, interbank rates are widely used as reference rates in a great

²² Sweeney and Warga (1986), Hirtle (1997), Elyasiani and Mansur (1998), Tai (2000), Ryan and Worthington (2004) or Faff et al. (2005) constitute good examples of the use of ten-year interest rates to measure the interest rate exposure on banking firms.

variety of adjustable-rate active and passive operations. Second, Spanish banks have made greater use of interbank market as source of funds for their asset side operations, mostly in the mortgage segment, within the framework of the Spanish housing boom.

Additionally, due to the widespread use of the one-year Euribor interest rate in the retail banking operations, the monthly average of this rate is also employed in the analysis. All the interest rate information has been collected from the Bank of Spain historical database.

3.2 Second stage data: bank-specific characteristics.

As for the bank-specific characteristics used in the investigation, end-year data from consolidated bank balance sheets and income statements are extracted from the Bankscope database maintained by Fitch/IBCA/Bureau Van Dijk. This database is considered the most comprehensive data set for banks worldwide.²³ Based on previous work and economic intuition, a large number of bank attributes are initially considered to be potential determinants of the level of interest rate exposure. These characteristics include equity capital, bank size, balance sheet composition, income structure, off-balance sheet activities, profitability, liquidity, credit risk, and efficiency. Table 3.2 defines the bank variables used in this study as well as the expected sign of their association with IRR and their use in prior literature. Table 3.3 presents the summary statistics (minimum, maximum, mean, and standard deviation) of these variables, whereas Table 3.4 reports the pairwise correlations among them. The bank-specific characteristics considered in this study are briefly discussed below.

²³ As Pasiouras and Kosmidou (2007) indicate, to use Bankscope database has obvious advantages. Apart from the fact that it has information for 11,000 banks, accounting for about 90% of total assets in each country, the accounting information at the bank level is presented in standardized formats, after adjustments for differences in accounting and reporting standards.

1. Non-interest income

The non-interest income ratio (*NONINT*), defined as the proportion of non-interest income relative to total revenue, is entered in the analysis as a proxy of non-traditional bank activities (e.g. investment banking, market trading, insurance, advisory activities, or asset management). The sign of the relationship between non-interest income and interest rate exposure is ambiguous a priori. On the one hand, it can be argued that banks that produce a significant portion of their operating income from non-interest sources are more diversified and less reliant on core intermediation business and should, *ceteris paribus*, be less dependent on interest rate movements. Thus, a negative association between this ratio and interest rate exposure is hypothesized. On the other hand, Fraser et al. (2002) provide a contrary explanation based on the assumption that a substantial proportion of the non-interest income reflects securities-related activities. According to this reasoning, higher interest rates reduce economic growth, so that the volume of IPO (Initial Public Offering) and acquisitions activity decline and thereby lowering banks' non-interest income. Consequently, banks that rely more on non-interest income should have greater exposure to IRR, yielding a positive relationship between non-interest income and bank IRR.

2. Equity capital

The equity capital ratio (*CAP*), calculated as equity capital as a proportion of bank's total assets, represents a measure of capital strength widely employed as a determinant of bank IRR (e.g. Fraser et al., 2002; Saporoschenko, 2002; Reichert and Shyu, 2003; Au Yong et al., 2009). Banks with higher capital ratios tend to present relatively lower dependence on external financing, hence lesser degree of financial leverage. Further, a high level of equity capital increases bank's creditworthiness and

reduces its cost of funding. Thus, interest rate changes are expected to have a smaller impact on bank revenue and, consequently, on stock returns of better capitalized banks. Likewise, banking firms with a solid capital position are safer and have a lower probability of financial distress and bankruptcy, therefore avoiding strong sell-off of bank stocks in response to negative shocks such as rising interest rates. Accordingly, a high level of capital can act as a structural hedge against abnormal increases in interest rates and other adverse market conditions. As a result, a negative relationship between equity capital and interest rate exposure is hypothesized.

3. Bank size

Bank size is another variable frequently used as a possible source of IRR (e.g. Hirtle, 1997; Saporoschenko, 2002; Reichert and Shyu, 2003; Au Yong et al., 2009). The bank size variable (*SIZE*), measured as the natural logarithm of total assets, is included to control for discrepancies in IRR that might be caused by factors such as differences in the type of businesses, products and customers, or distinct risk attitudes between large and small banks. From a theoretical point of view, bank size can either reduce or increase a bank's IRR. For example, larger banks have better access to capital markets, and greater economies of scale and diversification benefits compared to their smaller-size counterparts, providing one means of reducing their risk exposure. However, it is well known that very large banks may also present greater interest rate exposure due to moral hazard behaviour. Indeed, banks with a too big to fail status have a clear incentive to take greater risks (e.g. granting riskier loans or taking speculating positions) that are underwritten by the government's deposit insurance fund. As a result, the net effect of these competing forces on bank IRR is ambiguous and becomes an empirical matter.

4. Balance sheet composition

The composition of banks' assets and liabilities can also affect the extent of interest rate exposure. Two variables have been suggested in the literature to capture this linkage. First, the ratio of demand deposits to total deposits (*DDEPS*) provides insight into the weight of demand deposits on the liability side of a bank's balance sheet. The deposit base is typically viewed as a relatively stable and cheap source of funding for banks. In particular, a substantial part of total deposits, basically demand and savings deposits, exhibit limited interest rate sensitivity due to the fact that these kinds of deposits are mainly for savings rather than investment. Therefore, it is hypothesized that banks that rely more on deposits as source of funds depend less on wholesale funding and, hence, have lower interest rate exposure.

Second, the ratio of loans to total assets (*LOANS*) measures the relative importance of the loan portfolio on the asset side of a bank's balance sheet and it has been often used in prior research as an indicator of IRR. Traditionally, the duration of bank loans has been higher than the duration of bank liabilities, so that an increase in the proportion of loans did entail an expansion of the maturity mismatch between assets and liabilities, thus increasing bank's IRR. Nevertheless, due to the overwhelming prevalence of floating rate loans with repricing intervals of one year or less in the Spanish banking market since the mid-1990s, the former effect can be called into question since the duration of adjustable rate loans coincides with their repricing intervals. Hence, the sign of this association is a priori ambiguous.

5. Liquidity

The liquidity ratio (*LIQ*), defined as the ratio of liquid assets (cash, balance with other banks and money market instruments) to total assets, could significantly affect

bank IRR as well. Analogously to the equity capital ratio, a bank with ample and stable sources of liquidity may be better able to withstand short-term earnings pressures arising from adverse interest rate movements than a bank heavily dependent on wholesale short-term funding sources. Hence, liquidity can be seen as a substitute for hedging, and a negative association between liquidity and IRR is predicted.

6. Off-balance sheet activity

Since banks are major users of derivative instruments (e.g. forward rate agreements, interest rate swaps, futures or options) both as end-users and as dealers, and derivatives provide a relatively inexpensive means to alter interest rate exposure, the impact of derivatives usage on IRR has become a critical issue in literature on bank risk (e.g. Hirtle, 1997; Reichert and Shyu, 2003; Zhao and Moser, 2006; Au Yong et al., 2009). Taking into account that derivative activities conducted by banks are classified as off-balance sheet operations and there is not more detailed information about derivative positions in the Bankscope database, the ratio of off-balance sheet activities to total assets (*OBSA*) is employed as a proxy of the use of derivatives. Concerning the sign of the relationship between this indicator and the extent of IRR, two offsetting effects can be distinguished depending on the basic motivation underlying to the use of derivatives. On the one hand, if banks employ derivatives primarily to reduce interest rate exposure arising from their other banking activities (for hedging) a negative coefficient on *OBSA* is expected. On the other hand, a positive coefficient on *OBSA* would suggest that banks utilize predominantly derivative instruments to increase income (for speculation) because a greater use of derivatives implies in this case a higher risk exposure. As it is not clear a priori which of these two alternatives is more likely, the net contribution of derivatives to banks' IRR must be empirically established.

7. Bank profitability

To examine the effect of profitability on exposure to IRR, two popular measures of bank profits are included. First, the net interest margin ratio (*NIM*), calculated as net interest income divided by total assets, is a good baseline measure of the profitability of a bank's traditional intermediation activities (taking deposits and originating loans). A high *NIM* indicates a well managed bank and sends a positive signal to the market concerning the ability of that bank to generate enough profits from its core business to absorb losses caused by adverse economic shocks. Since *NIM* stands for the major source of net income for most banking firms, banks with wide and stable *NIM* should be perceived by the stock market as less risky. Accordingly, this ratio is expected to be negatively related to interest rate exposure.

Second, the return on average equity ratio (*ROAE*) is another prominent indicator of bank profitability. This ratio is defined as annualized net income divided by average equity, and it indicates the return to shareholders on their equity. However, an analysis of profitability based exclusively on *ROAE* ratios could be misleading because it would tend to disregard the effect of leverage. Higher profitability reduces the probability of financial distress. Therefore, banks with high profitability have a greater cushion to withstand unexpected shocks in interest rates and other adverse economic conditions. Hence, it is hypothesized a negative relationship between *ROAE* and bank IRR.

8. Credit risk.

The ratio of loan loss provisions to total loans (*CREDIT*) reflects the quality of a bank's loan portfolio and it is widely accepted as a reasonable proxy of credit or default risk. A high value of this ratio indicates poor asset quality and high credit risk. This

variable is included to examine whether there exists a systematic relationship between the levels of credit risk and IRR borne by banks. The sign of this association is also an empirical matter.

9. Efficiency

The cost to income ratio (*CIR*), defined as the operating costs (such as the administrative costs, staff salaries or property costs) over total operating income, is one of the most prominent benchmark measures in the banking industry. The higher this ratio the less efficient the bank. This indicator allows us to measure the impact of operational efficiency on bank IRR, although there is not *a priori* a specific prediction about the direction of influence of this variable.

It is worth noting that, although the maturity gap ratio is an important theoretical measure of bank's IRR, unfortunately this indicator could not be used due to the lack of any maturity buckets information in the Bankscope database.

4. Methodology

The methodology employed in this study follows closely the approach based on the role of bank-specific variables discussed in Section 2. Thus, analogously to Drakos (2001), Fraser et al. (2002), Saporoschenko (2002), or Au Yong et al. (2009), a two-stage procedure is adopted.

4.1 First stage: Estimation of banks' interest rate exposure.

Following the extensive literature on bank IRR, the sensitivity of individual bank stock returns to changes in interest rates is estimated using the standard two-index model postulated by Stone (1974). The following regression model is estimated by OLS:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \theta_i \Delta I_t + \varepsilon_{it} \quad (3.1)$$

where R_{it} denotes the return on bank i 's stock in period t , R_{mt} the return on the market portfolio, ΔI_t the change in the relevant interest rate and ε_{it} the error term for period t .

Under this approach, the coefficient on the market portfolio return, β_i , describes the sensitivity of the return on i th bank stock to general market fluctuations and, therefore, it can be viewed as a measure of market risk. In turn, the coefficient on the interest rate term, θ_i , reflects the sensitivity of the return on i th bank stock to movements in interest rates, controlling for changes in the return on the market. Hence, it can be interpreted as a measure of i th bank interest rate exposure. In particular, as Hirtle (1997), Reilly et al. (2007) and Czaja et al. (2009) argue, this coefficient is an estimate of the empirical duration of i th bank equity.²⁴ A negative empirical duration implies that the value of bank equity tends to decrease when interest rates rise, while a positive duration implies the opposite. In this regard, a negative duration is consistent with the traditional view of banks as short-term borrowers and long-term lenders.

As specified in Eq. (3.1), the empirical duration is only a *partial* or *marginal* measure of IRR in the sense that movements in interest rates may also affect the market return and, through that channel, bank stock returns. In order to get a *total* measure of each bank' interest rate exposure and following the lines of Lyngne and Zumwalt (1980), Hirtle (1997), Fraser et al. (2002), and Czaja et al. (2009), among others, the market return variable is orthogonalized with respect to the interest rate change variable. Thus,

²⁴ Specifically, the concept of duration, a measure of interest rate sensitivity widely used in fixed income securities, can be easily extended to common stocks. Thus, the empirical equity duration is an indicator of the degree of interest rate risk borne by that equity, and it is based upon the historical relationship between equity returns and interest rate changes.

the residual series from an auxiliary OLS regression of the stock market return variable on a constant and the interest rate change variable, by construction uncorrelated with interest rate fluctuations, is used to replace the original market return series in Eq. (3.1). The empirical duration obtained in this way will reflect both the direct effect of interest rate movements on bank equity values and the indirect effect through changes in the return on the market.

Since the empirical durations estimated in the first stage will be used as dependent variables in the second stage, a trade-off between a large enough number of empirical durations and the precision of these estimates arises. In this sense, as Reichert and Shyu (2003) and Au Yong et al. (2009) point out, the extant literature suggests that an estimation period of between 3 and 5 years provides a good approximation of interest rate exposure. Accordingly, in this study interest rate exposure is estimated with monthly data over a 5-year interval. The choice of this estimation period represents a balance between the need to have a long period to obtain precise empirical duration estimates versus the need to account for time variation in banks' interest rate exposure.

In particular, for each year t we apply Eq. (3.1) to estimate the interest rate exposure of each bank i using return data from the 5 years surrounding year t (from $t-2$ to $t+2$). Thus, the rolling regressions are conducted over a sample period of 15 years, or a total 13 overlapping 5-year windows to be used in second stage regressions.²⁵

4.2 Second stage: Association between interest rate exposure and bank-specific characteristics.

Consistent with prior empirical research (e.g. Fraser et al., 2002; Saporoschenko, 2002; Reichert and Shyu, 2003; Au Yong et al., 2009), the second stage consists of a

²⁵ It is worth noting that the empirical durations for the first and last years, 1994 and 2006, respectively, for each bank i are obtained with three years of sample data.

regression of the individual empirical durations estimated in stage one on a variety of potential explanatory variables that reflect both traditional on-balance and off-balance sheet activities. These variables are the ones explained in section 3. To that end, several linear empirical models are developed to investigate the determinants of interest rate exposure.

The association between interest rate exposure and bank-specific characteristics is examined both in a univariate and a multivariate setting for the majority of the models proposed. Univariate analysis allows us to obtain a first approximation regarding the variables that individually explain, to a greater extent, the IRR faced by banking firms. In turn, multivariate analysis allows testing the joint influence of a set of bank variables on IRR, taking into account the correlations and interactions amongst them. In addition, it permits for dealing with the omitted variable bias inherent in the univariate analysis.

Given the reduced number of banks in the sample and the large array of bank variables considered in comparison, an empirical strategy based on the information content associated to each bank-specific characteristic is implemented in order to construct the most suitable multivariate model without losing too many degrees of freedom.²⁶ The first step consists of selecting the variable with greater explanatory power of bank interest rate exposure, measured through the adjusted R-squared, in a univariate regression model. In the second step, the initial model is augmented with variables incorporating additional relevant information about IRR. To that end, the matrix of correlations between the residuals of the univariate model and each of the remaining potential explanatory variables is obtained and the bank variable that better explains the residuals is added to the model. This process is repeated until none of the

²⁶ Novales (2006) provides an excellent review of the main points of criticism on classical hypothesis testing based on the statistical significance in the area of applied research in economics. Instead, this author emphasizes the importance of using strategies based on the information content or explanatory power of the independent variables.

remaining variables produces a significant improvement of goodness of fit of the model. The objective of this strategy is to prevent irrelevant variables from being selected, and to provide more accurate and parsimonious multivariate models.

4.2.1. Model specification.

4.2.1.1. Model with the absolute value of the empirical durations as the dependent variable.

Since empirical duration estimates obtained in the first stage regressions may have both positive and negative signs, mixing the two kinds of exposure could lead to a misleading interpretation of the results. For example, for a bank with positive interest rate exposure a positive sign of the coefficient associated to a bank-specific characteristic in the exposure determinant model would mean that the variable would raise the bank's exposure even more. In contrast, for a bank with negative exposure a positive coefficient would imply a decrease in the absolute value of its exposure and, hence, a reduction in IRR.

To mitigate this “sign confusion effect” the absolute value of the empirical duration estimates is used as the dependent variable in the second stage regressions instead of the raw values of the empirical durations.²⁷ Thus, the model can be formulated as follows:

$$\left| \hat{\theta}_{i,t}^h \right| = \gamma_0 + \gamma_j X_{j,i,t} + \varepsilon_{i,t} \quad \forall j = 1, \dots, J \quad (3.2)$$

for $t = 1, 2, \dots, T$, where T is the number of periods observed, and $i = 1, 2, \dots, N$, where N is the total number of banks analyzed. Subscripts i and t refer to bank i and at time t , respectively. $\left| \hat{\theta}_{i,t}^h \right|$ denotes the absolute value of bank i 's empirical duration for period t

²⁷ The issue of “sign confusion” effect has been addressed by Nguyen and Faff (2003) and Nguyen et al. (2007) within the framework of exchange rate exposure.

estimated in stage one and $h = 10, 1, 3$ for 10-year, 1-year and 3-month interest rate fluctuations, respectively. $X_{j,i,t}$ is the j th determinant of interest rate exposure of bank i at time t , and $\varepsilon_{i,t}$ is an error term.

4.2.1.2. Regime switching model with zero threshold.

The use of the absolute value of the empirical duration estimates allows for identifying the determinants of the magnitude of interest rate exposure. However, this approach does not take into account the sign of the exposure. In an attempt to further address the “sign confusion” issue, and to obtain a clearer understanding of the main factors-affecting interest rate exposure, a model that examines whether the determinants of bank IRR differ depending on the sign of the exposure is developed. The model is specified as follows:

$$\hat{\theta}_{i,t}^h = \lambda_0 + \lambda_1 D_{it} + \sum_{j=1}^J \gamma_j X_{j,i,t} + \sum_{j=1}^J \delta_j (D_{it} X_{j,i,t}) + \varepsilon_{i,t} \quad (3.3)$$

where D_{it} is a dummy variable that takes the value of 1 if the empirical duration estimate for bank i in period t is equal or less than zero and 0 otherwise. Thus, the parameter γ_j reflects the marginal impact of the j th bank-specific variable on the degree of interest rate exposure of banks with positive exposure, whereas $\gamma_j + \delta_j$ captures the marginal effect of the variable $X_{j,i,t}$ on IRR of banks with negative exposure.²⁸

This specification permits to distinguish between two different processes depending on the sign of the empirical duration obtained previously. Therefore, using

²⁸ Since there may be colinearity among some of the explanatory variables, by marginal effect we mean the effect of variable X_j on the dependent variable θ not contained in the remaining explanatory variables.

this model is equivalent to estimate the determinants of IRR separately for banks with positive and with negative interest rate exposure.

This approach considers both the magnitude and the sign of exposure and represents, therefore, a clear improvement over the absolute value model. In spite of this, this regime switching model is not exempt of problems. Its main drawback lies in the arbitrary selection of the threshold value. Even though a priori it could seem reasonable to take zero as a breakpoint to distinguish between two different regimes, this value may not necessarily be the optimal threshold to separate two regimes concerning the determinants of interest rate exposure.

4.2.1.3. Regime switching model with optimal threshold.

This approach can be viewed as a refinement of the regime switching model with zero threshold outlined above. The central idea behind this model is to look for the optimal threshold which better allows us to differentiate two regimes regarding the factors affecting bank IRR. Thus, an analogous specification to that reported in Eq. (3.3) is used, although in this case the transition between regimes depends on the value of the empirical duration estimate which represents the optimal threshold. By construction, this model outperforms the previous one since the optimal threshold is selected as that value of the empirical duration estimate which leads to a better fit of the regime switching model.

The regime switching model for the determinants of bank interest rate exposure proposed here is very similar in spirit to the TAR (threshold autoregressive) models introduced by Tong (1978) and Tong and Lim (1980). In essence, the original TAR model based on an autoregressive process is extrapolated to the case of a standard linear regression model. Specifically, the model to be estimated is as follows:

$$\hat{\theta}_{i,t}^h = \lambda_0 + \lambda_1 D_{it} + \sum_{j=1}^J \gamma_j X_{j,i,t} + \sum_{j=1}^J \delta_j (D_{it} X_{j,i,t}) + \varepsilon_{i,t} \quad (3.4)$$

where D_{it} is a dummy variable that takes the value of 1 if the empirical duration estimate for bank i in period t is equal or less than the optimal threshold, T^* , and 0 otherwise.

This regime switching model allows the determinants of interest rate exposure being different depending on whether the level of bank IRR goes beyond a certain threshold or not. Thus, the parameter γ_j reflects the marginal impact of the bank variable X_j on the degree of interest rate exposure for empirical durations higher than the optimal threshold T^* , whereas $\gamma_j + \delta_j$ reports the marginal effect of the variable X_j on interest rate exposure for empirical durations equal or less than the threshold T^* .

The estimation of the two regimes model with optimal threshold requires knowing the value of the optimal threshold to be used. In order to determine the optimal threshold, a sequential OLS estimation method, which extensively searches the threshold level over all values of the empirical durations estimated in stage one, is applied. In particular, the optimal threshold is selected as that value of the empirical duration estimate which minimizes the sum of squared residuals of the regime switching model. Obviously, the level of the optimal threshold will depend on the specific variables included in the model to be estimated.

4.2.2. Estimation methods.

All above presented models for the determinants of bank interest rate exposure are estimated using several estimation methods in order to enhance the robustness of the results. First, pooled OLS is used as a simple benchmark for more sophisticated

techniques. Second, different panel data methods are applied to control for the presence of unobserved individual heterogeneity.

The pooled OLS method simply adds time-series and cross-sectional observations together and then uses the OLS technique. As is well known, pooled OLS regressions may suffer from an omitted variable bias due to unobserved heterogeneity, derived for example from differences in the quality of management, leading to inconsistent estimates of the parameters. Therefore, since treating banks as homogeneous entities constitutes a too strong restriction, pooled OLS estimation is complemented with panel data analysis that accounts for unobserved heterogeneity in the data.

Panel data methodology offers important advantages compared to conventional time-series or cross-section analyses often used in financial research. Firstly, panel data allow controlling for unobserved individual heterogeneity as well as for dynamic adjustment processes. Companies are heterogeneous; each one has its own behaviour. Therefore, there are always characteristics influencing financial decisions that are difficult to measure or hard to obtain, and consequently not entered in the models. As Baltagi (1995) notes, neglecting unobserved heterogeneity in time-series or cross-section estimations may lead to biased results. Secondly, the use of panel data eliminates the bias of aggregation, which arises when time-series models are applied to characterise the behaviour of individuals. Thirdly, the panel data mitigates the attrition bias. Some firms could file for bankruptcy, merge or be delisted, and consequently there would be no information available for all periods. In a cross-sectional analysis these companies cannot be studied but it is possible to take them into account in unbalanced

panel data. Lastly, panel data give more informative data, more variability, less collinearity among the variables, more degrees of freedom and more efficiency.²⁹

Accordingly, a more general version of Eq. (3.4) that incorporates individual effects can be derived in the context of panel data analysis. It takes the following form:

$$\hat{\theta}_{i,t}^h = \lambda_0 + \lambda_1 D_{it} + \sum_{j=1}^J \gamma_j X_{j,i,t} + \sum_{j=1}^J \delta_j (D_{it} X_{j,i,t}) + \eta_i + v_{i,t} \quad (3.5)$$

The error term has now two components: η_i , which captures the unobserved time-invariant heterogeneity across banks, and v_{it} , which is the time-variant error term.

Two primary types of static panel data models, fixed and random effects models, can be distinguished depending on the assumption about the unobserved individual heterogeneity. On the one hand, the fixed effects model assumes that the unobserved heterogeneity, η_i , is correlated with the explanatory variables. The fixed effects estimator (also known as the within estimator) considers the individual effects as time-invariant. In essence, it consists of subtracting from the observations of each individual the over time average of all the observations for that individual and then applying OLS on these transformed data. On the other hand, the random effects model assumes that the unobserved heterogeneity is uncorrelated with the explanatory variables, so that the individual effects can be considered as a random component of the error term. The random effects estimator is derived using feasible generalized least squares (FGLS).

In order to determine which panel data model is more appropriate, the Hausman test, which tests the null hypothesis that the coefficients estimated by the consistent fixed effects estimator are the same as the ones estimated by the efficient random effects estimator, is usually applied.

²⁹ See Hsiao (1986) and Baltagi (2001) for a detailed review of the major advantages of panel data analysis.

Nevertheless, the static panel data estimation methods also have some drawbacks. In particular, these techniques do not take into account either the potential endogeneity of some of the explanatory variables or the persistence in interest rate exposure over time. In our context, there might be a problem of endogeneity caused by the reverse causality between the degree of IRR and some bank variables. For instance, if a bank has a high interest rate exposure it is possible that managers try to lower this exposure via an increase of off-balance sheet activities or via an increase of non-interest income (such as fees and commissions). Further, bank interest rate exposure may present a tendency to persist over time, reflecting the difficulties faced by banks to alter their balance sheet structure, major sources of income, or improve their risk management systems.

In order to tackle these shortcomings, an instrumental variable estimator is chosen. Specifically, the system generalized method of moments (GMM) estimator developed for dynamic models of panel data by Arellano and Bover (1995) and Blundell and Bond (1998) is applied. As Fonseca and González (2010) point out, this methodology is specifically designed to address three relevant econometric issues: (1) the presence of unobserved firm-specific effects is eliminated by taking first-differences of all the variables; (2) the potential endogeneity of the explanatory variables is accounted for using as instruments lagged levels and lagged differences of the possibly endogenous regressors; (3) the persistence of the dependent variable is accounted for by including a lagged dependent variable among the regressors. Specifically, the system GMM estimator is based on a stacked system of equations in both first-differences and levels. More precisely, lagged levels of the variables are used as instruments in the first differenced equation and lagged first-differences of the variables as instruments in the equation in levels. The choice of this estimator is motivated by its better finite sample

properties. In fact, it not only greatly improves the precision but also largely reduces the finite sample bias.

Moreover, we use the two-step system GMM estimator with the Windmeijer (2005) finite-sample correction for standard errors.³⁰ The dynamic specification of the model for the determinants of interest rate exposure with optimal threshold takes the following form:

$$\hat{\theta}_{i,t}^h = \lambda_0 + \lambda_1 D_{it} + \lambda_2 \theta_{i,t-1} + \sum_{j=1}^J \gamma_j X_{j,i,t} + \sum_{j=1}^J \delta_j (D_t X_{j,i,t}) + \eta_i + \nu_{i,t} \quad (3.6)$$

where η_i is an unobserved time-invariant bank-specific term, and ν_{it} is an error term.

4.2.3 Principal component analysis

Since some of the bank-specific characteristics are highly correlated with one another, the results of previous estimations may suffer a loss of efficiency in the estimates. This loss of precision does not generate inconsistency problems (the estimators come close to the true value of the parameter), but it leads to estimators with higher variance. Thus, in conducting hypothesis tests concerning the parameters of the model the null hypotheses will tend to be rejected too frequently, which may lead to incorrect inferences. Another problem derived from the possible presence of multicollinearity in the model is the impossibility of separate direct and indirect effects for the accurate interpretation of the results.

For the reasons outlined above and as a complement to the previous analysis, a principal component analysis (PCA) is carried out. This approach can be used to

³⁰ System GMM estimators have two popular versions, namely the one-step and the two-step estimators. In the one-step estimator, the error terms are assumed to be independent and homoskedastic across the panel units and over time. In the two-step estimator, however, the residuals obtained in the one-step are used to construct a consistent estimate of the variance-covariance matrix, thus relaxing the assumptions of independence and homoskedasticity. The two-step estimator is thus asymptotically more efficient than the one-step estimator.

synthesize the information contained in the data set because it permits to determine the minimum number of common factors that would satisfactorily explain the correlations among the variables. Thus, the original correlated variables can be substituted for a smaller number of uncorrelated variables called principal components. The objective of PCA is to reduce the dimensionality of the data set but retain most of their original variability.

In order to facilitate the interpretation of the principal components, the varimax rotation technique is used to minimize the number of variables that have high loadings on the same factor. In other words, varimax rotation produces results which make the most likely to identify each variable with a single factor.

Thus, the model represented in Eq. (3.7) is estimated following the same procedure of regime switching with optimal threshold applied in Eqs. (3.4) to (3.6), but this time not using the original variables but their principal components for each of the different sample periods. The model to be estimated is as follows:

$$\hat{\theta}_{i,t}^h = \lambda_0 + \lambda_1 D_t + \lambda_2 \theta_{i,t-1} + \sum_{j=1}^J \gamma_j PC_{j,i,t} + \sum_{j=1}^J \delta_j (D_t PC_{j,i,t}) + \eta_i + v_{i,t} \quad (3.7)$$

where $PC_{j,i,t}$ denotes the value of the j th principal component of the bank-specific characteristics for bank i in period t . Note that J indicates the number of principal components of the model, which may be different for the various sample periods considered in the analysis.

5. Empirical results

5.1. First stage: estimation of the empirical duration coefficients

Table 3.5 provides summary statistics of the empirical duration and market beta coefficients estimated by OLS from Eq. (3.1) with the different proxies for market

interest rates. Standard errors are corrected for autocorrelation and heteroscedasticity using the Newey-West procedure. Panel A reports results for the entire sample period, while Panels B and C present results for the pre- and post-euro subperiods, respectively.

The first remarkable finding is that there exists considerable variation in interest rate exposure both across banks and over time, although most of the statistically significant empirical duration estimates carry a negative sign regardless of the proxy for market interest rates used, particularly during the pre-euro period. Thus, the percentage of banking firms with significant exposure at the 10% level for the whole sample period ranges from 37.73% of all the sample banks when movements in long-term bond yields are used to 18.18% when changes in short-term rates are considered. Furthermore, focusing on the cases with significant exposure, 76 out of 83 cases (91.57%) exhibit a negative empirical duration when long-term rates are employed. This percentage remains very high [40 out of 45 cases (88.89%), and 34 out of 40 cases (85%)] when one-year and three-month rates are used, respectively, as proxies of market interest rates in Eq. (3.1). In addition, both the mean and median empirical duration coefficients present take, consistently with the previous result, negative values across all the specifications estimated. This implies that Spanish bank stock returns are, on average, adversely affected by rises in interest rates. This finding is in line with the typical bank balance sheet maturity structure, in which long-term assets are financed by short-term liabilities (positive duration gap). The negative relationship between interest rate changes and bank stock returns also agrees with most of the prior empirical research (e.g. Flannery and James, 1984; Madura and Zarruk, 1995; Fraser et al., 2002; Hahn, 2004; Czaja et al., 2009).

The analysis by subperiods clearly reveals that the highest percentage of banks with significant interest rate exposure is associated to the pre-euro period. Thus, for the

period leading up to the introduction of the euro, 67%, 35% and 25% of our sample banks exhibit a significant empirical duration coefficient with regard to long-, medium-, and short-term rate changes, respectively. Further, the predominance of negative exposures is overwhelming during this subperiod (100% of banks with significant exposure to long- and medium-term rate changes, respectively, and 96% in the case of short-term rates). As expected, these percentages fall severely after the euro is launched. Specifically, only 13.33%, 8.33%, and 12.50% out of the banks in the sample have a significant exposure to movements in long-, medium- and short-term rates, respectively, during the post-euro era. Moreover, 56.25%, 50%, and 33.33% of the cases with significant exposure to IRR show negative interest rate sensitivity. Likewise, both the mean and median post-euro exposures have dramatically decreased in absolute value compared to the pre-euro period.

Interestingly, the sign of interest rate exposure becomes positive for a significant number of banks in the post-euro era, indicating that during that period banking firms benefit from rising interest rates. This effect is particularly important when the one-year Euribor rate is taken as the proxy for interest rates. Two main reasons may help to explain this result. First, the sizeable reduction in the traditional maturity mismatch between long-term assets and short-term liabilities caused by various recent developments that have largely influenced the behaviour of the Spanish banking system over the last years. On the one hand, the extraordinary growth in the use of adjustable rate products tied to short-term rates since the mid-1990s. Nowadays, interbank market rates are commonly used as reference rates for many banking retail operations, mainly in the mortgage segment. On the other hand, the unprecedented expansion of asset securitization, mostly outstanding in the residential mortgage area, along with the increasing use of interest rate derivatives, may also have played a critical role in this

context.³¹ Second, the positive impact of IRR on bank stock returns may reflect the serious difficulties of banking institutions to keep their profits at reasonable levels during periods of declining rates, especially in a situation of already low rates. Thus, a low level of interest rates should lead to a narrowing of lending-deposit rate spreads since a positive interest rate on bank deposit accounts is generally required. This argument is consistent with the evidence of a steady compression of bank margins in a scenario of falling interest rates and intense competition as observed in recent years.

Therefore, the results appear to suggest that the launch of the euro has led to a notable reduction in both the number of banks that have significant exposure to IRR and the extent of their exposure. A possible explanation for this finding is closely related to the greater stability in interest rates during the post-euro era in an environment of historically low interest rates as well as the development of better systems for measuring and controlling IRR. In this respect, firms in general and banks in particular could have taken advantage of the large-scale use of interest rate derivatives and the increasing depth and breadth of the post-euro European market for corporate bonds to implement a more effective management of their IRR.

Additionally, it is worth noting that the higher percentage of banks with significant interest rate exposure is detected for the three estimation periods when movements in long-term rates are used. This implies that long-term bond yields are those that exert a more powerful influence on the stock performance of Spanish commercial banks.

With regard to market risk, a positive and highly significant market beta coefficient is found for the great majority of individual banks irrespective of the proxy

³¹ According to Catarineu and Pérez (2008), nowadays the mortgage market constitutes the collateral of almost 80% of the asset-backed securities issued through a securitisation procedure in Spain.

for market interest rates and the sample period considered. In addition, a large proportion of the variability of bank stock returns is explained by the variations of the market portfolio return, whereas interest rate changes have a much less explanatory ability.³² As expected, this finding supports the conjecture that the overall market risk plays a dominant role in explaining the variability of bank stock returns.

5.2 Second stage: identification of the determinants of exposure to IRR

The alternative models for the determinants of bank interest rate exposure discussed in section 4.2.1 are estimated using pooled OLS and different panel data methods in order to gain a more complete insight into the main factors affecting the degree of IRR.

5.2.1. Model with the absolute value of the empirical durations as dependent variable.

As a preliminary exercise, a univariate analysis is performed estimating Eq. (3.2) by pooled OLS for each bank-specific characteristic. The results for the different periods of study and proxies of market interest rates are shown in Table 3.6.

With regard to long-term interest rate changes (Panel A), it can be seen that whereas for the whole sample period most of the coefficients are negative, none of them is statistically significant at the usual levels. The results for the pre- and post-euro subperiods are mixed. None of the coefficients is significant for both subperiods and even though there is no clear prevalence of positive or negative coefficients, when we look only at the statistically significant ones, they are negative in almost all cases. Only the *ROAE* ratio diverges from this pattern.

³² For the sake of brevity, the results of this analysis are not reported here, but are available upon request from the authors.

In relation to the evidence obtained with one-year rate fluctuations (Panel B), the ratios *OBSA*, *CAP* and, particularly, *NIM* exhibit the most consistent results. *CAP* and *OBSA* are inversely and directly related, respectively, to bank IRR, especially after the introduction of the euro. Instead, the ratio *NIM* displays a steady negative relationship with the IRR borne by banking firms regardless of the sample period considered.

Panel C reports the results with changes in three-month rates. This is the case where more individual variables have significant information content for interest rate exposure. Indeed, 7 out of 11 coefficients are significant for the entire sample period (including the previous three ones significant in Panel B), although when the analysis is limited to any of the two subperiods their statistical significance decreases. Again *NIM* emerges as the only ratio with relevant information content for all the sample periods. Analogously to the cases of changes in 10-year and 1-year rates, *NIM* shows an inverse relationship with bank IRR. The remaining significant coefficients generally show the expected sign.

Further, it is worthwhile to highlight that for the three proxies of market interest rates and sample periods considered, the adjusted R2 obtained in the univariate models that use the absolute value of exposure as the dependent variable are steadily low. Better models will be implemented in next steps in order to improve the results.

5.2.2. Model that takes into account the sign of the interest rate exposure.

Given that the estimation of the interest rate exposure yields empirical duration estimates with both positive and negative exposure, in this section we examine whether the impact of the bank variables varies depending on the sign of the exposure coefficient.

5.2.2.1 Univariate model

The results of the pooled OLS estimation of the model in Eq. (3.3) in a univariate framework are presented in Table 3.7. Panel A reports the interest rate exposure estimates obtained using changes in 10-year yields, and Panels B and C refer to changes in 1-year and 3-month rates, respectively. The first interesting point to note is the dramatic increase in the adjusted R2, especially pronounced during the post-euro period. In particular, the average of the adjusted R2 leaps from 1.53% in Eq. (3.2) to 51.22% in Eq. (3.3) for the entire sample period. This implies that a substantial improvement in terms of the explanatory power of the model is obtained when the sign of the interest rate exposure is taken into account.

For the whole sample period the coefficient λ_1 , associated to the dummy variable that discriminates the sign of the empirical duration, is negative and statistically significant regardless of the bank-specific characteristic and the proxy of market interest rates used.³³ This result indicates that two different regimes for the interest rate exposure can be distinguished depending on whether the sign of the empirical duration estimates is positive or negative.

With respect to 10-year yield changes, the ratios *CAP*, *CREDIT*, *NIM*, *LOANS* and *ROAE* are those that have a higher explanatory ability of bank exposure to IRR, mostly during the post-euro era. In relation to 1-year rate changes, *NIM*, *CAP* and *OBSA* appear as the ratios with the strongest impact on IRR. Concerning the 3-month rate fluctuations, *LIQ*, *LOANS*, *NIM* and *OBSA* are the variables with greater influence on IRR, particularly during the post-euro period. Analogously to the model based on the absolute value of empirical duration, *NIM* is the only ratio with significant information

³³ The coefficient on *LOANS* in Panel C of Table 3.7 is the only one not statistically significant.

content irrespective of the sample period and the proxy for interest rates under consideration.

In this case the highest number of individual bank-specific characteristics with significant explanatory power of IRR also appears by using changes in 3-month rates. Moreover, the highest number of bank variables with relevant explanatory ability for IRR is generally found during the post-euro era. It can be also highlighted that their associated coefficients present the expected signs.

In short, *NIM* also emerges in this regime switching model with zero threshold as the variable which has the more consistent effect on interest rate exposure.

5.2.2.2 Multivariate model

Table 3.8 reports the results of the pooled OLS estimation of the model in Eq. (3.3) in a multivariate setting. The multivariate models are constructed following the strategy based on the information content associated with the bank variables as described in Section 4.2.

Again, *NIM* is the variable that shows more consistent information content for interest rate exposure across different sample periods and proxies for interest rates, especially for banks with negative exposure. In particular, the significant coefficients on the ratio *NIM* take negative values when the interest rate exposure is positive and positive values when the exposure is negative. The result is, therefore, a negative association between *NIM* and IRR, indicating that banks with higher *NIM* ratios are perceived by the stock market as less vulnerable to IRR. Thus, *NIM* is regarded as a key indicator of the ability of banking firms to generate income, which constitutes the first line of protection against adverse economic shocks.

The *CIR* ratio (during the pre-euro period) and the *LIQ* and *OBSA* ratios (during the post-euro period) also appear, although to a lesser extent, as significant explanatory factors of IRR. *CIR* and *OBSA* show a direct relationship with IRR (their significant coefficients have identical sign to that of the empirical duration estimate), whereas the direction of the influence of *LIQ* is somewhat mixed.

Interestingly, almost all of the explanatory power associated to the *CAP* ratio found in the univariate framework disappears in the multivariate analysis. This may be due to the high correlation between the variables *CAP* and *NIM*. In fact, the inclusion of *NIM* in the multivariate model causes generally the loss of statistical significance of the *CAP* ratio.

In addition, it is worth noting that the adjusted R² takes, on average, values above 50%, especially in the post-euro period. This implies that the regime switching model based on the sign of interest rate exposure seems to fit reasonably well to the observed data.

5.2.3. Two-regimes model with optimal threshold.

5.2.3.1 Univariate analysis

Table 3.9 shows the descriptive statistics of the optimal thresholds calculated for each of the bank-specific characteristics. As can be seen, the mean and median values of the individual optimal thresholds are always below zero regardless of the proxy for interest rates and the sample period under consideration. This suggests that the intuitive threshold value of zero used in the previous model is not the level that better allows to distinguish two different regimes for the determinants of interest rate exposure.

Table 3.10 reports the pooled OLS regression results for the model in Eq. (3.4) in a univariate setting. With regard to changes in 10-year yields, *NIM*, *CAP* and

CREDIT are again identified as those that provide greater information content for interest rate exposure. For the 1-year rate fluctuations, *NIM*, *OBSA* and *SIZE* appear as the key drivers of IRR. As far as 3-month rates goes, *NIM*, *CAP* and *OBSA* are the most important ratios in terms of explanatory power.

The values of the adjusted R² are always higher than the achieved in the regime switching model with zero threshold, supporting the appropriateness of the model with optimal threshold.

5.2.3.2 Multivariate analysis

Table 3.11 presents the optimal thresholds computed for the multivariate models estimated by pooled OLS. As stated above, the final multivariate models are selected on the basis of the information content of the bank variables. It is shown that the values of the optimal thresholds depend on the specific interest rate proxy considered. This is due to the fact that both the dependent and the explanatory variables included in the multivariate model are different in each case.

Similarly to the univariate analysis, the optimal thresholds are below zero in the great majority of cases, especially in the pre-euro period and when long-term rates are considered. Thus, the use of a threshold value different from zero may lead to multivariate models made up of different variables from those included in the previous model (see Table 3.12).

Table 3.12 presents the results of the pooled OLS estimation of the multivariate model in Eq. (3.4). Once again, *NIM* consistently emerges as the most important variable in terms of information content for interest rate exposure regardless of the sample period and the proxy for interest rates under consideration, showing an inverse relationship with IRR. In particular, the statistical significance and the magnitude (in

absolute value terms) of the coefficients on *NIM* are always greater for the subset of banks with more negative exposure. The ratios *SIZE*, *CREDIT* and *CIR* also seem to play a non-negligible role in explaining banks' IRR, although the sign of the effect of *CREDIT* and *CIR* is unclear.

In an attempt to gain better insight into the main factors influencing the degree of bank IRR, these results are complemented with those obtained by using both static and dynamic panel data estimation methods.

Table 3.13 provides the results of the estimation of the multivariate model in Eq. (3.5) using static panel data analysis. Once again, *NIM* becomes the most important variable to be taken into account, mostly for banks with higher negative interest rate exposure. Analogously to the previous results, there seems to be an inverse relationship between *NIM* and IRR, so that banking firms with greater *NIM* ratio have less exposure to IRR. In addition, *CREDIT* and *CIR* also exhibit, especially during the post-euro period, some explanatory power on interest rate exposure, although the sign of their impact is ambiguous. The Hausman test statistics are significant at the usual levels in the great majority of cases, indicating that the fixed effects models are generally more appropriate than the random effects ones.

As a further step, Eq. (3.6) is also estimated using a dynamic system GMM approach that incorporates a lagged dependent variable among the regressors. Moreover, we consider the possibility that some of the explanatory variables such as *NIM*, *NONINT* and *OBSA* are not strictly exogenous. To address this potential endogeneity issue, we use different lags of both levels and first-differences of those variables as instruments.

As reported in Table 3.14, the coefficient on the lagged dependent variable is statistically significant in all cases but one, confirming the persistent nature of banks'

interest rate exposure and so justifying the use of dynamic models. Hence, a proper specification of the model should include an autoregressive term of interest rate exposure. In this case, the variables that have greater explanatory ability for banks' IRR are mostly *NIM* and, playing a secondary role, *SIZE*, *CREDIT* and *OBSA*.

In order to ensure the consistency of the GMM estimator, two specification tests are employed. First, the test proposed by Arellano and Bond (1991) is used to check the absence of serial correlation in the residuals. Second, the validity of the instruments is assessed by means of the Hansen test of over-identifying restrictions, which is robust to heteroskedasticity and autocorrelation.

The results of the Hansen test clearly indicate no evidence of over-identifying restrictions in all the specifications, providing support for our choice of the set of instruments. On the other hand, the Arellano Bond test statistics AR(1) and AR(2) show that only correlation of first order is present, whereas there is not correlation of second order. Non-rejection of first-order autocorrelation is expected by construction and it is not critical for the validity of the model. In fact, inconsistency will be implied if second-order autocorrelation was present. Therefore, the results of the specification tests suggest that the system GMM estimator is suitable for this study.

Overall, it can be stated that the results of the multivariate models are qualitatively similar across the different specifications and estimation methods employed. Among the bank-specific characteristics, *NIM* appears indisputably as the variable that has much greater and consistent explanatory power for bank interest rate exposure. It is also found that the *CREDIT*, *SIZE*, *OBSA* and *CIR* ratios seem to have, although to a lesser extent, a remarkable influence on the degree of IRR.

The *CREDIT* ratio is identified as a variable with significant information content regarding bank interest rate exposure, mainly during the post-euro period. Thus, there

seems to exist a certain connection between credit risk and IRR, although the sign of this relationship is ambiguous. This finding may reflect the fact that banks' provisions for bad loans affect bank stock returns. The direction of this effect is, however, not uniform across all banking firms.

Bank size appears as an important determinant of interest rate exposure as well, being its influence mostly of negative sign and more evident during the pre-euro period. This inverse relationship between *SIZE* and IRR suggests that Spanish large banks benefit from economies of scale and greater diversification, and their easier access to capital markets allow them to be better able to reduce IRR. This finding is similar to that of Chaudhry et al. (2000).

There is also some evidence that the *OBSA* ratio exerts a certain influence on the extent of interest rate exposure. The coefficients on this variable generally indicate a positive linkage between *OBSA* and IRR. Hence, the market seems to perceive that the use of financial derivatives corresponds to greater bank IRR. This result is in line with that reported by Hirtle (1997), Choi and Elyasiani (2003) or Au Yong et al. (2009), providing support to the argument that Spanish banks use derivative positions for speculative purposes rather than for risk hedging purposes.

Additionally, the *CIR* ratio appears to have some information content about interest rate exposure. In particular, a negative association between this variable and IRR is observed in the dynamic model. This finding implies that more efficient banks may have opted for strategies that lead to higher IRR in their effort to achieve increased levels of efficiency.

With regard to the remaining variables, the *LIQ* ratio has little consistent information content about IRR compared to the previous bank-specific characteristics.

This result suggests that the level of liquid assets held by Spanish banks is not seen by the stock market as a key driver of the extent of their interest rate exposure.

The *CAP* and *ROAE* ratios do not appear to play an important role either in explaining IRR. On the one hand, Spanish banks are, in general, well capitalized and hold a large cushion of equity capital as a protection against possible losses caused by unexpected economic shocks. In fact, it is quite possible that there is not sufficient variation in the sample banks' equity capital ratio to identify a significant effect of this variable on IRR. Therefore, equity capital is not considered as a relevant explanatory factor of interest rate exposure consistently with the findings of Au Yong et al. (2009). On the other hand, the lack of information content of the *ROAE* ratio reinforces the previous finding that the impact of bank profitability on the level of IRR is fundamentally quantified through the variable *NIM*.

Interestingly, the *LOANS* ratio also appears as a poor indicator of bank IRR. This finding, contrary to the previous literature (e.g. Chaudhry et al., 2000; Fraser et al., 2002), may be attributed to the composition of the asset side of the balance sheet of Spanish banks. Specifically, the clear predominance of adjustable rate loans in recent years in the Spanish banking industry can cause that the expansion of the maturity mismatch between assets and liabilities typically associated to the increase in the weight of loans does not fulfil in this case. As a result, the share of loans is not perceived by the market forces as a key explanatory factor of IRR.

In addition, the *DDEPS* ratio is not found in any of the estimated multivariate models as a critical explanatory factor of IRR. Demand deposits are not generally used for the purpose of earning interest, but rather to make transactions, so that their weight on the liability side of the balance sheet should be relatively stable. In this context, it

may occur that there is not enough variation in the *DDEPS* ratio of Spanish banks to capture a relevant influence of this variable on the extent of IRR.

Likewise, all the estimated models show that the *NONINT* ratio is not a critical determinant of interest rate exposure either. This result, identical to that of Au Yong et al. (2009) for Asia-Pacific banks, suggests that the ability to generate non-interest income is not considered a relevant indicator of the overall level of IRR faced by Spanish banks, in spite of the increasing relative importance of non-interest income.

5.2.4. Principal component analysis.

To check the robustness of the previous results, a principal component analysis (PCA) is performed on the set of bank-specific characteristics under consideration. PCA permits to jointly take into account the information provided by the 11 original bank variables and generate orthogonal factors to examine the determinants of interest rate exposure.

The first step is to determine the number of principal components to be considered. As usual, only those factors whose eigenvalues are greater than one are kept in the analysis. In this case, the information contained in the set of bank-specific characteristics can be summarized by four factors for the entire sample period and three factors for each one of the pre- and post-euro periods, respectively. Additionally, and as discussed in Section 4.2.3, the varimax factor rotation method is used to enhance the interpretability of the factors.

Table 3.15 illustrates the results achieved. The first two columns show the eigenvalues of each relevant component and the cumulative proportion of variance explained. The remaining columns display two measures of the relative importance of each characteristic on each principal component. First, the factor loadings of each bank

characteristic on the corresponding principal component; and second, the adjusted R² obtained in the regression of each principal component run on each individual bank characteristic. If a bank characteristic shows a high factor loading on a specific principal component, the R² of the individual regression is expected to be also high. Numbers in bold show the greater (in absolute terms) factor loadings and adjusted R² for each principal component.

As it can be seen, PC₁ condenses the information regarding the *LOANS* and *OBSA* ratios, exhibiting positive relationship with the former and negative with the latter. Both relationships are consistent across the two sub-samples. Likewise, PC₂ shows a high positive correlation with *NIM* and *CAP* ratios. In turn, PC₃ has a positive correlation with the *CREDIT* ratio and negative with the *ROAE* ratio. Finally, PC₄ displays a strong positive association with the *SIZE* ratio.

The analysis by sub-periods is quite consistent with the results already provided. In fact, the factors show the same unambiguous item pattern than the obtained for the entire period. Thus, the two first principal components in the pre- and post-euro periods are linked to the same bank ratios already stated for the entire period (*LOANS* and *OBSA* for PC₁, and *NIM* and *CAP* for PC₂, respectively). The remaining principal component in each subperiod shows that the influence of the bank characteristics most linked to the third principal component for the entire sample period, *ROAE* and *CREDIT* ratios, is due on the pre-euro subperiod, whereas the influence of *SIZE* on the fourth principal component is due on the post-euro subperiod.

Table 3.16 presents the optimal thresholds computed for the multivariate models that use the first few principal components as explanatory variables of interest rate exposure. As expected, the values of the optimal thresholds are totally in line with those

obtained previously, being negative in all cases when the empirical duration used refer to 10- and 1-year interest rate changes.

Table 3.17 shows the results of the system GMM estimation of the regime switching model with optimal threshold that uses principal components as explanatory variables. PC_2 appears as the factor with greatest information content regarding bank IRR irrespective of the sample period and proxy of interest rates used. This result is totally consistent with those obtained in the previous analysis since PC_2 has a strong positive correlation with *NIM*. Obviously, the sign of the coefficient on PC_2 is the same than the one found for the coefficient on the *NIM* ratio, indicating a negative relationship between the value of this principal component and the degree of banks' IRR.

PC_1 shows a positive association with IRR. This result can be mainly due to the *OBSA* ratio, which is behind the information content of this component, since as we have seen before the *LIQ* ratio appears as a non relevant variable in explaining banks' IRR. In contrast, PC_3 and PC_4 have scant explanatory power for interest rate exposure.

6. Concluding remarks

This chapter provides a comprehensive analysis of the main factors influencing the degree of interest rate exposure of Spanish commercial banks over the period 1993-2007. With that aim, a large set of potentially relevant bank-specific characteristics representative of both traditional on-balance sheet and off-balance sheet activities is used. Unlike the previous body of research that has investigated the determinants of bank IRR applying pure cross-sectional regression, the present study employs various panel data estimation methods to control for unobserved individual heterogeneity and potential endogeneity of the explanatory variables.

The empirical analysis reveals several interesting findings. First, overall the Spanish banking industry exhibits a remarkable level of interest rate exposure during the sample period, although the effect of IRR seems to have weakened to a large extent after the launch of the euro. This lower bank IRR may be explained by the greater financial stability and the increasing availability of improved tools for managing IRR during this period. Consistently with the classical view of banks as borrowing short-term and lending long-term, the sign of the interest rate sensitivity is predominantly negative. However, an emerging pattern of positive interest rate exposure is detected during the post-euro era, indicating an important change in the response of bank stock returns to movements in interest rates. This distinctive feature of the Spanish banking industry can be attributed to two major reasons. On the one hand, the typical maturity mismatch between assets and liabilities has decreased substantially due to the combination of various recent trends with great acceptance in the Spanish banking market such as the massive utilization of adjustable rate products, the extraordinary growth of asset securitization or the widespread use of financial derivatives. On the other hand, the positive exposure may also reflect the strong pressure on bank margins coming from an environment of sharp downward trend in interest rates and fierce competition in force over the last years.

Second, it is shown that interest rate exposure varies in a systematic way with a number of bank-specific characteristics. Specifically, net interest margin is perceived by the stock market as the most important determinant of banks' IRR in terms of information content, with a negative impact on interest rate exposure. A possible explanation of this result could be related to the fact that the traditional intermediation business still accounts for the major part of the revenue of Spanish banking firms. Accordingly, it seems reasonable to expect that the evolution of the interest rate-related

business has a critical influence on the performance of bank stock returns. Hence, a wide net interest margin is interpreted as a good indicator of bank soundness, which reduces the market perception of bank risk in general and IRR in particular.

Moreover, credit risk, bank size, off-balance sheet activities, and efficiency also seem to exert, although to a lesser degree, a substantial influence on bank interest rate exposure.

While it is clear that credit risk, as measured by the ratio of loan loss provisions to total loans, is a relevant explanatory factor of IRR, the direction of its effect is ambiguous. In turn, interest rate exposure decreases with bank size, indicating that larger Spanish banks have taken advantage of economies of scale, greater diversification and better access to capital markets to lower their IRR. Instead, off-balance sheet activities appear to have a positive association with the level of interest rate exposure, suggesting that speculation rather than hedging is likely to be the primary motivation behind the usage of financial derivatives by Spanish banks. This finding highlights the importance that bank supervisors closely monitor and control the use of derivatives by banks given their role as a potential source of additional IRR. In addition, more efficient banks seem to exhibit higher exposure to IRR. This finding is consistent with the hypothesis that some banks may take greater risks in an attempt to improve their levels of efficiency.

Interestingly, the evidence obtained shows unequivocally that neither the proportion of demand deposits in total deposits nor the share of non-interest income in total income exert a significant influence on the stock market assessment of banks' interest rate exposure.

The understanding of the factors that pre-dispose banks to higher exposure to IRR may be particularly relevant for various agents. For bank managers, it is critical to

know the main sources of interest rate exposure in order to achieve the desired IRR profile using strategies based on the alteration of those relevant factors. For investors, who are concerned about the impact of changes in interest rates on the value of bank stocks, the identification of the determinants of IRR would be very useful for purposes of asset allocation and risk management. Finally, also for bank supervisors, primarily interested in guaranteeing the stability and safety of the banking system, the knowledge of the major drivers of interest rate exposure would be a great help to take suitable measures in their effort of avoiding excessive levels of such risk.

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Annex: Tables and Graphs

Table 3.1
List of Banks and Descriptive Statistics of Bank and Market Monthly Returns

Bank	Ticker	Obs.	Mean	Std. Deviation	Minimum	Maximum	Skewness	Kurtosis (excess)	JB
Banco Alicante	ALI	52	-0.0092	0.0479	-0.1884	0.1849	0.5969*	8.6710***	165.9943***
Banco Andalucía	AND	156	0.0087	0.0496	-0.0953	0.1935	0.9725***	2.3030***	59.0667***
Argentaria	ARG	73	0.0121	0.0782	-0.2472	0.1652	-0.5116*	0.4815	3.8899
Banco Atlántico	ATL	126	0.0071	0.0383	-0.1476	0.1362	0.3585	4.9933***	133.6020***
Banco Bilbao Vizcaya	BBV	85	0.0253	0.0904	-0.3642	0.2601	-1.1010***	4.8225***	99.5434***
Banco Bilbao Vizcaya Argentaria	BBVA	107	-0.0003	0.0802	-0.2807	0.2410	-0.3761	2.3007***	26.1234***
Banco Central Hispano	BCH	63	0.0192	0.0885	-0.3001	0.2602	0.20735	2.5929***	18.10079***
Bankinter	BKT	156	0.0104	0.0853	-0.2498	0.3357	0.0671	1.9236***	24.1689***
Banesto	BTO	156	0.0055	0.0765	-0.3382	0.2863	-0.6277***	5.8762***	234.6922***
Banco Valencia	BVA	156	0.0161	0.0551	-0.1484	0.2820	1.1442***	4.6443***	174.2461***
Banco de Castilla	CAS	156	0.0081	0.0582	-0.1432	0.2498	1.2029***	3.9863***	140.9161***
Banco Crédito Balear	CBL	156	0.0097	0.0541	-0.1757	0.2487	1.1013***	4.0982***	140.7067***
Banco Exterior	EXT	39	-0.0103	0.0374	-0.1217	0.1207	0.3197	4.5327***	34.0522***
Banco Galicia	GAL	156	0.0093	0.0501	-0.1335	0.2879	1.6647***	8.6645***	560.0389***
Banco Guipuzcoano	GUI	156	0.0120	0.0490	-0.1494	0.1703	0.7858***	2.0463***	43.2745***
Banco Herrero	HRR	83	0.0037	0.0709	-0.1599	0.2856	1.7762***	5.7098***	156.3964***
Banco Pastor	PAS	156	0.0137	0.0619	-0.1547	0.2485	0.6958***	2.0509***	39.9300***
Banco Popular Español	POP	156	0.0112	0.0615	-0.1982	0.1985	0.0750	1.4554***	13.9162***
Banco Sabadell	SAB	68	0.0064	0.0649	-0.2283	0.1296	-1.0410***	2.5505***	30.7147***
Banco Santander	SAN	75	0.0254	0.0835	-0.2434	0.2636	-0.6942**	2.1328***	20.2404***
Banco Santander Central Hispano	BSCH	116	-0.0014	0.0819	-0.2755	0.1852	-0.8029***	1.4047***	22.0023***
Banco de Vasconia	VAS	156	0.0134	0.0653	-0.1418	0.3548	2.1132***	8.0057***	532.7151***
Banco de Vitoria	VIT	50	-0.0037	0.0744	-0.1535	0.3434	2.1948***	9.1686***	215.2782***
Banco Zaragozano	ZRG	118	0.0147	0.0682	-0.1464	0.3095	1.5136***	4.8942***	162.8344***
Market Portfolio	IGBM	156	0.0116	0.0550	-0.1937	0.1530	-0.3290*	1.0784***	10.3751***

JB is the Jarque-Bera test for normality of returns. This statistic is distributed as chi-squared with two degrees of freedom. ***, ** and * represent significance at the 1%, 5% and 10%, respectively.

Table 3.2
Variables: Definitions, Expected Signs and Literature Review

Variables	Definitions	Database	Expected Sign	Literature Review
Panel A. Stage 1: OLS Regression				
Bank Stock Return (R_{it})	Monthly Stock Returns	Madrid Stock Exchange		Flanery and James (1984) Faff and Howard (1999) Fraser et al. (2002) Au Yong et al. (2009)
Market Portfolio Return (R_{mt})	Monthly Stock Returns	Madrid Stock Exchange		Flanery and James (1984) Faff and Howard (1999) Chaudhry et al. (2000) Fraser et al. (2002) Au Yong et al. (2009)
Short Term Interest Rate (I_t)	Monthly average yield on ten-year Spanish government bonds Monthly average one-year Euribor Monthly average three-month rate of the Spanish interbank market	Bank of Spain		Flanery and James (1984) Faff and Howard (1999) Fraser et al. (2002) Au Yong et al. (2009)
Panel B. Stage 2: Panel Data Regression				
NONINT	Non Interest Income / Total Income	Bankscope	+	Fraser et al. (2002) Au Yong et al. (2009) Drakos (2001)
CAP	Equity / Total Assets	Bankscope	-	Fraser et al. (2002) Saporoschenko (2002) Reichert and Shyu (2003) Au Yong et al. (2009)
SIZE	Ln (Assets)	Bankscope	?	Fraser et al. (2002) Saporoschenko (2002) Reichert and Shyu (2003) Au Yong et al. (2009)
DDEPS	Demand Deposits / Total Deposits	Bankscope	-	Fraser et al. (2002) Saporoschenko (2002)
LOANS	Loans/ Total Assets	Bankscope	+	Fraser et al. (2002) Reichert and Shyu (2003) Au Yong et al. (2009)
LIQ	Liquid Assets/Total Assets	Bankscope	-	Chaudhry et al. (2000) Reichert and Shyu (2003) Au Yong et al. (2009)
OBSA	Off-balance sheet activity / Total Assets	Bankscope	?	Reichert and Shyu (2003) Au Yong et al. (2009)
NIM	Net Interest Income / Total Assets	Bankscope	-	Reichert and Shyu (2003) Au Yong et al. (2009)
ROAE	Return on Average Equity	Bankscope	-	
CREDIT	Loan Loss Provisions / Total Loans	Bankscope	?	Reichert and Shyu (2003)
CIR	Cost to income ratio	Bankscope	?	

The symbol ? indicates that the predicted sign is indeterminate.

Table 3.3
Descriptive statistics of the bank-specific characteristics in pre-euro and post-euro periods

	Mean	Std. Deviation	Minimum	Maximum
Panel A: Entire sample period				
NONINT	151.6162	137.6629	-310.0000	1605.5560
CAP	7.8820	2.9365	3.5700	16.9000
SIZE	8.7447	2.4385	1.1300	13.6338
DDEPS	26.0989	12.8359	5.6526	77.8548
LOANS	63.9171	16.4627	33.4700	94.1000
LIQ	19.0122	14.8813	0.4520	59.4561
OBSA	11.2750	7.6348	2.6242	41.7847
NIM	3.0755	1.1926	1.0279	6.5163
ROAE	13.4222	7.1442	-51.0400	36.9600
CREDIT	0.6344	0.6906	-0.3190	9.0994
CIR	57.2481	13.1544	31.9400	109.6100
Panel B: Pre-Euro period				
NONINT	183.3803	194.4629	-310.0000	1605.5560
CAP	7.7951	3.0490	3.5700	16.9000
SIZE	8.4920	2.2479	1.8200	12.3655
DDEPS	23.0971	12.4475	5.6526	55.1896
LOANS	54.3881	11.5523	33.4700	81.5200
LIQ	25.4469	14.6665	2.5019	59.4561
OBSA	7.9217	3.0985	2.6242	16.6804
NIM	3.4212	1.3094	1.4063	6.5163
ROAE	11.7006	9.4007	-51.0400	36.9600
CREDIT	0.7712	0.9726	-0.3190	9.0994
CIR	63.6987	12.2829	42.2800	109.6100
Panel C: Post-Euro period				
NONINT	125.3982	45.0091	41.0488	310.3117
CAP	7.9537	2.8506	4.1900	16.1600
SIZE	8.9533	2.5755	1.1300	13.6338
DDEPS	28.5776	12.6298	6.8518	77.8548
LOANS	71.7823	15.7683	36.8300	94.1000
LIQ	13.7010	12.8674	0.4520	52.6722
OBSA	14.2556	9.1095	4.0686	41.7847
NIM	2.7902	1.0057	1.0279	5.2749
ROAE	14.8433	4.0229	5.9100	32.9800
CREDIT	0.5215	0.2566	0.0519	1.9833
CIR	51.9239	11.3797	31.9400	80.0100

Table 3.4
Correlation matrix of the bank characteristics

	NONINT	CAP	SIZE	DDEPS	LOANS	LIQ	OBSA	NIM	ROAE	CREDIT	CIR
NONINT											
CAP	-0.302										
SIZE	0.037	-0.230									
DDEPS	-0.266	0.590	-0.476								
LOANS	-0.318	0.527	-0.244	0.636							
LIQ	0.283	-0.522	0.272	-0.688	-0.840						
OBSA	-0.141	0.068	0.054	0.146	0.524	-0.437					
NIM	-0.248	0.795	-0.216	0.446	0.318	-0.324	-0.196				
ROAE	-0.217	0.264	0.013	0.244	0.280	-0.299	0.087	0.261			
CREDIT	0.013	-0.071	0.007	-0.092	-0.125	0.072	-0.072	0.145	-0.589		
CIR	0.444	-0.556	0.126	-0.433	-0.737	0.673	-0.428	-0.340	-0.528	0.168	

Table 3.5
Descriptive Statistics of the Estimated Sensitivity of Bank Stock Returns to Interest Rate Movements and Market Returns [Eq. (3.1)]

	Mean	S.D	Median	Maximum	Minimum	Positive	N. significant (*)	Negative	N. significant (*)	% significant	Obs.
Panel A- Entire sample period											
<i>10-year interest rate</i>											
θ	-2.7408	3.7881	-3.0872	9.8254	-10.829	43	7	177	76	37.73%	220
β	0.5604	0.3956	0.4283	1.6175	0.0006	220	169	0	0	76.82%	220
<i>1-year interest rate</i>											
θ	-1.2142	3.9421	-1.7086	15.0667	-13.9262	68	5	152	40	20.45%	220
β	0.5722	0.3991	0.4221	1.6294	0.0100	220	170	0	0	77.27%	220
<i>3-month interest rate</i>											
θ	-1.2028	4.8399	-0.9968	24.3771	-18.3989	70	6	150	34	18.18%	220
β	0.5756	0.3980	0.4327	1.6457	0.0128	220	176	0	0	80.00%	220
Panel B- Pre-Euro period											
<i>10-year interest rate</i>											
θ	-4.1005	2.3812	-4.2082	1.2905	-10.5166	3	0	97	67	67.00%	100
β	0.5873	0.3712	0.4878	1.4322	0.0006	100	81	0	0	81.00%	100
<i>1-year interest rate</i>											
θ	-2.5942	1.9793	-2.439	2.1243	-8.5962	8	0	92	35	35.00%	100
β	0.6101	0.3729	0.4894	1.4273	0.0195	100	83	0	0	83.00%	100
<i>3-month interest rate</i>											
θ	1.5784	2.006	-1.4404	4.6175	-9.9342	14	1	86	24	25.00%	100
β	0.6132	0.3715	0.5130	1.4313	0.0266	100	85	0	0	85.00%	100
Panel C- Post-Euro period											
<i>10-year interest rate</i>											
θ	-1.6076	4.3409	-1.5987	9.8254	-10.829	40	7	80	9	13.33%	120
β	0.5381	0.4151	0.3979	1.6175	0.0097	120	88	0	0	73.33%	120
<i>1-year interest rate</i>											
θ	-0.0642	4.7335	0.0016	15.0667	-13.9262	60	5	60	5	8.33%	120
β	0.5405	0.4187	0.3928	1.6294	0.0100	120	87	0	0	72.50%	120
<i>3-month interest rate</i>											
θ	-0.8898	6.2885	-0.3248	24.3771	-18.3989	56	10	64	5	12.50%	120
β	0.5443	0.4179	0.3844	1.6497	0.0128	120	91	0	0	75.83%	120

The coefficient estimates reported in this table are obtained from the augmented market model, i.e. Eq. (3.1). (*) The significance level to consider a coefficient as statistically significant has been 10%.

Table 3.6
Univariate analysis: model with the absolute value of the empirical durations as dependent variable

	Entire sample period		Pre-Euro period		Post-Euro period	
Panel A: Dependent variable $\theta_{i,t}^{10}$						
	γ_1	Adj R^2 (%)	γ_1	Adj R^2 (%)	γ_1	Adj R^2 (%)
NONINT	-0.0993	0.54	-0.2394**	4.83	0.1279	0.76
CAP	-0.0646	-0.03	0.0890	-0.21	-0.1795**	2.47
SIZE	-0.0548	-0.15	0.0241	-0.96	-0.0911	0.02
DDEPS	-0.0488	-0.22	-0.0130	-1.00	-0.0489	-0.60
LOANS	-0.0784	0.17	0.1120	0.20	-0.1156	0.56
LIQ	0.0206	-0.42	-0.0490	-0.78	0.0131	-0.83
OBSA	0.0273	-0.40	0.0060	-1.02	0.0780	-0.29
NIM	-0.0781	0.17	-0.0114	-1.01	-0.1922**	3.03
ROAE	0.0787	0.16	0.2310**	4.53	-0.1094	0.23
CREDIT	-0.0987	0.56	-0.1867*	2.62	-0.0287	-0.76
CIR	-0.0271	-0.38	-0.3349***	10.62	0.1348	0.94
Panel B: Dependent variable $\theta_{i,t}^1$						
	γ_1	Adj R^2 (%)	γ_1	Adj R^2 (%)	γ_1	Adj R^2 (%)
NONINT	-0.0223	-0.41	-0.0081	-1.01	0.0605	-0.49
CAP	-0.1349**	1.40	-0.1049	0.11	-0.1638*	1.92
SIZE	-0.0363	-0.32	-0.2178**	3.85	0.0166	-0.82
DDEPS	-0.0146	-0.44	-0.1263	0.54	-0.0180	-0.81
LOANS	0.0565	-0.13	-0.0586	-0.69	-0.0233	-0.79
LIQ	-0.1054	0.67	0.0054	-1.02	-0.0762	-0.25
OBSA	0.2649***	6.98	0.0787	-0.40	0.2606***	6.14
NIM	-0.2867***	8.02	-0.3055***	8.37	-0.2569***	6.09
ROAE	0.0241	-0.40	0.0114	-1.01	-0.0418	-0.69
CREDIT	-0.0866	0.32	-0.0619	-0.62	-0.1334	0.98
CIR	-0.0857	0.29	-0.1463	1.20	0.0554	-0.55
Panel C: Dependent variable $\theta_{i,t}^3$						
	γ_1	Adj R^2 (%)	γ_1	Adj R^2 (%)	γ_1	Adj R^2 (%)
NONINT	-0.0195	-0.42	0.0612	-0.64	0.1261	0.72
CAP	-0.1287***	1.24	-0.0955	-0.08	-0.1737*	2.26
SIZE	-0.0624	-0.06	-0.3043***	8.49	-0.0508	-0.58
DDEPS	0.0821	0.21	-0.1470	1.09	0.0611	-0.47
LOANS	0.1758***	2.71	-0.0789	-0.41	0.0259	-0.78
LIQ	-0.2219***	4.54	-0.0049	-1.02	-0.1558*	1.67
OBSA	0.2905***	9.25	-0.0530	-0.74	0.2203**	4.55
NIM	-0.3441***	11.75	-0.2998***	8.02	-0.3370***	11.08
ROAE	0.0398	-0.30	0.0683	-0.53	-0.1359	0.82
CREDIT	-0.1290*	1.28	-0.1456	1.19	-0.1285	0.85
CIR	-0.2207***	4.50	-0.1566	1.53	-0.0801	-0.22

This table shows the estimated interest rate exposure in the model with the absolute value of the empirical durations as dependent variable (univariate analysis). The model corresponding with equation (3.2) is formulated as follows:

$$|\hat{\theta}_{i,t}^h| = \gamma_0 + \gamma_j X_{j,i,t} + \varepsilon_{i,t} \quad \forall j = 1, \dots, J$$

for $t = 1, 2, \dots, T$, where T is the number of periods observed, and $i = 1, 2, \dots, N$, where N is the total number of banks analyzed. Subscripts i and t refer to bank i and at time t , respectively. $|\hat{\theta}_{i,t}^h|$ denotes the absolute value of bank i 's empirical duration for period t estimated in stage one and $h = 10, 1, 3$ for 10-year, 1-year and 3-month interest rate fluctuations, respectively. $X_{j,i,t}$ is the j th determinant of interest rate exposure of bank i at time t , and $\varepsilon_{i,t}$ is an error term. ***, ** and * represent significance at the 1%, 5% and 10% levels, respectively.

Table 3.7
Univariate analysis: Regime switching model with zero threshold

	Entire sample period				Pre-Euro period				Post-Euro period			
Panel A: Dependent variable $\theta_{i,t}^{10}$												
	λ_1	γ_j	$\gamma_j + \delta_j$	R^2 (%)	λ_1	γ_j	$\gamma_j + \delta_j$	R^2 (%)	λ_1	γ_j	$\gamma_j + \delta_j$	R^2 (%)
NONINT	-0.8045***	-0.0663	0.0822	55.55	-0.4124**	-0.1140	0.1945**	13.21	-0.4926***	0.2110*	-0.1583	60.94
CAP	-1.0466***	-0.2816**	0.1383	56.16	-0.2171	0.2271	-0.1035	9.28	-1.2216***	-0.2770**	0.2798**	62.16
SIZE	-0.7414***	0.0690	0.0601	55.42	-0.5190	-0.2876	0.01749	9.40	-0.8653***	0.0748	0.1607	61.04
DDEPS	-0.8701***	-0.1504	0.0245	55.41	-0.2889	0.2591	0.0282	9.47	-0.9256***	-0.1780*	0.0095	60.92
LOANS	-1.0498***	-0.2002*	0.1069	56.01	0.0226	0.4184	-0.2168	10.05	-1.2016***	-0.2383***	0.2119	62.38
LIQ	-0.6872***	0.2001	0.0389	55.91	-0.4790	-0.3673	0.0464	9.50	-0.7275***	0.2054**	0.1266*	62.46
OBSA	-0.8371***	-0.1767	-0.0492	55.22	0.0178	0.8013	-0.0772	9.34	-0.8886***	-0.2436*	-0.0671	62.01
NIM	-0.9397***	-0.1421	0.1431*	55.56	-0.2615	0.3739	0.0334	9.72	-1.1130***	-0.1431	0.2538**	61.33
ROAE	-0.4176***	0.3374*	-0.1341	55.92	-0.2442	0.3553	-0.2287**	13.93	-0.7498***	0.1204	0.1129	60.58
CREDIT	-0.6430***	0.4435**	0.0718	56.69	-0.3930***	-0.4033	0.2218**	13.86	-0.7609***	0.1272	0.1212	61.37
CIR	-0.6904***	0.1376	0.0464	56.03	-1.0743	-0.4641	0.5561	18.68	-0.3916	0.1920**	-0.2316	61.35
Panel B: Dependent variable $\theta_{i,t}^1$												
NONINT	-0.7162***	0.09451	0.00954	55.00	-0.3966	0.7124	0.0146	23.14	-0.6422***	0.0096	-0.1151	55.98
CAP	-1.0359***	-0.1639*	0.1915**	55.93	-0.3048	0.2768	0.0124	23.40	-1.0521***	-0.0975	0.2507*	56.98
SIZE	-0.5405***	0.1893*	-0.0292	56.08	-0.8938**	-0.1744	0.3716*	27.37	-0.5435**	0.1592	-0.0658	56.59
DDEPS	-0.7911***	-0.0599	-0.0103	55.08	-0.4576**	0.1554	0.1002	24.07	-0.7585***	-0.0658	-0.0638	56.17
LOANS	-0.6094***	0.0314	-0.1113	55.10	-0.6472	-0.0682	0.1114	23.10	-0.8209***	-0.0316	0.0402	55.79
LIQ	-0.8049***	0.0037	0.1035*	55.65	-0.6038***	-0.2416	0.0392	23.16	-0.8053***	0.0300	0.1304*	56.86
OBSA	-0.4846***	0.1798**	-0.2164***	57.45	-0.5262	-0.1043	-0.0547	23.33	-0.4816***	0.1224	-0.2692***	57.97
NIM	-1.2397***	-0.2352**	0.3894***	58.80	-0.8202**	-0.1704	0.3149**	28.36	-1.1895***	-0.1092	0.3819***	58.99
ROAE	-0.7034***	0.0287	-0.0267	54.97	-0.6206	-0.2793	-0.055	23.44	-0.7895***	0.0694	0.1171	56.38
CREDIT	-0.7434***	0.0918	0.0654	55.44	-0.5800***	-0.5998	0.1089	24.25	-0.9583***	0.0046	0.2513**	57.74
CIR	-0.9362***	-0.0212	0.1895	55.34	-0.3051	0.3309	0.0531	26.14	-0.5598*	0.0176	-0.1823	55.93

Panel C: Dependent variable $\theta_{i,t}^3$												
NONINT	-0.5335***	0.2621	-0.0019	39.39	-0.3696	1.0115	-0.0819	33.14	-0.3921*	0.0447	-0.2841*	48.04
CAP	-0.8855***	-0.1034	0.2068*	40.10	-0.6670**	-0.0275	0.0802	32.83	-1.0009***	-0.0282	0.3320**	49.15
SIZE	-0.4192*	0.2272**	0.0257	41.27	-0.7305*	0.1621	0.3462	40.07	-0.5339*	0.1708	0.0289	48.10
DDEPS	-0.5759***	-0.0503	-0.1314	40.08	-1.0277***	-0.5166*	0.1191	35.32	-0.6016***	-0.0149	-0.1202	47.05
LOANS	-0.2597	0.0110	-0.3978***	41.85	-1.8502***	-0.6964**	0.5686*	35.57	-0.6298**	-0.0157	-0.0799	49.26
LIQ	-0.7535***	0.0623	0.2582***	43.78	-0.2446***	0.8026*	-0.0461	35.57	-0.7750***	0.0491	0.2170**	49.90
OBSA	-0.3930***	0.0524	-0.3142***	46.64	-0.7255***	-0.1276	0.0428	32.73	-0.4790***	0.00005	-0.2676***	50.06
NIM	-1.2471***	-0.2320**	0.5318***	46.51	-1.1207***	-0.3039	0.3619***	37.70	-1.2464***	-0.1117	0.5408***	53.54
ROAE	-0.7643***	-0.1754	-0.0190	39.56	-0.9238***	-0.6397	-0.0559	34.39	-1.0107***	-0.0553	0.2837	47.47
CREDIT	-0.6999***	-0.0526	0.1164*	40.15	-0.6986**	-0.3658	0.1446*	34.52	-0.8749***	-0.0167	0.1926	47.68
CIR	-1.2607***	-0.1107	0.5894***	42.35	-0.0045	0.5065	-0.1482	37.18	-0.8878***	-0.0666	0.1287	46.89

This table shows the estimated interest rate exposure in the regime switching model with zero threshold (univariate analysis). The model corresponds with equation (3.3) in the particular case of each determinant j :

$$\theta_{i,t}^h = \lambda_0 + \lambda_1 D_{it} + \gamma_j X_{j,i,t} + \delta_j (D_{it} X_{j,i,t}) + \varepsilon_{i,t} \quad \forall j=1, \dots, J.$$

where D_{it} is a dummy variable that takes the value of 1 if the empirical duration estimate for bank i in period t is equal or less than zero and 0 otherwise. Thus, the parameter γ_j reflects the marginal impact of the j th bank-specific variable on the degree of interest rate exposure of banks with positive exposure, whereas $\gamma_j + \delta_j$ captures the marginal effect of the variable $X_{j,i,t}$ on IRR of banks with negative exposure. .***, ** and * represent significance at the 1%, 5% and 10% levels, respectively.

Table 3.8
Multivariate analysis: Regime switching model with zero threshold

		Entire sample period			Pre-Euro period			Post-Euro period		
		10-year interest rate	1-year interest rate	3-month interest rate	10-year interest rate	1-year interest rate	3-month interest rate	10-year interest rate	1-year interest rate	3-month interest rate
	λ_1	-0.0017	-0.7454**	-1.3315***	0.1918	-5.6936	1.0334	-0.7190**	-0.9886***	-1.3356***
NONINT	γ_1	-0.0059								
	$\gamma_1 + \delta_1$	0.0537								
CAP	γ_2						0.5356			
	$\gamma_2 + \delta_2$						0.4671***			
SIZE	γ_3		0.1734	0.1702	0.3923	-1.0531	0.6448*			0.1596
	$\gamma_3 + \delta_3$		0.0784	0.1533	-0.1975	0.7747*	0.0844			0.0044
LOANS	γ_4									
	$\gamma_4 + \delta_4$									
LIQ	γ_5		0.2331*	-0.0913				0.2140**		-0.0311
	$\gamma_5 + \delta_5$		-0.0666	0.2321***				0.1511**		0.2929***
OBSA	γ_6		-0.0452	-0.0305					0.0810	
	$\gamma_6 + \delta_6$		0.2154**	-0.1473**					-0.2852***	
NIM	γ_7		-0.2960**	-0.2174**	1.0887	-1.1396			-0.1202	-0.00926
	$\gamma_7 + \delta_7$		0.3664***	0.5763***	0.3497**	0.9734***			0.2284	0.6520***
ROAE	γ_8	0.5520**						0.1748	0.1091	
	$\gamma_8 + \delta_8$	-0.0078						0.1458	0.3244	
CREDIT	γ_9	0.3936*						0.0670		
	$\gamma_9 + \delta_9$	0.1146*						0.1308		

CIR	γ_{10}	0.2847**			0.5840***			-1.3229			1.0661**		
	$\gamma_{10} + \delta_{10}$	-0.0964			-			1.8068			-0.2990		
	Adj. R^2 (%)	58.27	61.23	56.23	28	49.03	51.70	66.43	60.23	59.57			
	<i>F</i> statistic	34.97	37.85	30.98	7.42	14.61	16.14	31.79	24.80	26.05			

This table shows the estimated interest rate exposure in the regime switching model with zero threshold (Multivariate analysis). The model corresponding with equation (3.3) is formulated as follows:

$$\hat{\theta}_{i,t}^h = \lambda_0 + \lambda_1 D_{it} + \sum_{j=1}^J \gamma_j X_{j,i,t} + \sum_{j=1}^J \delta_j (D_{it} X_{j,i,t}) + \varepsilon_{i,t}$$

where D_{it} is a dummy variable that takes the value of 1 if the empirical duration estimate for bank i in period t is equal or less than zero and 0 otherwise. Thus, the parameter γ_j reflects the marginal impact of the j th bank-specific variable on the degree of interest rate exposure of banks with positive exposure, whereas $\gamma_j + \delta_j$ captures the marginal effect of the variable $X_{j,i,t}$ on IRR of banks with negative exposure. . ***, ** and * represent significance at the 1%, 5% and 10% levels, respectively.

Table 3.9
Descriptive statistics of the optimal thresholds

	Mean	S.D	Median	Maximum	Minimum	Obs.
Panel A- Entire sample period						
<i>10 year interest rate</i>	-2.2790	0.0866	-2.2790	-2.1290	-2.3790	11
<i>1 year interest rate</i>	-0.2989	0.2483	-0.3762	0.1237	-0.5762	11
<i>3 month interest rate</i>	-4.0807	1.1044	-4.6989	-1.8989	-5.6989	11
Panel B- Pre-Euro period						
<i>10 year interest rate</i>	-3.9484	0.1055	-3.9666	-3.8166	-4.1666	11
<i>1 year interest rate</i>	-3.1826	0.3279	-3.0462	-2.7462	-3.6962	11
<i>3 month interest rate</i>	-1.8843	0.2098	-1.9843	-1.5343	-2.2343	11
Panel C- Post-Euro period						
<i>10 year interest rate</i>	-1.4381	0.6057	-1.5290	-0.4290	-2.3790	11
<i>1 year interest rate</i>	-0.4762	0.4189	-0.3762	0.2237	-1.0262	11
<i>3 month interest rate</i>	-2.4126	0.9644	-2.6990	-0.1489	-3.6490	11

Table 3.10
Univariate analysis: OLS estimation of regime switching model with optimal threshold

	Entire sample period				Pre-Euro period				Post-Euro period			
	Panel A: Dependent variable $\theta_{i,t}^{10}$											
	λ_1	γ_j	$\gamma_j + \delta_j$	R^2 (%)	λ_1	γ_j	$\gamma_j + \delta_j$	R^2 (%)	λ_1	γ_j	$\gamma_j + \delta_j$	R^2 (%)
NONINT	-0.8161***	-0.1348*	0.0591	61.55	-0.8016***	-0.0086	-0.0293	64.30	-0.6524***	0.1269	-0.0505	62.59
CAP	-1.0868***	-0.1978***	0.1574*	62.10	-0.8563***	0.0135	0.0630	64.41	-1.2220***	-0.2370***	0.2534**	64.93
SIZE	-0.8839***	0.0137	0.1166	61.08	-1.2553***	-0.0356	0.4553***	67.10	-1.0575***	-0.1004	0.1883	62.54
DEPS	-0.8358***	-0.0667	-0.0141	60.95	-0.8082***	-0.0029	-0.0076	64.27	-0.9237***	-0.1308	0.0289	62.44
LOANS	-0.7041***	0.0230	-0.0663	60.82	-1.1030***	-0.1174	0.2044	64.61	-1.1835***	-0.2213***	0.1847	63.47
LIQ	-0.8314***	-0.0130	0.0499	60.92	-0.8179***	0.0157	0.0254	64.29	-0.7640***	0.1411**	0.1152	63.66
OBSA	-0.6969***	0.0837	-0.0577	60.43	-0.6671***	0.0497	-0.1196	64.63	-0.9144***	-0.2495**	-0.0811	64.29
NIM	-0.1107***	-0.1578**	0.2366***	62.25	-1.0987***	-0.0463	0.2919**	66.09	-1.0963***	-0.0411	0.3045**	63.78
ROAE	-0.6328***	0.1476***	-0.0457	62.00	-0.8030***	-0.0632	-0.0554	64.61	-0.7215***	0.1250	0.0796	62.98
CREDIT	-0.8890***	-0.020	0.1204**	61.63	-0.9557***	0.0372	0.2387***	66.70	-0.7784***	0.1605**	0.1496	64.17
CIR	-1.1479***	-0.0948	0.2882*	61.48	-0.6889**	0.1130	0.02781	64.67	-0.5505**	0.1341*	-0.1257	62.99
	Panel B: Dependent variable $\theta_{i,t}^1$											
NONINT	-0.8439***	-0.1792**	0.0207	55.08	-0.7821***	-0.0596	-0.0037	53.99	-0.5471***	-0.0193	-0.2372	56.72
CAP	-1.0741***	-0.1766*	0.196**	55.99	-0.8060***	0.0998	0.1922	54.48	-1.0670***	-0.0893	0.2708*	57.19
SIZE	-0.5414***	0.2468***	0.0045	57.69	-1.4870***	-0.1007	0.7321***	61.10	-0.6026***	0.2054**	0.0339	58.36
DEPS	-0.7952***	-0.0812	-0.0510	55.23	-0.6718***	0.1417	0.0760	55.13	-0.7254***	-0.0884	-0.1258	56.75
LOANS	-0.5523***	0.0289	-0.1833	55.16	-1.0026***	0.0894	0.3573	55.78	-0.7955***	-0.0542	-0.0038	55.95
LIQ	-0.8329***	0.0057	0.1247**	55.78	-0.7241***	-0.1319	-0.1642	55.23	-0.8042***	0.0410	0.1415*	57.11
OBSA	-0.4844***	0.1966**	-0.2130***	57.50	-0.8234***	0.0236	0.1156	53.96	-0.4773***	0.1349	-0.2590***	57.86
NIM	-1.2934***	-0.2575***	0.3929***	58.88	-0.9904***	0.0889	0.3926***	57.93	-1.1678***	-0.0778	0.3930***	59.17
ROAE	-0.5113***	0.2231	-0.0749	55.22	-0.0507	0.0908	-0.6201***	57.60	-0.7773***	0.1356	0.1718	57.65
CREDIT	-0.7459***	0.1421	0.0622	55.50	-0.9806***	-0.1242*	0.1932*	58.13	-0.9570***	0.0046	0.2492**	57.74
CIR	-1.0439***	-0.0478	0.2702	55.35	-1.4199***	0.0393	0.7500**	55.04	-0.4358	0.0146	-0.3047	56.25

Panel C: Dependent variable $\theta_{i,t}^3$												
NONINT	-0.5735***	-0.0656	-0.1527	44.08	-0.7620***	-0.1331	0.0159	48.43	-0.3589*	0.0589	-0.3219*	52.80
CAP	-0.9615***	-0.0216	0.3055**	44.68	-0.5876***	0.2229**	0.0921	51.38	-1.1256***	-0.0761	0.3828***	54.25
SIZE	-0.4821***	0.1866***	0.0320	44.79	-1.3190***	0.1032	0.7723	61.03	-0.4761**	0.2205**	-0.0190	55.11
DEPS	-0.1598	0.0222	-0.4911***	45.39	-0.6789***	0.0173	-0.0065***	48.03	-0.6110***	-0.0528	-0.1704	53.24
LOANS	-0.1113	0.1352**	-0.4385**	45.37	-0.6038*	0.0964	-0.0016	48.67	-0.7680**	-0.0333	0.0179	52.40
LIQ	-0.8437***	-0.0786	0.1732**	45.94	-0.7720***	-0.0765	0.0076	48.37	-0.7763***	0.0521	0.1723**	53.59
OBSA	-0.3855***	0.2602***	-0.1347	43.51	-0.0277	0.0101	-0.6798***	51.16	-0.4870***	-0.0422	-0.2896***	51.47
NIM	-1.2176***	-0.1591**	0.4921***	47.04	-0.8799***	0.1077	0.3308**	52.20	-1.2450***	-0.1233	0.4718***	56.46
ROAE	-0.8236***	0.0726	0.2481	44.57	-0.5926***	0.0680	-0.0642	48.61	-0.8813***	-0.0141	0.1586	52.41
CREDIT	-0.6141***	-0.0260	-0.0719	43.62	-0.8971***	-0.0679	0.1928*	50.73	-0.6179***	0.0432	-0.0536	52.53
CIR	-0.7396***	-0.1522***	-0.0953	45.83	-0.5631***	-0.0571	-0.2436	49.16	-0.8487***	-0.0366	0.0981	52.53

This table shows the estimated interest rate exposure in the regime switching model with optimal threshold (univariate analysis). The model corresponding with equation (3.4) in the particular case of each determinant j :

$$\theta_{i,t}^h = \lambda_0 + \lambda_1 D_{it} + \gamma_j X_{j,i,t} + \delta_j (D_{it} X_{j,i,t}) + \varepsilon_{i,t}$$

where D_{it} is a dummy variable that takes the value of 1 if the empirical duration estimate for bank i in period t is equal or less than the optimal threshold, T^* , and 0 otherwise. ***, **, and * represent significance at the 1%, 5% and 10% levels, respectively.

Table 3.11
Optimal threshold T^* for the multivariate model

	Entire sample period	Pre-Euro period	Post-Euro period
<i>10-year interest rate</i>	-2.3790	-4.0666	-0.9290
<i>1-year interest rate</i>	-0.3762	-2.7462	-0.3762
<i>3-month interest rate</i>	-0.1489	-1.7343	0.9510

Table 3.12
Multivariate analysis: OLS estimation of regime switching model with optimal threshold

		Entire sample period			Pre-Euro period			Post-Euro period		
		<i>10-year interest rate</i>	<i>1-year interest rate</i>	<i>3-month interest rate</i>	<i>10-year interest rate</i>	<i>1-year interest rate</i>	<i>3-month interest rate</i>	<i>10-year interest rate</i>	<i>1-year interest rate</i>	<i>3-month interest rate</i>
	λ_1	-0.8265***	-0.6889**	-2.4811***	-1.8711***	-1.8989***	-1.7654***	-1.3224***	-1.0317***	-1.2106***
NONINT	γ_1	-0.0491		0.4677						
	$\gamma_1 + \delta_1$	0.0673		-0.0782						
CAP	γ_2							-0.1650		
	$\gamma_2 + \delta_2$							0.4220***		
SIZE	γ_3		0.2425***	0.1451	-0.1377	-0.1213	0.0695		0.1525	0.1321
	$\gamma_3 + \delta_3$		0.0991	0.1012	0.6538***	1.0064***	0.9062***		0.0690	0.0947
LOANS	γ_4		0.1822*							
	$\gamma_4 + \delta_4$		-0.1461							
LIQ	γ_5					-0.1351		0.0531		
	$\gamma_5 + \delta_5$					-0.3715**		0.1591**		

OBSA	γ_6	0.02515			0.0051				
	$\gamma_6 + \delta_6$	-0.1606**			-0.3016**				
NIM	γ_7	-0.2969***	-0.2405**	-0.1796	-0.0953	-0.0691	0.1264	-0.1182	-0.0286
	$\gamma_7 + \delta_7$	0.3289***	0.3952***	0.7374***	0.6232***	0.2712**	0.4761***	0.3778***	0.5342***
ROAE	γ_8	0.4380***						0.1393	
	$\gamma_8 + \delta_8$	-0.1059						0.0448	
CREDIT	γ_9	0.2847***						-0.0631	
	$\gamma_9 + \delta_9$	0.1838***						-0.00529	
CIR	γ_{10}							0.1567**	
	$\gamma_{10} + \delta_{10}$							0.1433	
Adj. R^2 (%)	66.15		62.94	56.92	71.52	67.03	66.14	66.93	61.23
<i>F</i> statistic	48.55***		40.63***	33.15***	36.51***	29.75***	28.62***	35.41***	27.85***
									52.66
									19.91***

This table shows the estimated interest rate exposure in the regime switching model with optimal threshold (Multivariate analysis). The model corresponding with equation (3.4) is formulated as follows:

$$\hat{\theta}_{i,t}^h = \lambda_0 + \lambda_1 D_{it} + \sum_{j=1}^J \gamma_j X_{j,i,t} + \sum_{j=1}^J \delta_j (D_{it} X_{j,i,t}) + \varepsilon_{i,t}$$

where D_{it} is a dummy variable that takes the value of 1 if the empirical duration estimate for bank i in period t is equal or less than the optimal threshold, T^* , and 0 otherwise. ***, ** and * represent significance at the 1%, 5% and 10% levels, respectively.

Table 3.13
Multivariate analysis: Estimation of regime switching model with optimal threshold and individual effects

		Entire sample period			Pre-Euro period			Post-Euro period		
		10-year interest rate	1-year interest rate	3-month interest rate	10-year interest rate	1-year interest rate	3-month interest rate	10-year interest rate	1-year interest rate	3-month interest rate
	λ_1	-0.6943***	-0.7894***	-2.4811***	-1.8952***	-0.6041	-1.0280	-1.1993***	-1.0298***	-1.2106***
NONINT	γ_1	0.0567		0.4677						
	$\gamma_1 + \delta_1$	-0.0103		-0.0782						
CAP	γ_2							-0.2948		
	$\gamma_2 + \delta_2$							0.2150		
SIZE	γ_3		0.5025	0.1451	-0.1888	-0.0765	1.3167		-0.1890	0.1321
	$\gamma_3 + \delta_3$		0.4615	0.1012	0.6153***	-0.3197	1.4967		-0.2925	0.0947
LOANS	γ_4		0.0586							
	$\gamma_4 + \delta_4$		-0.2072							
LIQ	γ_5					-0.2822**		0.1250		
	$\gamma_5 + \delta_5$					0.1306		0.2033**		
OBSA	γ_6		-0.1151		-0.0286					
	$\gamma_6 + \delta_6$		-0.3380***		-0.1982					
NIM	γ_7	-0.3961***	-0.5741***	-0.1796	-0.1829	-0.0234	-0.0568		-0.2187	-0.0286
	$\gamma_7 + \delta_7$	0.0626	0.1441	0.7374***	0.5558***	0.1541	0.2241		0.3666*	0.5342***
ROAE	γ_8	0.3999***						0.0194		
	$\gamma_8 + \delta_8$	0.00680						-0.0833		
CREDIT	γ_9	0.3313***					-0.00239	0.1602**		
	$\gamma_9 + \delta_9$	0.2899***					0.0368	0.2490**		

CIR	γ_{10}			-0.2945**					0.1697**	
	$\gamma_{10} + \delta_{10}$			1.2257***					0.2762	
<i>F statistic</i>	38.44***	36.51***	33.15***		10.70***	8.76**		23.34***	20.87***	19.91***
χ^2 statistic					150.38***					
R^2 (%)	63.81	42.07	56.92		73.11	38.56	30.72	63.40	47.49	52.66
<i>LM Test</i>	6.36**	6.10**	1.95		15.79***	11.84***	2.47	0.87	0.28	0.02
<i>F test fixed effects</i>	2.22**	2.88***	0.75		4.18***	3.57***	1.97**	1.91**	1.59*	1.17
<i>Hausman test</i>	52.96***	51.67***	7.81		7.03	92.41***	12.44*	37.03***	20.63***	18.73***

This table shows the estimated interest rate exposure in the regime switching model with optimal threshold and individual effects (Multivariate analysis). The model corresponding with equation (3.5) is formulated as follows:

$$\hat{\theta}_{i,t}^h = \lambda_0 + \lambda_1 D_{it} + \sum_{j=1}^J \gamma_j X_{j,i,t} + \sum_{j=1}^J \delta_j (D_{it} X_{j,i,t}) + \eta_i + v_{i,t}$$

The error term has two components: η_i , which captures the unobserved time-invariant heterogeneity across banks, and v_{it} , which is the time-variant error term.

Fixed and random effects models can be distinguished depending on the assumption about the unobserved individual heterogeneity. The fixed effects model assumes that the unobserved heterogeneity, η_i , is correlated with the explanatory variables. The within estimator considers the individual effects as time-invariant; it consists of subtracting from the observations of each individual the over time average of all the observations for that individual and then applying OLS on these transformed data. Random effects model assumes that the unobserved heterogeneity is uncorrelated with the explanatory variables, so that the individual effects can be considered as a random component of the error term. The random effects estimator is derived using feasible generalized least squares (FGLS). *LM test* is the Breusch-Pagan LM test for random effects for $Var(v_{i,t}) = 0$.

Hausman test contrast the null hypothesis that the coefficients estimated by the consistent fixed effects estimator are the same as the ones estimated by the efficient random effects estimator. Finally, ***, ** and * represent, as usual, significance at the 1%, 5% and 10% levels, respectively.

Table 3.14
Multivariate analysis: Dynamic panel-data estimation, two-step System GMM

		Entire sample period			Pre-Euro period			Post-Euro period		
		<i>10-year interest rate</i>	<i>1-year interest rate</i>	<i>3-month interest rate</i>	<i>10-year interest rate</i>	<i>1-year interest rate</i>	<i>3-month interest rate</i>	<i>10-year interest rate</i>	<i>1-year interest rate</i>	<i>3-month interest rate</i>
	λ_0	0.0471	0.0458	0.0358	0.0681	0.0509	-0.0495	0.1235**	0.0659	0.0119
	λ_1	-0.3687**	-0.6357**	-2.5547***	-2.4466**	-2.8387***	-2.4646***	-0.8870***	-1.3297**	-2.4547***
	λ_2	0.4405***	0.2673**	0.1606***	-0.3456**	-0.4195***	-0.4529**	0.2947**	0.1460	0.2457***
NONINT	γ_1	-0.0120		0.3567						
	$\gamma_1 + \delta_1$	0.0410		-0.0407						
CAP	γ_2							0.0163		
	$\gamma_2 + \delta_2$							0.4717***		
SIZE	γ_3		0.0201	0.0339	-0.3257	-0.3098	0.0832		0.0406	0.0146
	$\gamma_3 + \delta_3$		0.1873**	0.1924	0.7021**	1.1901**	1.3157**		0.2129	0.1820
LOANS	γ_4		0.1344							
	$\gamma_4 + \delta_4$		-0.0865							
LIQ	γ_5					-0.2280		0.1544		
	$\gamma_5 + \delta_5$					-0.3276		0.2448***		
OBSA	γ_6		0.1423***		-0.0881					
	$\gamma_6 + \delta_6$		-0.2042*		-0.4351**					
NIM	γ_7	-0.1908**	-0.1779	-0.1697	-0.2665	-0.2202	0.1575		-0.1228	-0.0798
	$\gamma_7 + \delta_7$	0.1571*	0.2555*	0.6849***	0.8425***	0.5781***	0.8767***		0.5490***	0.6853***
ROAE	γ_8	0.3621**							0.1644*	
	$\gamma_8 + \delta_8$	-0.0551							0.0717	

CREDIT	γ_9	0.2760**			-0.3284			0.0933**		
	$\gamma_9 + \delta_9$	0.1765			-0.3992*			0.0129		
CIR	γ_{10}	-0.2746						-0.0995		
	$\gamma_{10} + \delta_{10}$	1.1900**						1.0480**		
	<i>Obs.</i>	198	189	198	79	79	79	102	102	102
	<i>Number of groups</i>	22	22	22	21	21	21	16	16	16
	<i>F statistic</i>	129.77***	48.30***	98.34***	17.06***	15.75***	7.19***	149.60***	23.69***	18.77***
	<i>Hansen test χ^2</i>	6.41	10.72	13.74	2.96	9.49	14.50	4.26	7.58	3.97
	<i>p-value</i>	(0.844)	(0.467)	(0.248)	(0.399)	(0.577)	(0.206)	(0.641)	(0.270)	(0.681)
	<i>AR₁</i>	-2.53	-2.29	-2.48	-1.67	-1.56	-1.82	-2.17	-2.27	-1.87
	<i>p-value</i>	(0.011)	(0.022)	(0.013)	(0.096)	(0.118)	(0.069)	(0.030)	(0.023)	(0.062)
	<i>AR₂</i>	-0.84	-0.56	0.29	-0.81	-1.42	-0.98	0.80	-1.05	-0.86
	<i>p-value</i>	(0.400)	(0.576)	(0.775)	(0.417)	(0.154)	(0.325)	(0.421)	(0.293)	(0.390)

This table shows the estimated interest rate exposure with the two-step system GMM estimator and the robust adjustment for small samples proposed by Windmeijer (2005). According to the equation (3.6), the dynamic specification of the model for the determinants of interest rate exposure with optimal threshold takes the following form:

$$\hat{\theta}_{i,t}^h = \lambda_0 + \lambda_1 D_{it} + \lambda_2 \theta_{i,t-1} + \sum_{j=1}^J \gamma_j X_{j,i,t} + \sum_{j=1}^J \delta_j (D_{it} X_{j,i,t}) + \eta_i + v_{i,t}$$

where η_i is an unobserved time-invariant bank-specific term, and v_{it} is an error term. *Hansen test χ^2* is the overidentifying restrictions test statistic. Under the null hypothesis of joint validity of the full instrument set (instruments are exogenous) it is distributed as a chi-square. *AR₁* and *AR₂* are statistics of the Arellano and Bond test for the first and second-order serial correlation in the first-differenced residuals and they are asymptotically normally distributed. As usual, ***, **, and * represent significance at the 1%, 5% and 10% levels, respectively.

Table 3.15
Principal Component Analysis

Panel A: Entire sample period (1994-2006)													
	Eigenvalue	Cumulative Variance	Eigenvectors										
			NONINT	CAP	SIZE	DDEPS	LOANS	LIQ	OBSA	NIM	ROAE	CREDIT	CIR
PC1	3.3337	30.31%	-0.1810	0.1053	-0.0355	0.2249	0.4891	-0.4486	0.5513	-0.0801	0.0275	0.0238	-0.3901
Adj. R² (%)			18.10	30.55	5.18	42.63	85.59	78.58	46.66	7.89	11.88	1.16	68.08
PC2	2.3952	52.08%	-0.291	0.5011	-0.0059	0.1992	0.0217	-0.0570	-0.3657	0.6456	0.1388	0.1678	-0.1511
Adj. R² (%)			21.72	76.67	6.74	39.62	20.63	24.67	3.01	85.43	12.09	0.07	27.62
PC3	1.6605	67.18%	-0.0335	-0.0266	-0.0240	-0.0086	0.0042	-0.0287	0.0824	0.0365	-0.6515	0.7355	0.1518
Adj. R² (%)			1.03	4.62	-0.46	2.94	5.58	3.73	-0.03	0.37	79.11	79.39	18.01
PC4	1.3344	79.31%	-0.3809	-0.0264	0.7403	-0.4323	-0.0794	0.1617	0.1640	0.0016	0.1041	0.1199	-0.1865
Adj. R² (%)			5.75	7.63	75.69	44.50	7.71	14.02	1.47	5.42	-0.29	0.03	-0.46
Panel B: Pre Euro period (1994-1998)													
PC1	3.3264	30.24%	0.3384	0.2402	-0.4236	0.3731	0.3955	-0.4217	0.3847	0.1455	0.0149	0.0038	-0.0740
Adj. R² (%)			-0.51	58.91	43.46	71.81	75.11	77.02	27.1	46.22	7.27	-0.85	33.85
PC2	2.8234	55.91%	-0.6807	0.3094	0.1045	0.1547	0.1370	-0.1038	-0.1202	0.4043	0.1422	0.1449	-0.3968
Adj. R² (%)			48.61	65.05	8.56	48.14	46.62	42.5	0.96	69.15	22.02	-0.98	67.6
PC3	1.8591	72.81%	-0.1609	-0.0426	0.0022	-0.0354	-0.0172	0.0043	0.2713	0.0324	-0.6168	0.6886	0.2037
Adj. R² (%)			-0.98	5.43	-0.65	3.28	2.22	1.35	10.12	1.91	82.18	76.14	21.41
Panel C: Post Euro period (1999-2006)													
PC1	3.9702	36.09%	-0.3970	0.1772	0.0025	0.1244	0.4134	-0.4168	0.4283	0.0983	0.2395	-0.1303	-0.4283
Adj. R² (%)			65.85	38.89	1.61	23.29	80.3	73.39	29.12	25.88	16.44	3.07	70.53
PC2	2.1313	55.47%	-0.1292	0.4587	-0.0291	0.2163	0.0503	0.0228	-0.5341	0.5974	0.0759	0.2702	-0.0380
Adj. R² (%)			20.16	66.5	1.03	23.44	16.67	8.79	20.72	87.9	4.12	4.8	12.07
PC3	1.8699	72.47%	-0.1978	-0.0798	0.5812	-0.4849	-0.1813	0.1605	0.0456	0.0513	0.4207	0.3517	-0.1327
Adj. R² (%)			0.19	5.71	63.53	55.41	15.89	12.75	-0.87	-0.35	21.84	22.41	-0.83

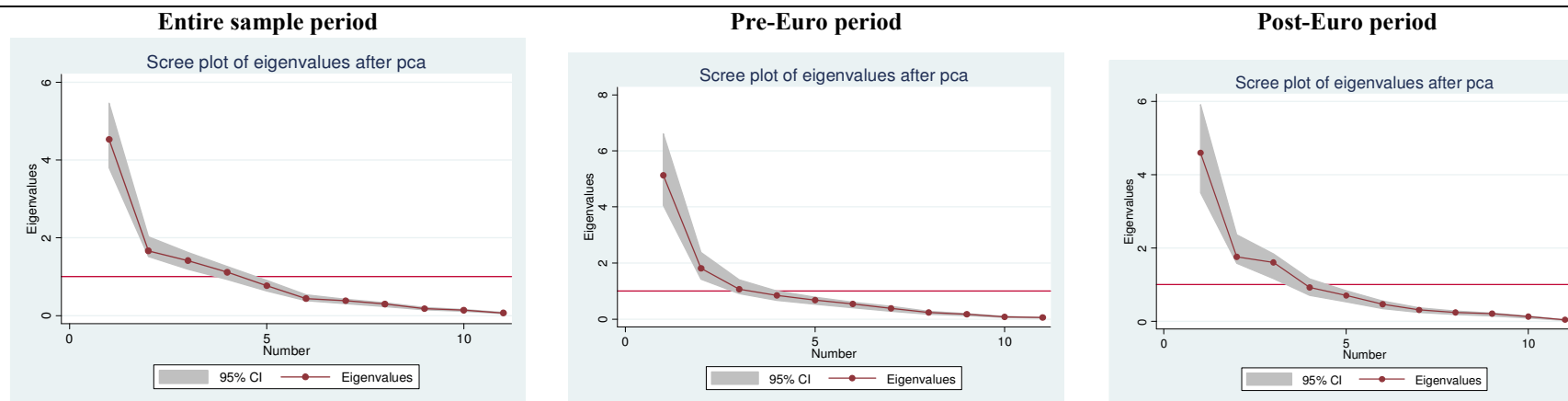


Table 3.16
Optimal threshold T^* for the model with principal components

	Entire sample period	Pre Euro period	Post Euro period
<i>10-year interest rate</i>	-2.3790	-4.3666	-0.4290
<i>1-year interest rate</i>	-0.3762	-3.3962	-0.3262
<i>3-month interest rate</i>	0.9510	-1.7343	0.9510

Table 3.17
Principal Components: Dynamic panel-data estimation, two-step System GMM

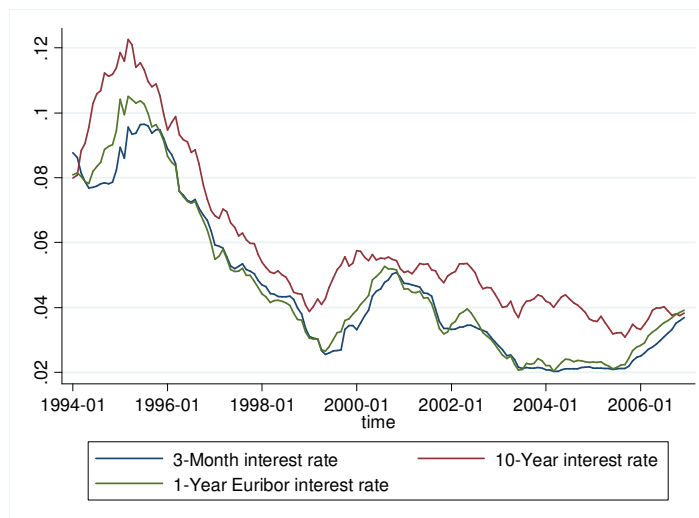
		Entire sample period			Pre-Euro period			Post-Euro period		
		10-year interest rate	1-year interest rate	3-month interest rate	10-year interest rate	1-year interest rate	3-month interest rate	10-year interest rate	1-year interest rate	3-month interest rate
	β_0	0.0316	0.0714	0.0519	-0.0585	-0.0629	0.0518	0.1984	0.0854	0.1613
	β_1	0.4157***	0.2613**	0.3705**	0.2496**	0.2991***	0.4772**	-0.2442*	-0.2104**	-0.5481*
	β_2	-0.5265***	-0.5293***	-0.2197***	-0.5526***	-0.4716***	-0.2563**	-0.8405***	-0.6330***	-0.2467**
PC1	γ_1	0.0946	0.2790***	0.4839**	0.1558	0.0892	0.07380	-0.5085	0.1127	0.2959
	$\gamma_1 + \delta_1$	-0.0453	-0.1294*	-0.2118	-0.1687	0.0472	-0.3831*	-0.1749	0.0578	-0.2690
PC2	γ_2	-0.1655*	-0.2600**	-0.0845	-0.4508**	-0.1988**	0.4442	0.0588	-0.0819	-0.2700
	$\gamma_2 + \delta_2$	0.0637	0.1351*	0.1559	0.0855	-0.0198	0.4224*	0.2399*	0.2405*	0.2942
PC3	γ_3	-0.3220	-0.1669	-0.0447	-0.5601*	-0.2981	0.1013	0.1109	0.2858	0.5841
	$\gamma_3 + \delta_3$	-0.1284	0.0827	0.0171	-0.2621	-0.0523	0.2379	0.1741	0.3120*	0.3330
PC4	γ_4	0.0709	0.0295	0.7079***						
	$\gamma_4 + \delta_4$	0.0978*	0.0439	0.0886						
	<i>Obs.</i>	189	189	189	79	79	79	93	93	93
	<i>Number of groups</i>	22	22	22	21	21	21	16	16	16
	<i>F statistic</i>	55.79***	64.94***	30.23***	21.67***	50.08***	4.76***	7.77***	7.02***	10.11***
	<i>Hansen test</i>	13.24	11.30	11.01	3.09	6.50	3.75	7.95	8.98	7.66
	<i>p-value</i>	(0.278)	(0.418)	(0.443)	(0.378)	(0.592)	(0.290)	(0.047)	(0.030)	(0.054)
	AR_1	-2.54	-2.22	-1.75	-2.13	-1.95	-2.14	-1.11	-0.63	0.91
	<i>p-value</i>	(0.011)	(0.026)	(0.081)	(0.033)	(0.051)	(0.033)	(0.268)	(0.527)	(0.364)
	AR_2	-1.98	-0.49	-1.42	0.96	-1.29	-1.03	-1.24	0.48	-0.98
	<i>p-value</i>	(0.048)	(0.625)	(0.156)	(0.338)	(0.197)	(0.303)	(0.216)	(0.628)	(0.325)

This table shows the estimated interest rate exposure with two-step system GMM estimator with the robust adjustment for small samples proposed by Windmeijer (2005). The model is estimated following the same procedure used for the regime switching with optimal threshold applied in Eqs. (3.4) to (3.6), but instead of using the original variables, their principal components for each of the different sample periods have been employed. The model to be estimated is as follows:

$$\hat{\theta}_{i,t}^h = \lambda_0 + \lambda_1 D_t + \lambda_2 \theta_{i,t-1} + \sum_{j=1}^J \gamma_j PC_{j,i,t} + \sum_{j=1}^J \delta_j (D_t PC_{j,i,t}) + \eta_i + v_{i,t}$$

where $PC_{j,i,t}$ denotes the value of the j th principal component of the bank-specific characteristics for bank i in period t . Note that J indicates the number of principal components of the model, which may be different for the various sample periods considered in the analysis. η_i is an unobserved time-invariant bank-specific term, and v_{it} is an error term. *Hansen test* χ^2 is the overidentifying restrictions test statistic. Under the null hypothesis of joint validity of the full instrument set (instruments are exogenous) it is distributed as a chi-square. AR_1 and AR_2 are statistics of the Arellano and Bond test for the first and second-order serial correlation in the first-differenced residuals and they are asymptotically normally distributed. As usual, ***, ** and * represent significance at the 1%, 5% and 10% levels, respectively.

Graph 3.1
Level of Interest Rates



Resumen*

El tema central de la presente tesis es el estudio del riesgo de interés en el sector bancario español. El trabajo se divide en tres capítulos en los cuales se analiza, respectivamente: (i) el impacto de las variaciones de los tipos de interés y su volatilidad condicional en la distribución de rendimientos de las acciones bancarias españolas; (ii) la utilización de diversas metodologías para calcular la exposición al riesgo de interés; y, por último, (iii) la identificación de los principales determinantes de la exposición al riesgo de interés en el sector bancario español.

A continuación se resumen los capítulos 2 y 3 de la tesis dado que son éstos los escritos en una lengua no oficial de la Universitat de València.

Capítulo 2: Sensibilidad lineal y no lineal del rendimiento de las acciones bancarias en España ante los cambios de los tipos de interés.

En la actualidad es generalmente aceptado que el riesgo de interés constituye una de las principales formas de riesgo que afectan a las entidades financieras debido a su peculiar naturaleza, pues las variaciones de los tipos de interés afectan directamente a los flujos de costes y de ingresos de las entidades bancarias. Además, el sustancial incremento de la volatilidad de los tipos de interés en los últimos años y el elevado nivel de endeudamiento financiero para muchas entidades constituyen factores adicionales que han contribuido a incrementar la relevancia que para las empresas tiene controlar la exposición al riesgo de interés.

* El presente resumen se ha realizado en cumplimiento de la Disposición Adicional cuarta de la Normativa reguladora de los procedimientos de elaboración, autorización, nombramiento del Tribunal, defensa y evaluación de las tesis doctorales de la Universitat de València, aprobada en Consejo de Gobierno el 6 de Junio de 2006.

Como se ha comentado ya en el primer capítulo de esta tesis, la influencia del riesgo de interés en el valor de una empresa ha sido objeto de gran número de trabajos a lo largo de las tres últimas décadas. La mayoría de los estudios empíricos siguen la metodología clásica consistente en la estimación del modelo lineal de dos factores propuesto por Stone (1974). Este modelo es una versión aumentada del modelo de mercado donde, además de los rendimientos de la cartera de mercado, como segundo factor se incluyen las variaciones de los tipos de interés en un intento de explicar de mejor manera la variabilidad de los rendimientos de las acciones. Este tipo de estudios se basan principalmente en empresas del sector financiero debido a la propia naturaleza del negocio bancario (Mansur y Elyasiani, 1995; Dinenis y Staikouras, 1998; Elyasiani y Mansur, 1998 y 2004; o Joseph y Vezos, 2006).

La mayor parte de estos trabajos documentan una relación negativa y significativa entre las variaciones de los tipos de interés y los rendimientos de las acciones bancarias, la cual es atribuida principalmente al tradicional desfase de vencimientos entre los activos y los pasivos financieros. Por lo tanto, tanto las ganancias como el resultado de una entidad se verán afectados negativamente en un entorno de tipos de interés en ascenso, puesto que el coste de los pasivos bancarios se incrementará más rápidamente que el rendimiento de sus activos. Además, en la línea de lo que señalan Faff y Howard (1999), Ryan y Worthington (2004), y Joseph y Vezos (2006) para otros mercados, en el caso español se constata que la sensibilidad de los rendimientos de las acciones bancarias a los tipos de interés ha disminuido con el tiempo sobre todo como consecuencia del desarrollo de mejores sistemas de medición y gestión del riesgo de interés.

Teniendo en cuenta que las fluctuaciones de los tipos de interés no sólo afectan a las expectativas sobre los flujos de caja esperados, sino también a las tasas de descuento empleadas para actualizar dichos flujos, podría ser interesante examinar si se puede identificar un componente no lineal significativo entre los tipos de interés y el valor de una empresa. En este sentido, como ocurre con los valores de renta fija, que presentan un perfil de exposición no lineal cuantificado a través del término de convexidad, las acciones bancarias podrían verse afectadas por cambios en los tipos de interés de una manera más compleja que la estrictamente lineal.

Además, también podría ser posible que la exposición al riesgo de interés tuviera un carácter asimétrico. Esta asimetría puede plasmarse en dos sentidos diferentes. En primer lugar, que variaciones de los tipos de interés de idéntica cuantía pero distinto signo provoquen diferentes efectos en valor absoluto sobre la sensibilidad de los rendimientos de las acciones bancarias (asimetría de signo). En segundo lugar, que las fluctuaciones grandes de los tipos de interés puedan tener en términos relativos un efecto diferente sobre el valor de la empresa a las fluctuaciones pequeñas de éstos (asimetría de tamaño o magnitud). Obviamente, en estos casos, los métodos tradicionales para medir la exposición lineal de los tipos de interés no serían los más adecuados.

Existen dos razones importantes por las que los modelos convencionales pueden no capturar con precisión la exposición al riesgo de interés o quizás detectar una falta de exposición al riesgo cuando ésta realmente existe. En primer lugar, utilizar la misma forma funcional para cada entidad puede ser restrictivo y potencialmente podría reflejar bajos niveles de exposición al riesgo de interés. Esto es especialmente cierto si las empresas difieren en la forma en que se ven afectadas por los movimientos de los tipos

de interés. De hecho, un argumento frecuente en la literatura es que el grado de exposición al riesgo depende de la empresa y características propias del sector. Y en segundo lugar, existe un gran número de trabajos sobre la exposición al riesgo de cambio que argumentan que la relación entre los tipos de cambio y los rendimientos de las acciones no sigue una forma funcional invariante en el tiempo. Esta idea puede ser extrapolada al caso de la exposición al riesgo de interés.

Siguiendo esta idea, en este capítulo se considera un enfoque no paramétrico para estimar la exposición al riesgo de interés que permita trabajar con una forma funcional específica para cada empresa y que, adicionalmente, ésta pueda cambiar en el tiempo.

Con todo, hay que destacar, sin embargo, que la suposición implícita sobre la exposición al riesgo de interés en la literatura es, con muy pocas excepciones, que el riesgo de interés tiene un efecto lineal. Así, mucha menor atención ha sido prestada a otras estructuras de posible riesgo de interés que no estén basadas en los supuestos de exposición uniforme, simétrica y lineal. De hecho, la mayoría de los estudios empíricos sobre la exposición de las empresas a riesgos macroeconómicos (como el de tipo de cambio, tipo de interés o el riesgo de inflación) que investigan la presencia de exposición no lineal o asimétrica se han centrado en el riesgo de cambio (véase, por ejemplo Di Iorio y Faff, 2000 Koutmos y Martin, 2003; y Bartram, 2004).

A pesar de lo comentado anteriormente, es posible encontrar algunos (si bien pocos) trabajos que presentan perfiles de exposición al riesgo de interés más complejos que el clásico lineal. En concreto, Chen y Chan (1989) estudian la posible existencia de efectos asimétricos en los rendimientos de las acciones de instituciones financieras de EE.UU. durante diferentes ciclos de tipos de interés. Sus resultados revelan una

asimetría significativa de los rendimientos de las acciones durante los ciclos alcistas y bajistas de los tipos de interés, lo que sugiere que dicha sensibilidad depende en gran medida del periodo muestral considerado. En esta línea, Hallerbach (1994) proporciona evidencia de una cierta no estacionariedad en las sensibilidades de los rendimientos de las acciones a los tipos de interés en el mercado holandés, y señala que un modelo no lineal podría ayudar a explicar la asimetría observada entre la sensibilidad a las subidas y bajadas de los tipos de interés. Por último, Bartram (2002) presenta evidencia empírica de la existencia de una significativa exposición lineal y no lineal respecto a diversos tipos de interés en el mercado alemán.

La medición de la exposición al riesgo de interés mediante modelos no paramétricos ha recibido, si cabe, mucha menos atención que los modelos no lineales y asimétricos. De hecho, según el conocimiento de los autores, no existe en la literatura sobre exposición de los rendimientos de las acciones al riesgo de interés ningún trabajo que utilice metodología no paramétrica. Hasta ahora, los únicos dos estudios que utilizan esta metodología se basan en analizar la exposición al riesgo de cambio (Gou y Wu, 1998 y Aysun y Guldi, 2009).

Por todo lo anterior, el principal objetivo de este capítulo es el análisis del impacto de riesgo de interés en el sector bancario español utilizando diversas metodologías; en particular, se examina el modelo lineal, no lineal, dos modelos asimétricos (de signo y magnitud) y un modelo no paramétrico. En todos los casos se trabaja tanto a nivel de acciones individuales como a nivel de carteras.

La base de datos utilizada está compuesta por series históricas de frecuencia diaria de precios bursátiles y de tipos de interés. En relación a los datos bursátiles, se han utilizado las series de precios de cierre diarios, ajustados por ampliaciones de

capital, splits y dividendos, de las acciones de todos los bancos negociados en el Sistema de Interconexión Bursátil Español (SIBE) durante el período muestral 1993-2008 (23 entidades en total) para calcular los rendimientos semanales de cada una de las acciones bancarias. A su vez, la cartera de mercado utilizada es el Índice General de la Bolsa de Madrid (IGBM). Todos los datos bursátiles proceden de Sociedad de Bolsas, S.A.

Respecto a los tipos de interés, se ha tomado, por un lado, el tanto interno de rendimiento medio semanal de las obligaciones del Estado a diez años negociadas en el mercado secundario de deuda pública anotada y por otro, la media semanal del tipo de interés a 1 año (Euribor) y a tres meses del mercado interbancario como variables representativas de los tipos a largo y a corto plazo, respectivamente. Estos datos han sido obtenidos de las series históricas de mercados financieros publicadas por el Banco de España.

Respecto a la metodología utilizada en este capítulo, ésta se divide en dos grupos de modelos estimados, los modelos paramétricos y no paramétricos. En los primeros se estima la exposición al riesgo de interés para cada una de las acciones y carteras bancarias con (i) un modelo lineal en los parámetros y variaciones de tipos de interés siguiendo la metodología tradicional, modelo de dos índices de Stone (1974); (ii) un modelo lineal en los parámetros pero no lineal respecto a las variaciones de tipos (concretamente empleando una función cúbica); (iii) un modelo asimétrico de signo, en el que se trata de observar el efecto diferencial del impacto de variaciones positivas y negativas de los tipos de interés sobre los rendimientos de las acciones y carteras bancarias; y (iv) un modelo asimétrico de tamaño o magnitud, que trata de diferenciar como afectan las variaciones de distinto tamaño de los tipos de interés (ya sean positivas

o negativas) a los rendimientos de las acciones. Respecto al segundo grupo, se estima un modelo no paramétrico siguiendo el método de regresión lineal local de Stone (1977).

Una vez se han estimado los diferentes modelos se estudian principalmente dos cuestiones. En primer lugar, se comparan los coeficientes estimados para la exposición al riesgo de interés con los distintos modelos en base a su signo y significatividad estadística. En segundo lugar, se observan las diferencias entre ellos en base al contenido informativo que proporciona cada uno a partir del estudio de la serie de residuos de cada modelo. Concretamente, se analizan los estadísticos descriptivos de las series de residuos estimadas, el nivel de correlación que existe tanto entre dichas series como entre ellas y cada una de las variables dependientes y, finalmente, se contrasta la igualdad de dichas series mediante el test de rangos de Wilcoxon.

La principal contribución de este capítulo es la de realizar un análisis completo de la exposición al riesgo de interés de las entidades bancarias utilizando un enfoque paramétrico (modelos lineal, no lineal y asimétrico) y no paramétrico tanto a nivel de entidades financieras como a nivel de carteras de acciones con el objetivo de explorar si existen entre los distintos modelos; (i) en cuanto a la sensibilidad de los rendimientos de las acciones y carteras bancarias a las variaciones de los tipos de interés y, (ii) en lo referente al contenido informativo de las variables explicativas en cada uno de ellos. Otra aportación ha sido examinar los efectos en la exposición al riesgo de interés en el sector bancario a raíz de la introducción del Euro.

Capítulo 3: Determinantes de la exposición al riesgo de interés del sector bancario español

La exposición al riesgo de interés por parte de las entidades financieras ha sido el objetivo de un gran número de trabajos a lo largo de estos últimos años. La aproximación más comúnmente utilizada ha sido estimar la sensibilidad de las variaciones en los precios de las acciones, normalmente usados para identificar el valor de una entidad bancaria, a las variaciones de los tipos de interés, controlando los movimientos del mercado (Lynge y Zumwalt, 1980; Madura y Zarruk, 1995; Dinenis y Staikouras, 1998; Faff y Howard, 1999). Por el contrario, existe mucha menos evidencia empírica sobre los factores que explican la sensibilidad a las variaciones de los tipos de interés entre bancos y en el tiempo (Flannery y James, 1984; Hirtle, 1997; Fraser et al., 2002; Au Yong et al., 2009).

Se pueden distinguir dos líneas principales de investigación en este sentido. Los trabajos iniciales que investigan los determinantes del riesgo de interés en el sector bancario utilizan como variable clave la diferencia de vencimientos, también llamada *maturity gap*, entre los activos y pasivos bancarios, para calcular la exposición al riesgo de interés de las entidades bancarias. En concreto, *maturity gap*, (la diferencia entre activos y pasivos que vencen o se reprecian al plazo de un año) es la variable más comúnmente empleada para medir el desequilibrio entre los vencimientos de los activos y pasivos bancarios.³⁴ El trabajo de Flannery y James (1984) proporciona evidencia empírica de que el desfase en el vencimiento entre activos y pasivos nominales de una entidad puede ser utilizado para explicar la variación en sección cruzada de la

³⁴ *Maturity gap* constituye el método clásico para cuantificar el riesgo de interés y está basado en comparar la variación potencial en el valor de los activos y pasivos en respuesta a los movimientos de los tipos de interés en intervalos relevantes predefinidos.

sensibilidad a los tipos de interés (*maturity mismatch hypothesis*). De esta manera, los bancos que llevan a cabo una transformación de vencimientos mayor tienen un mayor riesgo de interés y, en consecuencia, los rendimientos de sus acciones presentan una sensibilidad más alta a los tipos de interés. Este resultado ha sido confirmado en estudios posteriores como los de Brickley y James (1986), Yourougou (1990), Kwan (1991), y Akella y Greenbaum (1992).

Sin embargo, este enfoque presenta graves inconvenientes, dadas las conocidas limitaciones que poseen los indicadores de *gap* estáticos, junto con la dificultad de obtener medidas precisas y exactas, año a año para la mayoría de los bancos. Por esta razón, una alternativa interesante, que sin embargo ha recibido poca atención en la literatura, es examinar la relación entre el riesgo de interés estimado de cada entidad bancaria y un conjunto de características bancarias específicas que tengan un papel potencialmente importante en la explicación de dicha exposición al riesgo, como el tamaño, el capital social, la composición del balance o las actividades fuera de balance.

La evidencia empírica obtenida muestra que, en general, el nivel de riesgo de interés está relacionado sistemáticamente con algunas variables específicas bancarias, tales como el tamaño de la entidad, el ratio capital respecto de activo total, el ratio préstamos respecto de activo, depósitos a la vista respecto del total de depósitos, o el ratio de ingresos no financieros (que no forman parte del margen de intermediación) respecto de los ingresos totales.

La base de datos, como en el capítulo anterior, está formada por todos los bancos españoles que cotizan en el SIBE en el periodo 1993-2007. De acuerdo con el Banco de España, la banca comercial representa el 56% del activo del sector bancario español a finales de 2007. Se han utilizado las series de precios de cierre diarios de todos los

bancos para calcular los rendimientos mensuales de cada una de las acciones bancarias. Los datos bursátiles y el Índice General de la Bolsa de Madrid (IGBM) que se ha utilizado como aproximación a la cartera de mercado proceden de Sociedad de Bolsas, S.A.

Los tipos de interés utilizados, son los mismos que en el capítulo 2. Por un lado, se ha tomado el tanto interno de rendimiento medio semanal de las obligaciones del Estado a diez años negociadas en el mercado secundario de deuda pública anotada como representación de los tipos a largo plazo y por otro, la media semanal del tipo de interés a 1 año (Euribor) y a tres meses del mercado interbancario como variables representativas de los tipos a corto plazo. Estos datos han sido obtenidos de la base de datos del Banco de España.

En relación a los datos de las características específicas bancarias, se han tomado los datos consolidados a final de cada año de las cuentas de los balances y resultados de las entidades financieras de la base de datos Bankscope.

Siguiendo tanto la línea de trabajo habitual en la literatura como la intuición económica, se considera un elevado número de potenciales determinantes de la exposición al riesgo de interés. Estas características incluyen capital social, tamaño de la entidad, composición del balance, estructura de ingresos, actividades fuera de balance, rentabilidad, liquidez, riesgo de crédito y eficiencia.

La metodología empleada para identificar los principales determinantes de la exposición al riesgo de interés sigue un procedimiento que se desarrolla en dos etapas, de la misma manera que en Drakos (2001), Fraser et al. (2002), Saporoschenko (2002), o Au Yong et al. (2009). En la primera etapa se estima la exposición al riesgo de interés

para cada una de las entidades y en cada uno de los años de la muestra siguiendo el modelo lineal clásico de dos índices de Stone (1974). Siguiendo esta aproximación, el coeficiente estimado que acompaña a las variaciones de los tipos de interés, refleja la sensibilidad del rendimiento de las acciones bancarias a las variaciones esperadas de los tipos de interés, una vez controladas las variaciones de los rendimientos de la cartera de mercado. Este coeficiente puede ser interpretado como medida de la exposición al riesgo de interés de cada entidad y puede ser interpretado como estimación de la duración empírica de cada acción bancaria.³⁵

Y en la segunda etapa del análisis, se relacionan las duraciones empíricas estimadas en la etapa anterior con el conjunto de características bancarias que incluyen tanto actividades del balance como operaciones fuera de balance. Para estimar los determinantes de la exposición al riesgo de interés se han empleado diversas metodologías, examinando tanto modelos univariantes como multivariantes para la mayoría de los modelos que se proponen. El análisis univariante permite obtener una primera aproximación de la relación existente entre las duraciones empíricas y cada uno de los factores explicativos mientras que el análisis multivariante permite examinar la influencia de los potenciales determinantes de manera conjunta teniendo en cuenta las correlaciones existentes entre ellos y además, evita el sesgo de variables omitidas consustancial al análisis univariante.

Para llevar a cabo el análisis multivariante los potenciales determinantes del riesgo de interés son incluidos en el modelo atendiendo al contenido informativo de las variables. Es decir, partiendo de los resultados estimados en el análisis univariante, la

³⁵ En concreto, el concepto de duración, una medida de la sensibilidad de tipo de interés utilizado en valores de renta fija, se puede extender fácilmente a las acciones. Por tanto, la duración empírica de las acciones es un indicador de su grado de riesgo de interés y está basado en la relación histórica entre los rendimientos de las acciones y las variaciones de los tipos de interés.

primera variable incluida en el modelo será aquella que presente un mayor R^2 respecto a las duraciones de manera individual. De este modelo individual, se extrae la serie de residuos y se calculan las correlaciones entre dicha serie de residuos y el resto de potenciales determinantes del riesgo de interés y se incluye en el modelo, como segunda variable, aquella que presenta una correlación superior y suponga, por tanto, que dicha variable contiene contenido informativo para el modelo. El procedimiento se repite hasta que una nueva variable no contenga información nueva que no esté ya incluida en el modelo.

Las especificaciones propuestas son las que se exponen a continuación:

- i) Siguiendo la línea de trabajos anteriores, se examinan los determinantes del grado de exposición al riesgo de interés utilizando el valor absoluto de las duraciones empíricas estimadas como variable dependiente. El uso de los valores absolutos tiene como objetivo primordial el no incurrir en el llamado *efecto de confusión de signo*, ya que como las duraciones estimadas tienen signos tanto positivos como negativos, la interpretación de la exposición al riesgo de interés es diferente dependiendo del signo de la duración.
- ii) Dado que la especificación previa sólo tiene en cuenta la magnitud de la exposición al riesgo de interés, se propone un modelo de cambio de régimen que también considera el signo de dicha exposición mediante la introducción de una variable ficticia que discrimina si las duraciones empíricas estimadas son positivas o negativas con el objetivo de analizar si los determinantes del riesgo de interés son diferentes en función del signo de la duración estimada.
- iii) Un posible defecto del modelo anterior es que el umbral de cero elegido a priori no sea el umbral óptimo para distinguir entre dos regímenes de

exposición al riesgo de interés y, por tanto, no sea el modelo que mejor ajuste las duraciones empíricas en relación a dichas características. Para superar este inconveniente se plantea un modelo similar al anterior en el que se determina previamente el umbral óptimo para cada una de las características individuales así como para un modelo multivariante.

Se han utilizado distintos métodos de estimación para cada uno de los modelos propuestos. En primer lugar y a modo de referencia se estiman mediante MCO. Teniendo en cuenta que los datos constituyen un panel y que en este caso es necesario tener en cuenta la heterogeneidad inobservable existente en los datos, se estima un modelo con efectos. Dado que los modelos estáticos de datos de panel presentan el problema de no controlar la potencial endogeneidad de las variables explicativas y la posible persistencia en el tiempo del grado de exposición al riesgo de interés, se propone un modelo de datos de panel dinámico. Para ello, se utiliza un estimador de variables instrumentales, concretamente el estimador de método generalizado de momentos (MGM) desarrollado por Arellano y Bover (1995) y Blundell y Bond (1998).

Las especificaciones de los modelos y las distintas metodologías de estimación anteriormente mencionadas se han aplicado sobre las características bancarias originales así como sobre sus componentes principales, aunque en este último caso sólo se presentan algunos de los resultados más importantes.

Este estudio contribuye a la literatura existente de tres formas. En primer lugar, según el conocimiento de los autores, éste es el primer trabajo que analiza específicamente los determinantes de la exposición al riesgo de interés en el sector bancario español. De hecho, la mayoría de los trabajos se han centrado en países con un alto nivel de desarrollo, principalmente EE.UU. y sólo más recientemente Alemania,

Japón o Australia. En segundo lugar, se aplican técnicas de estimación de datos de panel en lugar del clásico enfoque de regresión con datos de sección cruzada. En concreto, se estiman diversos modelos de datos de panel para identificar los principales factores explicativos del grado de exposición al riesgo de interés. Al respecto, destaca el estimador basado en el método generalizado de momentos (MGM) para datos de panel dinámicos propuesto por Arellano y Bover (1995) y Blundell y Bond (1998), que tiene en cuenta la potencial endogeneidad y la heterogeneidad no observable de los datos así como la persistencia de la variable dependiente. En tercer lugar, se considera un número de características bancarias más amplio que el utilizado en otros trabajos, incluyendo no sólo las tradicionales actividades dentro de balance sino también las operaciones fuera de balance.

Una cuestión abordada en los tres capítulos de la presente tesis hace referencia a si la introducción del euro como moneda única a partir de enero de 1999 ha tenido un efecto significativo sobre el grado de sensibilidad del rendimiento de las acciones bancarias ante las variaciones de los tipos de interés. Dado que el sector bancario español ha experimentado una profunda transformación durante las dos últimas décadas, caracterizada por un intenso proceso de desregulación, liberalización y consolidación que ha llevado aparejado un fuerte aumento de la competencia, este sector ofrece un marco muy interesante para explorar si la introducción del euro, con sus implicaciones en términos de una mayor estabilidad financiera inducida por una política monetaria común y de unos mercados financieros más amplios y profundos, ha afectado a la naturaleza y magnitud de la exposición al riesgo de interés de las entidades financieras.

Conclusiones

En la presente tesis se han aplicado diferentes técnicas econométricas para analizar diversas cuestiones relacionadas con el riesgo de tipo de interés. En particular, los tres temas centrales son: (1) la influencia del impacto de las variaciones de los tipos de interés y su volatilidad condicional sobre la distribución de rendimientos de las acciones bancarias españolas; (2) el cálculo de la sensibilidad a las variaciones de los tipos de interés mediante distintos modelos paramétricos y un modelo no paramétrico y (3) la identificación de los factores o características específicas bancarias más importantes de la exposición al riesgo de interés en el sector bancario español.

El análisis empírico efectuado en los dos capítulos revela algunos resultados interesantes. El sector bancario español en su conjunto presenta un notable grado de exposición al riesgo de interés durante el período muestral, si bien es cierto que la influencia del riesgo de interés parece haberse debilitado sustancialmente tras la introducción del euro. Esta menor exposición de las entidades bancarias al riesgo de interés puede tener su origen en la mayor estabilidad financiera y la creciente disponibilidad de mejores herramientas para la gestión del riesgo de interés a partir de la entrada del euro. En consonancia con la visión clásica de los bancos como tomadores de fondos a corto plazo y prestamistas a largo plazo, el signo de la sensibilidad del rendimiento de las acciones bancarias ante los cambios de los tipos de interés es predominantemente negativo. No obstante, un patrón de exposición positiva al riesgo de interés es detectado durante el periodo posterior a la introducción del euro, lo que sugiere un cambio importante en la respuesta del rendimiento de las acciones bancarias ante los movimientos de los tipos de interés. Este rasgo distintivo de la industria bancaria española puede ser atribuido a dos razones básicas. Por un lado, el tradicional

desequilibrio de vencimientos entre activos y pasivos bancarios ha disminuido considerablemente debido a la combinación de varias tendencias recientes con gran aceptación en el mercado bancario español, tales como la utilización masiva de productos indexados, el extraordinario crecimiento de la titulización de activos o el uso generalizado de los derivados financieros. Por otro, la exposición positiva al riesgo de interés puede reflejar también la fuerte presión sobre los márgenes bancarios en un contexto de marcada tendencia bajista de los tipos de interés y de fuerte competencia como el vigente en los últimos años.

Centrándonos específicamente en los resultados obtenidos en el segundo capítulo, se observa que el perfil no lineal de exposición al riesgo de interés es económicamente más importante que la exposición lineal. Este resultado puede tener importantes consecuencias prácticas en términos de gestión del riesgo de interés.

Con respecto a los modelos asimétricos se constata la no existencia de asimetrías de tamaño en el impacto de los cambios de los tipos de interés sobre el rendimiento de las acciones bancarias para el período muestral completo. El análisis por subperíodos, no obstante, sí revela algunas asimetrías de tamaño, si bien únicamente para el caso de los bancos de mayor tamaño durante el período anterior a la introducción del euro. Este resultado obedece al hecho de que tanto el nivel como la variabilidad de los tipos de interés son mucho más altos durante el período anterior que posterior a la introducción del euro (debido al proceso de convergencia de los tipos de interés), es más probable, por tanto, que exista una asimetría en la sensibilidad del rendimiento de las acciones bancarias.

Los coeficientes de exposición al riesgo de interés obtenidos con el modelo no paramétrico son muy similares a los del modelo paramétrico lineal. Sin embargo, las

desviaciones estándar de los estimadores son mucho más bajas en el caso no paramétrico, lo que confiere una mayor fiabilidad en relación al verdadero valor y a la significatividad estadística de los coeficientes estimados.

Comparando las series de residuos resultantes de los modelos paramétricos estimados, el modelo con mayor poder explicativo es en la mayoría de los casos el modelo asimétrico de tamaño, independientemente de la cartera y de la proxy de tipo de interés considerados.

Analizando las diferencias entre períodos muestrales, se observa que, con independencia del modelo considerado, la desviación estándar de los residuos y la correlación entre éstos y los rendimientos de las carteras son más altas en el periodo post-euro. Estos resultados confirman que el ajuste de los modelos es mejor en el período previo a la introducción del euro.

Finalmente, las series de residuos obtenidas con los modelos paramétricos son estadísticamente diferentes entre sí. De esta forma, a pesar de que los coeficientes de correlación entre dichas series son muy altos, las variables explicativas consideradas en los cuatro modelos paramétricos parecen no tener el mismo contenido informativo acerca de la variabilidad del rendimiento de las carteras bancarias.

En relación a los resultados específicos del tercer capítulo, se constata que la exposición al riesgo de interés varía de forma sistemática con varias características bancarias. En concreto, el margen de intermediación es percibido por el mercado como el determinante más importante del riesgo de interés bancario en términos de contenido informativo, existiendo una relación negativa entre el margen de intermediación y el grado de exposición al riesgo de interés. Una posible explicación de este resultado

podría estar relacionada con el hecho de que el tradicional negocio de intermediación bancaria representa todavía la principal fuente de ingresos de las entidades bancarias españolas. Así pues, parece razonable esperar que la evolución del negocio bancario relacionado con los tipos de interés tenga una influencia crítica sobre el rendimiento de las acciones bancarias. Por lo tanto, un amplio margen de intermediación es interpretado como un indicador de solidez bancaria, de forma que reduce la percepción en el mercado del riesgo bancario en general y, del riesgo de interés en particular.

Asimismo, el riesgo de crédito, el tamaño de las entidades, las operaciones fuera de balance y la eficiencia, también tiene aunque en menor grado, un efecto significativo sobre el grado de exposición al riesgo de interés de las entidades financieras.

El riesgo de crédito, medido por el ratio de provisiones por pérdidas en préstamos sobre préstamos totales, es un factor explicativo relevante de la exposición al riesgo de interés, aunque el signo de su influencia es ambiguo. A su vez, el grado de exposición al riesgo de interés disminuye con el tamaño bancario, lo que indica que los grandes bancos españoles han aprovechado las economías de escala, su mayor diversificación y su mejor acceso a los mercados de capital para reducir su nivel de riesgo de interés. En cambio, las operaciones fuera de balance parecen tener una relación positiva con el nivel de de exposición al riesgo de interés, lo que sugiere que la principal motivación subyace al uso de derivados financieros por parte de los bancos españoles es la especulación antes que la cobertura. Este resultado pone de relieve la importancia para los supervisores bancarios de vigilar y controlar el uso de derivados por parte de los bancos, dado su papel como potencial fuente adicional de riesgo de interés. Además, los bancos más eficientes parecen mostrar una mayor exposición a al riesgo de interés. Este resultado es consistente con la hipótesis de que algunos bancos

pueden asumir mayores niveles de riesgo en un intento de mejorar sus niveles de eficiencia.

Asimismo, la evidencia obtenida muestra claramente que ni el ratio de depósitos a la vista sobre depósitos totales ni el ratio de ingresos no financieros sobre ingresos totales ejercen una influencia significativa sobre la exposición bancaria al riesgo de interés.

La adecuada comparación de la exposición al riesgo de interés así como la identificación de los factores que predisponen a las entidades bancarias a un mayor nivel de exposición al riesgo de interés puede ser particularmente relevante para diversos agentes. Para los gestores bancarios es esencial conocer las principales fuentes de exposición al riesgo de interés con el fin de alcanzar el perfil de riesgo deseado mediante estrategias basadas en la alteración de estos factores clave. Para los inversores, preocupados por el impacto de las variaciones de los tipos de interés sobre el valor de las acciones bancarias, la identificación de los determinantes resultaría muy útil a efectos de asignación de activos y gestión de riesgos. Por último, para los supervisores bancarios, básicamente interesados en garantizar la estabilidad y la seguridad del sistema bancario, el conocimiento de los principales determinantes de la exposición al riesgo de interés puede ser de gran ayuda de cara a tomar las medidas adecuadas en su esfuerzo por evitar excesivos niveles de dicho riesgo.

References

- Akella, S.R. and Greenbaum, S.I. (1992): "Innovations in interest rates, duration transformation and bank stock returns". *Journal of Money, Credit and Banking*, 24, 27-42.
- Akella, S. R. and Chen, S. J. (1990): "Interest Rate Sensitivity of Bank Stock Returns: Specification Effects and Structural Changes". *Journal of Financial Research* 13 (2): 147-154.
- Amigo, L. and Rodríguez, F. (2007): "Alteraciones en el comportamiento bursátil de las acciones de empresas tecnológicas inducidas por el vencimiento de derivados". *Revista Española de Financiación y Contabilidad* XXXVI (133): 123-146.
- Amor, B. Tascón, M.T. and Fanjul, J.L. (2008): "Factores determinantes de la rentabilidad anormal de los bancos de la OCDE". *Revista Española de Financiación y Contabilidad* XXXVII (139): 469-499.
- Arellano, M. and Bover, O. (1995): "Another look at the instrumental variable estimation of error-components models". *Journal of Econometrics*, 68, 29-52.
- Au Yong, H.H., Faff, R. and Chalmers, K. (2009): "Derivative activities and Asia-Pacific banks' interest rate and exchange rate exposures". *Journal of International Financial Markets, Institutions and Money*, 19, 16-32.
- Aysun, U. and Guldi, M. (2009): "Exchange rate exposure: A nonparametric approach". Working Paper 2009-18.
- Baillie, R.T. and DeGennaro, R.P. (1990) : "Stock Returns and Volatility". *Journal of Financial and Quantitative Analysis* 25 (2): 203-214.
- Baltagi, B. (2001): *Econometric Analysis of Panel Data*. John Wiley & Sons. United Kingdom.
- Bartram, S.M. (2002): "The Interest Rate Exposure of Nonfinancial Corporations". *European Finance Review*, 6, 101-125.

- Bartram, S.M. (2004): "Linear and nonlinear foreign exchange rate exposures of German Nonfinancial Corporations". *Journal of International Money and Finance*, Vol 23, No 4, pp. 673-699.
- Benink, H. and C. Wolff (2000): "Survey Data and the Interest Rate Sensitivity of US Bank Stock Returns". *Economic Notes*, 29 (2): 201-213.
- Bollerslev, T. (1986): "Generalized Autoregressive Conditional Heteroscedasticity". *Journal of Econometrics* 31 (3): 307-327.
- Blundell, R. and Bond, S. (1998): "Initial conditions and moment restrictions in dynamic panel data models". *Journal of Econometrics*, 87, 115-143.
- Brewer, E., Jackson, W.E. and Moser, J.T. (2001): "The value of using interest rate derivatives to manage risk at U.S. banking organizations". *Economic Perspectives*, 3Q/2001, 49-66.
- Brewer, E. Carson, J.M. Elyasiani, E. Mansur, I. and Scott, W.L. (2007): "Interest Rate Risk and Equity Values of Life Insurance Companies: A GARCH-M Model". *Journal of Risk and Insurance* 74 (2): 401-423.
- Brickley, J.A. and James, C.M. (1986): "Access to deposit insurance, insolvency rules and the stock returns of financial institutions". *Journal of Financial Economics*, 16, 345-371.
- Campbell, J.Y. and Hentschel, L. (1992): "No News is Good News: An Asymmetric Model of Changing Volatility in Stocks Returns". *Journal of Financial Economics* 31 (2): 281-318.
- Catarineu, E. and Pérez, D. (2008): "La titulización de activos por parte de las entidades de crédito: el modelo español en el contexto internacional y su tratamiento desde el punto de vista de la regulación prudencial". *Estabilidad Financiera*. Banco de España. *Estabilidad Financiera*, 14, 87-121.
- Chaudhry, M.K., Christie-David, R., Koch, T.W., and Reichert, A.K. (2000): "The risk of foreign currency contingent claims at US commercial banks". *Journal of Banking and Finance*, 24, 1399-1417.
- Chen, C.R. and Chan, A. (1989): "Interest rate sensitivity, asymmetry, and the stock returns of financial institutions", *Financial Review*, Vol 24, No 3, pp. 457-473.

- Choi, J.J. and Elyasiani, E. (1997): "Derivative exposure and the interest rate and exchange rate risks of U.S. banks". *Journal of Financial Services Research*, 12, 267-286.
- Czaja, M., Scholz, H., and Wilkens, M. (2009): "Interest Rate Risk of German Financial Institutions: The Impact of Level, Slope, and Curvature of the Term Structure". *Review of Quantitative Finance and Accounting*, 33, 1-26.
- Czaja, M., Scholz, H., and Wilkens, M. (2010): "Interest Rate Risk Rewards in Stock Returns of Financial Corporations: Evidence from Germany". *European Financial Management*, 22, 124-155.
- Diamond, D.W. (1984): "Financial intermediation and delegated monitoring". *Review of Economic Studies*, 51, 393-414.
- Di Iorio, A. and Faff, R.W. (2000): "An analysis of asymmetry in foreign currency exposure of the Australian equities market", *Journal of Multinational Financial Management*, Vol 10, No 2, pp. 133-159.
- Dinenis, E. and Staikouras, S.K. (1998): "Interest rate changes and common stock returns of financial institutions: evidence from the UK". *European Journal of Finance*, 2, 113-127.
- Deshmukh, S.D. Greenbaum, S.I. and Kanatas, G. (1983): "Interest Rate Uncertainty and the Financial Intermediary's Choice of Exposure". *Journal of Finance* 38 (1): 141-147.
- Drakos, K. (2001): "Interest rate risk and bank common stock returns: Evidence from the Greek Banking sector". *Working Paper*. London Guildhall University.
- Elyasiani, E. and Mansur, I. (1998): "Sensitivity of the bank stock returns distribution to changes in the level and volatility of interest rate: A GARCH-M Model". *Journal of Banking and Finance*, 22, 535-563.
- Elyasiani, E. and Mansur, I. (2004): "Bank Stock Return Sensitivities to the Long-term and Short-term Interest Rate: A Multivariate GARCH Approach". *Managerial Finance*, 30, 32-45.
- Engle, R. F. (1982): "Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation". *Econometrica* 50 (4): 987-1007.

- Engle, R.F. and Lilien, D.M. Robins, R.P. (1987): "Estimating time varying risk premia in the term structure: The ARCH-M model". *Econometrica* 55 (2): 391-407.
- Engle, R.F. and Ng, V.K. (1993): "Measuring and Testing the Impact of News on Volatility". *Journal of Finance* 48 (5): 1749-1778.
- Faff, R.W. Hodgson, A. and Kremmer, M.L. (2005): "An Investigation of the Impact of Interest Rates and Interest Rate Volatility on Australian Financial Sector Stock Return Distributions". *Journal of Business Finance & Accounting* 32 (5-6): 1001-1032.
- Faff, R.W. and Howard, P.F. (1999): "Interest rate risk of Australian financial sector companies in a period of regulatory change". *Pacific-Basin Finance Journal*, 7, 83-101.
- Fama, E.F. (1975): "Short-term interest rates as predictors of inflation". *American Economic Review*, 65, 269-282.
- Fama, E.F. (1976): "Inflation Uncertainty and Expected Returns on Treasury Bills". *Journal of Political Economy*, 34, 427-448.
- Fama, E.F. and Gibbons, M. (1982): "Inflation, Real Returns, and Capital Investments". *Journal of Monetary Economics*, 9, 297-324.
- Fama, E.F. and French, K.R. (1993): "Common Risk Factors in the Returns on Stocks and Bonds". *Journal of Financial Economics* 33 (1): 3-56.
- Fan, J. and Gijbels, I. (1992): "Variable bandwidth and local linear regression smoothers". *The Annals of Statistics*, 20, 2008-2036.
- Ferrer, R., Santomá, J. and Sebastián, A. (1999): "El Riesgo de Interés en el Mercado Español de Acciones. Una Aproximación Sectorial". *Revista Española de Financiación y Contabilidad* XXVIII (98): 43-75.
- Ferrer, R. González, C. and Soto, G. (2008): "Análisis Sectorial de la Exposición al Riesgo de Interés de las Empresas Españolas". *Información Comercial Española. Revista de Economía*, Marzo-Abril 841: 135-148.
- Ferrer, R. González, C. and Soto, G. (2010): "Linear and nonlinear interest rate exposure in Spain". *Managerial Finance*, Vol. 36, Nº 5, 431-451.

- Flannery, M.J. and James, C.M. (1984): “The effect of interest rate changes on the common stock returns of financial institutions”. *Journal of Finance*, 39,1141-1153.
- Fonseca, A.R. and González, F. (2010): “How bank capital buffers vary across countries: The influence of cost of deposits, market power and bank regulation”. *Journal of Banking and Finance*, 34, 892-902.
- Fraser, D.R., Madura, J. and Weigand, R.A. (2002): “Sources of Bank Interest Rate Risk”. *Financial Review*, 37, 351-368.
- French, K., Ruback, R. and Schwart, G. (1983): “Effects of Nominal Contracting on Stock Returns”. *Journal of Political Economy*, 91, 70-96.
- French, K.R., Schwert, G.W. and Stambaugh, R.F. (1987):. “Expected Stock Returns and Volatility”.. *Journal of Financial Economics* 19: 3-29.
- García Blandón, J. (2008): “Rendimientos estacionales en la Bolsa española: importancia del tamaño de la empresa”. *Revista Española de Financiación y Contabilidad XXXVII* (139): 527-540.
- Glosten, L.R., Jagannathan, R. and Runkle, D., (1993):.“On the Relationship between the Expected Value and the Volatility on the Nominal Excess Returns on Stocks”. *Journal of Finance* 48 (5): 1779-1801.
- Guo, J.T., and Wu, R.C. (1998):, “Financial liberalization and the exchange-rate exposure of the Taiwanese firm”. *Multinational Finance Journal*, 2, 1, 37-61.
- Hallerbach, W.G. (1994), “Theoretical and Empirical Aspects of the Relation between Interest Rates and Common Stock Returns”, D’Ecclesia, R.L. and Zenios, S.A. (Eds.), *Operations Research Models in Quantitative Finance*, Physica/Springer Verlag, Heidelberg, pp. 112-133.
- Hahm, J.H. (2004): “Interest rate and exchange rate exposures of banking institutions in pre-crisis Korea”. *Applied Economics*, 36, 1409-1419.
- Hirtle, B.J. (1997): “Derivatives, Portfolio Composition, and Bank Holding Company Interest Rate Risk Exposure”. *Journal of Financial Services Research* 12, 243-266.
- Hsiao, C. (1986): “Analysis of data panel”. *Cambridge University Press*, New York.

- Jareño, F. (2006): “Sensibilidad de los rendimientos sectoriales a tipos de interés reales e inflación”. *Investigaciones Económicas*, 30, 577-610.
- Jareño, F. (2008): “Spanish stock market sensitivity to real interest and inflation rates: an extension of the Stone two-factor model with factors of the Fama and French three-factor model”. *Applied Economics*, 40, 3159-3171.
- Joseph, N.L. and Vezos, P. (2006), “The sensitivity of US banks’ stock returns to interest rate and exchange rate changes”, *Managerial Finance*, Vol 32, No 2, pp. 182-199.
- Kessel, R. (1956): “Inflation-Caused Wealth Redistribution: A Test of a Hypothesis”. *American Economic Review*, 46, 128-141.
- Kwan, S.H. (1991): “Re-examination of interest rate sensitivity of commercial bank stock returns using a random coefficient model”. *Journal of Financial Services Research*, 5, 61-76.
- Koutmos, G. and Martin, A.D. (2003), “Asymmetric exchange rate exposure: theory and evidence”, *Journal of International Money and Finance*, Vol 22, No 3, pp. 365-383.
- Koutmos, G., and Knif, J., (2002): “Estimating systematic risk using time varying distributions”. *European Financial Management* 8, 59–73.
- Lynge, M.J. and Zumwalt, J.K. (1980): “An empirical study of the interest rate sensitivity of commercial bank returns: A multi-index approach”. *Journal of Financial and Quantitative Analysis*, 15, 731-742.
- Madura, M. and Zarruk, E. (1995): “Bank exposure to interest rate risk: A global perspective”. *Journal of Financial Research*, 18, 1-13.
- Mansur, I. and Elyasiani, E. (1995), “Sensitivity of bank equity returns to the level and volatility of interest rates”, *Managerial Finance*, Vol 21, No 7, pp. 57-77.
- Merton, C. (1973): “An Intertemporal Capital Asset Pricing Model. *Econometrica*, 41, 867-887.
- Nguyen, H. and Faff, R.W. (2003): “Can the use of foreign currency derivatives explain variations in foreign exchange exposure? Evidence from Australian companies”. *Journal of Multinational Financial Management*, 13, 193-215.

- Nguyen, H., Faff, R.W., and Marshall, A. (2007): "Exchange rate exposure, foreign currency derivatives and the introduction of the euro: French evidence". *International Review of Economics and Finance*, 16, 563-577.
- Novales, A. (2006): "Too much testing, poor testing: a review essay of research in empirical economics". Departamento de Economía Cuantitativa. Universidad Complutense de Madrid, Spain.
- O'Neal, E.S. (1998): "Why electric utility stocks are sensitive to interest rates". *Financial Review*, 33, 147-162.
- Pagan, A.P. and A. Ullah (1999), *Nonparametric Econometrics*, Cambridge Mass.: Cambridge University Press.
- Pasiouras, F. and Kosmidou, K. (2007): "Factors influencing the profitability of domestic and foreign commercial banks in the European Union". *Research in International Business and Finance*, 21, 222-237.
- Poon, S.H. and Granger, C.W.J., (2003): "Forecasting Volatility in Financial Markets. A Review". *Journal of Economic Literature* 41 (2): 478-539.
- Priestley, R. and Odegaard, B.A (2007): "Linear and nonlinear exchange rate exposure". *Journal of International Money and Finance*, Elsevier, 26(6), 2007, 1016-1037.
- Reichert, A. and Shyu, Y. (2003): "Derivative activities and the risk of international banks: a market index and VaR approach". *International Review of Financial Analysis*, 12, 489-511.
- Reilly, F.K., Wright, D.J. and Johnson, R.R. (2007): "Analysis of the interest rate sensitivity of common stocks". *Journal of Portfolio Management*, 33, 85-107.
- Rilstone, P., (1991): "Nonparametric hypothesis testing with parametric rates of convergence". *International Economics Review*, 32, 209-227.
- Ross, S., (1976): "The Arbitrage Theory of Capital Asset Pricing". *Journal of Economic Theory*, 13, 341-360.
- Ryan, S. and Worthington, A.C. (2004): "Market, interest rate and foreign exchange rate risk in Australian banking: A GARCH-M approach". *International Journal of Applied Business and Economic Research*, Vol 2, No 2, pp. 81-103.

- Saporoschenko, A. (2002): "The sensitivity of Japanese bank stock returns to economic factors - An examination of asset/liability differences and main bank status". *Global Finance Journal*, 13, 253-270.
- Schrand, C.M. (1997): "The association between stock-price interest rate sensitivity and disclosure about derivative instruments". *The Accounting Review*, 72, 87-109.
- Singh, A. (2009): "The interest rate exposure of lodging firms". *International Journal of Hospitality Management*, 28, 135-143.
- Soto, G.M., Ferrer, R. and Gonzalez, C. (2005): "Determinants of interest rate exposure of Spanish nonfinancial firms". *European Review of Economics and Finance*, 4, 55-71.
- Song, F., (1994): "A Two factor ARCH Model for Deposit-Institution Stock Returns". *Journal of Money, Credit and Banking* 26 (2): 323-340.
- Staikouras, S.K. (2003): "The interest rate risk exposure of financial intermediaries: A review of the theory and empirical evidence". *Financial Markets, Institutions and Instruments*, 12, 257-289.
- Staikouras S.K. (2006): "Financial intermediaries and interest rate risk: II", *Financial Markets, Institutions and Instruments*, 15, 225-272.
- Stone, B.K., (1974): "Systematic interest rate risk in a two-index model of returns". *Journal of Financial and Quantitative Analysis*, 9, 709-721.
- Stone (1977): "Consistent nonparametric regression". *The Annals of Statistics*, 5, 595-620.
- Stultz., (2005): *Demystifying Financial Derivatives*. The Milken Institute Review. Third Quarter , 20-31.
- Sweeney, R.J. and Warga, A.D. (1986), "The pricing of interest rate risk: evidence from the stock market", *Journal of Finance*, Vol 41, No 2, pp. 393-410.
- Tai, C. S., (2000): "Time-Varying Market, Interest rate, and Exchange rate Risk Premia in the US Commercial Bank Stock Returns". *Journal of Multinational Financial Management* 10 (3-4): 397-420.
- Tai, C. S., (2005): "Asymmetric currency exposure of US bank stock returns", *Journal of Multinational Financial Management*, 15, 455-472.

- Tong, H., (1978): "On a Threshold Model" in *Pattern Recognition and Signal Processing*, ed. by C. H Chen. Amsterdam: Sijhoff and Noordhoff.
- Verma and Jackson (2008): "Interest rate and bank stock returns asymmetry: Evidence from US banks", *Journal of Economics and Finance*, 32, 105-118.
- Wilcoxon, F., (1945): "Individual comparisons by ranking methods". *Biometrics I* (1945) 80-82.
- Windmeijer, F. (2005): "A finite sample correction for the variance of linear two-step GMM estimators". *Journal of Econometrics*, 126, 25-51.
- Yong, H., and Faff, R. (2007): "Asia-Pacific banks risk exposures: Pre and post the Asian financial crisis", *Applied Financial Economics*, 18, 431-449.
- Yourougou, P. (1990): "Interest-rate risk and the pricing of depository financial intermediary common stock". *Journal of Banking and Finance*, 14, 803-820.
- Zhao, F. and Moser, J. (2006): "Use of derivatives and bank holding company interest rate risk". Working Paper, Siena College, USA.