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**MACROECONOMIC AND MICROECONOMIC
APPROACHES TO THE ANALYSIS OF MERGER WAVES
IN THE UK**

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**A Thesis Submitted in Partial Fulfillment of the Requirements of the Degree of
Doctor of Philosophy**

Warwick Business School

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**PAGE
NUMBERS
CUT OFF
IN
ORIGINAL**

To my parents,
Andreas and Katerina,
and my sister *Anna*

Αφιερωμένη
Στους γονείς μου, *Ανδρέα και Κατερίνα,*
και στην αδελφή μου, *Άννα*

-για όλα όσα χρωστάει στην οικογένεια μου η διατριβή αυτή

TABLE OF CONTENT

ABBREVIATIONS	viii
ACKNOWLEDGEMENTS.....	x
DECLARATION.....	xi
SUMMARY.....	xii
PART 1: INTRODUCTION.....	1
CHAPTER 1: INTRODUCTION.....	1
PART 2: MACROECONOMIC ANALYSIS.....	10
CHAPTER 2: MERGER WAVES –THE ECONOMY-WIDE PERSPECTIVE.....	10
2.1 Introduction	10
2.2. Analysis of Aggregate Mergers.....	12
2.2.1 Statistical Properties of Merger Series	12
2.2.2 Aggregate and Macro-determinant of Mergers.....	15
2.3. The Extent and Character of UK Merger Activity	23
2.3.1 The Early Waves of the 1890s and the 1910s-1920s	25
2.3.2 The Waves of the 1950s and 1970s.....	26
2.3.3 The Wave of the 1980s	29
2.3.4 The Wave of the 1990s	30
2.3.5 A New Wave?	31
2.3.6 Summary of UK Merger Activity	32
2.4. The Role of the UK Authorities in Merger Activity	34
2.4.1 The UK Competition Policy.....	35

2.4.2 Interaction between the UK Competition Commission and the Economic Consequences of Mergers.....	40
2.5. Concluding Remarks.....	43
CHAPTER 3: UK MERGER WAVES?	44
3.1. Introduction.....	44
3.2. An Introduction to Spectral Analysis.....	48
3.2.1 Univariate Spectral Analysis.....	48
3.2.2 Estimation of Power Spectrum	51
3.2.3 Extension of Spectral Analysis to the Multivariate Case.....	52
3.3. Requirements for Applying Spectral Techniques	55
3.3.1 Extracting the Cyclical Component of the Series	55
3.3.2 Filtering Techniques	58
3.4 Univariate Analysis of UK Mergers	64
3.4.1 Data Description	64
3.4.2 Univariate Results : Cyclical Component of UK Mergers	66
3.4.3 Discussion of Univariate Results	70
3.5 Is there a Synchronization of Cycles?.....	78
3.5.1 Data Description	80
3.5.2 Multivariate Results	80
3.5.3 Discussion of Multivariate Results	89
3.6 Concluding Remarks.....	91
PART 3: MICROECONOMIC ANALYSIS	94
CHAPTER 4: MERGER ACTIVITY – THE FIRM LEVEL PERSPECTIVE.....	94
4.1. Introduction.....	94
4.2. Industrial Organization Perspective in Analyzing Mergers.....	96
4.2.1 Theoretical Models of Mergers within a Static Framework	97

4.2.2 A theory of Pre-emptive Mergers	102
4.2.3 Theoretical Models of Sequential Mergers	107
4.2.4 Interim Summary	112
4.3. Finance Perspective in Analyzing Mergers.....	115
4.4. Concluding Remarks.....	121
CHAPTER 5: A THEORETICAL MODEL OF MERGER TIMING.....	123
5.1. Introduction.....	123
5.2. A Deterministic Model of Merger Timing.....	125
5.3. Determinants of bidding by potential acquirers	127
5.3.1 Stock Effects-----	127
5.3.2. Order Effects-----	129
5.3.3 Herd Effects-----	130
5.3.4 Rank Effects -----	132
5.4. A Stochastic Model of Merger Timing.....	135
5.5 The Empirical Approach.....	136
5.6. Herd Effects	141
5.7 Concluding Remarks.....	143
CHAPTER 6: DATA AND ESTIMATION.....	144
6.1 Introduction.....	144
6.2. Sample Selection.....	147
6.3. Survival Time Data	151
6.4. Definition and Measurements of Dependent and Explanatory Variables	156
6.5. Nonparametric Analysis of Survival Data	164
6.6. Parametric Analysis of Survival Time Data.....	170
6.6.1 Endogeneity Issues.....	170
6.6.2 Estimation of Parametric Models.....	172
6.6.3 Choosing Among Parametric Models	180
6.6.4 Diagnostics of the Estimated Models.....	182

6.7. Generalizing the Parametric Regression Model.....	184
6.8. Effects of Explanatory Variables on Survival Time of a Firm	188
6.9. Herd Effect of Merger Activity.....	195
6.10. Discussion of the Results	197
6.11. Concluding Remarks.....	204
PART 4: THE OVERVIEW	207
PART 4: THE OVERVIEW	207
CHAPTER 7: DISCUSSION AND CONCLUDING REMARKS	207
7. 1 Summary of the Findings.....	207
7.2 Contribution to Knowledge.....	211
7.3 Concluding Remarks and Further Research.....	213
APPENDICES	218
REFERENCES.....	250

LIST OF TABLES

Table 2.1: Expenditure upon, Numbers of, and Financing of Mergers by Companies 28 in the UK and Abroad, 1969-2005.....	28
Table 2.2: UK Mergers Considered by the Office of Fair Trading.....	36
Table 2.3: Mergers Examined by Office of Fair Trading and 39 References to Competition Commission	39
Table 3.1: Mergers and Acquisitions in the UK from 1969-2005 Quarterly-Summary Statistics 65	65
Table 3.2: Duration of Regular Cycles by Sector, and of Aggregate Mergers using 70 HP and BK Filtered Data	70
Table 3.3: Variance Decomposition of Merger Activity by the Periodicity Component..... 74	74
Table 3.4: Canova Test (D) for UK Merger Cycles..... 77	77
Table 3.5: Coherence and Phase Difference over Different Sector Cycles..... 81	81
Table 3.6: Phase Differences between Aggregate Mergers and Interest Rates, Stock Prices, 88 GDP growth along Cycles with Different Periodicities	88
Table 6.1: Sector representation in the Sample used in Survival Analysis 149	149
Table 6.2: Composition of the Sample used in Survival Analysis..... 150	150
Table 6.3: Summary of the Sample used in Survival Analysis 155	155
Table 6.4: Definition and Measurement of Explanatory Variables used 158 in the Survival Analysis	158
Table 6.5: Auxiliary Statistical Model for Correcting for Endogenous Stock Variable..... 171	171
Table 6.6: Maximum Likelihood Estimates of the Gamma, Lognormal, 174 and Loglogistic Models	174
Table 6.7: Summary of Likelihood Ratio Statistics 177	177
Table 6.8: Likelihood Ratio Test for Testing Nested Models..... 180	180
Table 6.9: Comparison of AIC Values for Lognormal and Loglogistic Models..... 181	181
Table 6.10: Likelihood ratio Test for Frailty Model 185	185
Table 6.11: Effects of Explanatory Variables on Survival Time of a Firm..... 188	188
Table 6.12: Effects of Stock and Order per Sector 193	193
Table 6.13: Maximum Likelihood Estimate of Loglogistic Model with no Covariates..... 195	195
Table B1: Different error term distributions imply different AFT models 234	234
Table B2: Example of Episode Splitting..... 244	244

LIST OF FIGURES

Figure 3.1: Sample Power Spectrum.....	50
Figure 3.2: Transfer Function for the HP and BK Filters	63
Figure 3.3: Cyclical Component of Aggregate Merger Series using HP and BK Filters	67
Figure 3.4: Univariate Estimated Spectrum of Aggregate Mergers using HP and BK Filtered Data	69
Figure 3.5: Cyclical Component of UK Aggregate Mergers, Interest Rates, Stock Prices,	83
and GDP Growth using HP Filter	
Figure 3.6: Univariate Spectrum of Interest rates, Stock Prices, GDP Growth,	84
and Aggregate Mergers	
Figure 3.7: Explained Variance of Aggregate Mergers in terms of Stock prices,.....	86
Interest Rates, and GDP Growth	
Figure 6.1: Companies' Life Histories over the Sampling Period 1990-2004	154
Figure 6.2: Kaplan-Meier Survival Estimate	167
Figure 6.3: Nelson-Aalen Cumulative Hazard Estimate	167
Figure 6.4: Smoothed Hazard Estimate	169
Figure 6.5: Graphical Analysis of Final Model Overall Fit	183
Figure 6.6: Mean Individual Hazard Function.....	187
Figure 6.7: Population Hazard Function	187
Figure 6.8: Effect of Stock on Survival Time of a Firm	190
Figure 6.9: Effect of Order on Survival Time of a Firm	192
Figure 6.10: Effect of Size on Survival Time of a Firm.....	194
Figure 6.11: Hazard Function with no Covariates	196
Figure B1: Right Censoring of Survival Time Data	226
Figure B2: Left Censoring of Survival Time Data.....	227
Figure B3: Left Truncation of Survival Time Data.....	228
Figure B4: Example of a Firm's Survival Profile	240

LIST OF APPENDIXES

APPENDIX A: UNIVARIATE SPECTRUM OF SECTOR MERGERS ..	218
APPENDIX B	223
THE SCOPE OF SURVIVAL ANALYSIS	223
B1. Introduction	223
B2 Survival time data.....	223
B2.1 The definition of failure times.....	224
B2.2 Censoring of survival time data.....	225
B2.3 Truncation of survival time data	227
B3. The hazard rate and survivor function.....	228
B4. Accelerated failure time (AFT) models.....	233
B5. Estimation of the survivor and hazard functions.....	236
B5.1 Nonparametric analysis	236
B5.2 Parametric analysis.....	238
B6. Unobserved heterogeneity ('frailty').....	244
 APPENDIX C: DESCRIPTIVE STATISTICS OF DATA	 247
USED IN SURVIVAL ANALYSIS	
 APPENDIX D: EFFECTS OF STOCK AND ORDER BY.....	 248
SECTOR AND OVER TIME	

ABBREVIATIONS

AGR:	Total Assets Growth
BK:	Baxter and King Filter
CC:	Competition Commission
CR:	Current Assets divided by Total Assets
DIV	Book Value of Cash Dividends to Common Shareholders divided by the Book Value of Earnings
DS series:	Difference Stationary series
EAR:	Earnings before Interest and Taxes
EC:	European Community
EPSGR:	Growth in Earnings per Share
HP:	Hodrick and Prescott Filter
LDMV:	Long Term Debt divided by Market Value of Equity
LR:	Long Run Periodicity Band
MC:	Merger Cycles Band
MMC:	Monopolies and Mergers Commission
MTBV:	Market of a firm divided by its Book Value
NS:	Net Sales
O:	Expected change in the cumulative number of acquisitions in sector j in the interval $[t, t+1]$
OFT:	Office of Fair Trading
PE:	Market Price per share divided by earnings per common share
q:	Tobin's q ratio
ROA:	Return on Assets
ROE:	Return on Equity
S:	Cumulative number of acquisition in sector j up to and including time t
SGR:	Net Sales Growth

SR:	Short Run Periodicity Band
TA:	Total Assets
TLTA:	Total Liabilities divided by Total Assets
TS series:	Trend Stationary series
WCS:	Net Working Capital divided by Sales
WCTA:	Net Working Capital divided by Total Assets

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DECLARATION

Except for commonly understood and accepted ideas, or where specific reference is made, the work reported in this dissertation is my own and includes nothing that is the outcome of work done in collaboration. No part of this dissertation has been previously submitted to any university for any degree, diploma or other qualification.

Zafeira Kastrinaki

Warwick Business School, University of Warwick, December 2006

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SUMMARY

This study attempts to improve our understanding of the nature of mergers and their timing. It is motivated by the inability of empirical evidence at the micro-level to provide strong statistical results for the motivation of mergers in different periods. At the macro-level, the apparently stronger results of some studies have been insufficient to form the basis for a widely accepted theory of merger timing. Although the predictions are closer to the observed procyclical and episodic behaviour of the process, the findings of the macro-literature have been limited, in most cases, to confirmation of what is evident by casual observation.

This study purports to create a framework that encompasses both the macro- and micro-environment of a company which may enhance understanding of the dynamic behaviour of merger activity in the UK. At the macro-level, we use frequency domain techniques to empirically examine the existence of merger waves and their relation to economic fundamentals. The empirical approach taken allows the identification of merger waves with different duration, regularity, and power, and reports their relation to macro- and financial factors along these waves. Having identified the explanatory power of macro- and financial factors, as well as the timing pattern of aggregate mergers, we search for complementary driving forces of the process at the micro-level.

At the micro-level, a theoretic-decision model is constructed to explain merger timing which incorporates the most prevalent theoretical and empirical explanations, suggested by industrial organization and finance literature, into a dynamic framework. The model exploits the dynamics of the merger process by assuming that motives change over time because of changes in firm-specific characteristics and in merger activity per se. The model stresses the endogenous character of mergers by explicitly incorporating past, current, and future mergers.

The theoretical model is estimated, using merger data from the UK from 1990 to 2004. The empirical approach taken is survival analysis. Such an approach explicitly allows for dependency over time, in that it estimates the conditional probability of merger; that is, the probability of merger by time t , given that it has not occurred by time $t-1$. It is ideally suited to empirically examine the merger timing, since it allows us to investigate whether, given that a firm has

survived up to a certain point in time, changes in firm-specific characteristics or changes in merger activity per se will lead to a change in the timing of a merger.

Findings of the macro-level provide evidence that fairly regular long waves as well as a less regular, less powerful waves of mergers exist. Even though no two merger waves are identical, they usually have some important features in common. Their coherence with macro- and financial factors varies in strength over waves of different duration and regularity. The findings at the micro-level provide strong evidence of the endogenous character of mergers. A combination of a range of micro-forces is the driving force within a wave which keeps the bandwagon rolling at full speed. As a consequence, macro-factors may pave the way for the development of initial merger activity, while micro-forces fuel merger diffusion and build the dynamics within a wave.

PART 1: INTRODUCTION

CHAPTER 1: INTRODUCTION

In 1890, Alfred Marshall claimed that economics of mergers and competition is a “*subject on which it would be rash to speak confidently. We of this generation, being hurried along in a world of change, cannot measure accurately the forces at work and it is probable that the best guesses we can make will move the smiles of future generations.*”¹ Although we can now approach this subject with greater confidence, Marshall’s remark may still be appropriate for some aspects of the merger phenomenon more than one hundred years after it was made. In fact, Brealey and Myers (2002, p.923) consider the wave² behaviour of mergers as being among the ten most important unsolved problems in financial economics.

During the last century, significant upsurges in the numbers of takeovers³ have been recorded in the UK in the 1920s and the 1950s, in the early 1960s, late 1960s to early 1970s, late 1980s and late 1990s (see, for example, Hannah, 1983; Hughes, 1993). With respect to their relative importance, Hughes and Singh

¹ Alfred Marshall, *Some Aspects of Competition*, reprinted in R. L. Smyth (ed.) *Essays in the Economics of Socialism and Capitalism*, 1964, p.101; reproduced from Hannah (1974)

² The terms ‘wave’ and ‘cycle’ are used interchangeably throughout this study.

³ The terms “takeover”, “acquisition”, “merger” are used interchangeably throughout this study.

(1987) report that in the period 1948-1958, UK mergers accounted for more than two-thirds of corporate deaths, and in the period 1959 to 1972, for four-fifths. In the decade 1972-1982, one in three of the largest 730 quoted companies were acquired, whilst in the mid-1980s, 137 of the largest 1000 non-financial companies were taken over in just four years (1982 to 1986). The magnitude of merger activity in 1990s is unprecedented in terms of takeover value of merger deals (see chapter 2). These figures show that merger activity is an important feature of the UK economy.

A significant body of theoretical and empirical research has attempted to explain the driving forces of merger activity. At the micro level, the industrial organization literature stresses the efficiency-increasing power of it by the exploitations of synergies, or growth opportunities and the market power hypothesis which perceives the struggle for market share and price-setting power as the dominant motive for mergers. This stream of literature can be further divided into three main sub-groups, which, although they assume similar motives for mergers, provide a different analysis of merger activity. The first sub-group refers to the early industrial organization literature that claims that firms have an incentive to merge if the profits of the participating firms increase relative to their combined profits before the merger (see, for example, Salant et al, 1983; Perry and Porter, 1985; Deneckere and Davidson, 1985). However, empirical evidence on the performance of mergers provides mixed results. Bild et al (2002) by employing the residual income approach find that mergers result in a significant improvement in profitability but acquirer's pre-merger value is destroyed by 30 percent. Profitability-based studies seem to question the profit-enhancing character of takeovers by finding a negative effect on the profitability

of the acquirer (see, for example, Cosh et al., 1980; Cowling et al., 1980; Mueller, 1980; Ravenscraft and Scherer, 1987; Hughes, 1987; Chatterjee and Meeks, 1996; Ghosh, 2001; Gugler et al., 2003).

On the other hand, event studies suggest that mergers benefit the target firms' shareholders, while the acquiring firms, at best, do not lose. The combined gains are mainly positive (see, for example, Franks and Harris, 1989; Franks and Mayers, 1996; Barber and Lyon, 1997; Higson and Elliot, 1998; Mitchell and Stafford, 2000; Cosh and Guest, 2001; Graham et al., 2002; Raj and Forsyth, 2003; Danbolt, 2004;). However, more recent long run event studies have shown consistently negative returns to acquirers, questioning the gains of the merger activity (see, for example, Limmack, 1991, 1997; Agrawal et al., 1992; Gregory, 1997; Cosh and Guest, 2001; Conn et al., 2003).

That gap between theoretical models and empirical evidence has led to a merger puzzle of why unprofitable mergers occur, and how the value of firms increases when profits are reduced. Recent theoretical models have attempted to explain that puzzle⁴. Thus, the second sub-group refers to the so-called "pre-emptive mergers". The pre-emptive theory of mergers is based on synergies, market power and competition for targets and suggests that is rational for a firm to pre-empt its rival's merger, in an attempt to avoid the larger loss of profits it would have suffered had its rival been successful (see, for example, Colangelo;

⁴ Alternative theories consider these mergers inefficient and explain them by questioning the managers' rationality, the managers' commitment to value-maximization or the efficiency of financial markets. See the hubris theory by Roll (1986), agency theories by Amihud and Lev (1981), Jensen (1986), irrational financial markets theories by Shleifer and Vishny (2003), RhodesKropf and Viswanathan (2004) and merger arbitrage by Mitchell, Pulvino and Stafford (2004). In contrast, other literature explains these facts by stressing that mergers actually raise productivity and cash flow (Maksimovic and Phillips, 2001 and Harris et al., 2005).

Horn and Persson, 2001b; Brito, 2003; Fauli-Olier, 2000). Finally, the third subgroup refers to growing theoretical work on sequential mergers (see, for example, Kamien and Zang, 1990, 1991, 1993; Nilssen and Sorgard, 1998; Horn and Persson, 2001a; Matsushima, 2001).

On the other hand, finance literature claims that the “market for corporate control”⁵ facilitates the dismissal of low quality management or management that pursues goals other than shareholders’ value maximization. Fundamental to this perspective has been the attempt to identify factors that discriminate between acquirers and their targets in terms of their respective economic and financial characteristics. Empirical evidence has shown that the main discriminator is size, while targets do not seem to be generally inefficient firms (see, for example, Cosh et al., 1980; Levine and Aaranovitch, 1980; Palepu, 1986; Powell and Thomas, 1994; Powell, 1997). Furthermore, Singh (1971, 1975) gives early evidence of an overlap of characteristics between acquirers and their targets during “merger booms”. More recent evidence suggests that discriminating factors vary in strength and nature on whether the period under study is a merger boom or a normal merger activity period (see, for example, Cosh et al., 1990; Antoniou et al., 1998).

A common characteristic of all studies at the micro-level has been the lack of strong statistical results in discriminating between competing theories. Even though a growing body of literature on pre-emptive and sequential mergers has emerged, there is no supporting empirical evidence. Furthermore, an important weakness of the micro-framework for analyzing mergers is its inability to explain

⁵ The term originates with Manne (1965), and refers to the market for ownership of corporations via acquisitions.

or incorporate the recorded upsurge in merger activity during some periods.⁶ Apparently, theories based on the micro-level cannot explain, by themselves, why there are some periods with intense merger activity.

Another line of research deals with the cyclical behaviour of aggregate mergers. Research on the timing and determinants of aggregate mergers can be separated into three groups. The first area is related to attempts to understand the nature of aggregate merger activity. Evidence from this group suggests the general presence of merger waves, stochastic trends and, more recently, non-linear dynamics (see, for example, Shoughart and Tollison, 1984; Golbe and White, 1988, 1993; Town, 1992; Chowdhury, 1993; Linn and Zhu, 1997; Resende, 1996, 1999, Barkoulas et al, 2001). The second group seeks to explain the process by reference to macroeconomic and financial aggregates that display a similar (cyclical) pattern. Evidence suggests that merger activity is mostly positively related to aggregate share price levels (see, for example, Weston, 1953; Nelson, 1959; Melicher et al, 1983, Guerard, 1985; Clark et al. 1988; Benzing, 1991, 1993; Clarke and Ioannidis, 1996).⁷ With respect to other aggregate or economy-wide measures, evidence is more disperse (see, for example, Nelson, 1959; Melicher et al, 1983, Poloncheck and Sushka, 1987; Holly and Longbottom, 1988; Golbe and White, 1988; King, 1989; Crook, 1995, 1996). Generally, the findings show some relevance of economic aggregates to merger activity, but different periods, data sets and econometric treatment often

⁶ A notable exception is the work on sequential merger. However, there is not yet any supporting empirical evidence.

⁷ Recently theoretical models have also been developed on the relation between merger activity and stock prices; see, for example, Shleifer and Vishny (2003), Rhodes-Kropf and Viswanathan (2004), and Morellec and Zhdanov (2005).

present conflicting results. Overall, existing research finds a weak and uncertain relationship between merger activity and macroeconomic variables, while the most pronounced relationship seems to be with financial variables. Finally, the third group suggests that the timing of merger activity is related to “economic disturbance” induced by surprises when it becomes cheaper to “buy than to make” (Gort, 1969). This theory of merger activity embraces a wide range of possible drivers, such as globalization, trade liberalization, changes in tax, accounting, government regulation, and antitrust policy (see, for example, Ravenscraft, 1987; Mitchell and Mulherin, 1996; Schoenberg and Reeves, 1999; Jovanovic and Rousseau, 2002).

Weston et al. (1990) describe the need for a complete theory of mergers: “*[a] complete theory of mergers should have implications on the timing of merger activity. As the matter stands, there does not exist an accepted theory which simultaneously explains motivations behind mergers, characteristics of acquiring and acquired firms, and the determinants of the levels of aggregate merger activity*”.⁸ However, attempts to develop such a theory of mergers have proved to be very difficult. Most of the studies focus only on some aspects of the merger phenomenon. In this thesis, it is suggested that the lack of a complete theory of mergers may be due to two related factors. The first is the lack of understanding of the dynamic behaviour of the process, and the second, the non-existence of a unified framework for analyzing merger activity that incorporates both micro- and macro-forces.

This study attempts to improve our understanding of the nature of merger and their timing. It is motivated by the inability of empirical evidence at the micro-

⁸ Weston et al. (1990), p.276.

level to provide statistical results on motivation of mergers in different periods. In addition, existing studies on aggregate mergers by using techniques from the time domain cannot characterize the quasi-cyclical dynamics of merger series—different durations, explanatory power, and regularity. This would imply that results from the macro-merger research are subject to the spurious correlation problem (Yule, 1926). Thus, there is a need to understand the nature of the process before attempting to explain it. Having understood merger dynamics and its relation to the macro-environment, we focus on the micro-level of analysis. We claim that micro-perspectives, industrial organization and finance, may have some effect on merger intensity, and suggest a multicause model for merger timing. Specifically, the two central objectives of this study are: a) to examine whether there are merger waves and, if yes, their duration, regularity and relation to economic fundamentals; and b) to identify and analyze the dynamics within a merger wave.

The study proposes that by extending some of the research on mergers and the combining micro- and macro-level of analysis, much of the disparate research on the topic can be woven together into a single framework that illuminates the dynamics of merger waves. The findings herein and the analytical framework of this study are expected to provide a tool for academics, professionals and the authorities in their attempts to identify the elusive determinants of merger waves.

The remainder of the thesis is divided into three parts. The second part consists of Chapters 2 and 3 and provides a macroeconomic analysis of mergers. The third part consists of Chapters 4, 5, and 6 and analyses mergers at the microeconomic level. Finally, the fourth part, Chapter 7, summarizes the results

of both the macro- and micro-analysis. Specifically, the remainder of the thesis is organized as follows.

Chapter 2 provides an economy-wide perspective of merger activity. It reviews studies on aggregate mergers and their relation to economic fundamentals. It also presents studies of the statistical properties of merger series. The UK experience is then described. It offers an overview of UK merger activity over the last 100 years. In this historical overview, five merger waves are identified through casual observation of available data and relevant existing literature. Finally, the role of UK authorities on mergers and their influence on shareholders, industry structure, and conduct of firms is described in order to provide a complete picture of the merger phenomenon in the UK.

Chapter 3 employs spectral techniques to empirically examine mergers in the UK. Specifically, it first provides a univariate analysis of mergers, where the existence and duration of merger cycles at the aggregate and sector levels are investigated. Having identified cycles of different duration and regularity, multivariate spectral techniques are employed to investigate synchronization of cycles; synchronization over merger cycles in different sectors, and synchronization of the aggregate merger cycle with a business or capital market cycle.

Chapter 4 reviews studies on mergers at the firm level. It discusses the most prevalent theoretical explanation for, and empirical evidence on, mergers, as depicted in industrial organization and finance literature. This literature is categorized into four main groups, which we argue can be extended in an attempt to provide an explanation of the nature and timing of mergers.

Chapter 5 constructs a decision-theoretic model of merger timing by combining the most prevalent theoretical and empirical explanations as discussed in Chapter 4. This model exploits the dynamics of mergers by incorporating different motives simultaneously within a dynamic framework. It provides satisfactory explanations of the nature and timing of mergers

Chapter 6 estimates the model constructed in Chapter 5 in order to assess empirically which factors play an important role in the timing of mergers in the UK. The empirical approach taken is that of survival analysis. Such an approach explicitly allows for dependency over time, for the survival analysis methodology estimates the conditional probability of merger. It is ideally suited for estimating our model, since it allows us to investigate whether a company that has survived up to a certain point in time changes in terms of the factors influencing merger (as described in Chapters 4 & 5), would change the timing of merger.

Chapter 7 summarizes the results of this study. It discusses conclusions of both the macro- and micro-levels of analysis which open new avenues of research that may lead towards a complete theory of M&A.

PART 2: MACROECONOMIC ANALYSIS

CHAPTER 2: MERGER WAVES –

THE ECONOMY-WIDE PERSPECTIVE

2.1 Introduction

This chapter has three objectives. First, it reviews academic studies of the aggregate level of merger activity and its relation to economic fundamentals. It describes whether merger phenomenon can be explained using macroeconomic and financial variables, and discusses the time series data on mergers in order to reveal their non-random character.

Second, it offers an overview of UK merger activity over the last 100 years. In this historical overview, five merger waves are identified through casual observation of available data and relevant existing literature.

Third, it describes the role of the UK authorities in takeovers and their level of intervention. It discusses the costs to shareholders arising from referrals of proposed mergers to the Competition Commission, as well as the consequences of the enforcement of UK competition law on industry structure and the conduct of firms.

The structure of the chapter is as follows. Section 2.2 reviews literature on aggregate merger activity. Section 2.3 describes the extent and character of UK merger activity. Section 2.4 describes the role of UK authorities in mergers and

their influence on shareholders, industry structure, and the conduct of firms.

Finally, Section 2.5 summarizes.

2.2. Analysis of Aggregate Mergers

Empirical evidence on aggregate M&A activity is divided into two branches.¹ The first aims at understanding the time series patterns in aggregate merger activity, and investigates whether these series exhibit a wave pattern or stochastic trend, while the second seeks explanation of merger wave patterns in terms of economy-wide macroeconomic and financial variables that display a similar cyclical pattern. In what follows, we present these two branches of research.

2.2.1 Statistical Properties of Merger Series

An early proponent of the view that mergers occur in waves was Nelson (1959, 1966). He indicated that mergers could be described by bursts of high activity, followed by long periods of low activity. Research has made significant progress in defining waves and econometrically estimating the wave-like behaviour of mergers since Nelson's work first appeared. Shughart and Tollison (1984), using data on US merger activity from 1895-1979, do not reject the null hypotheses that the merger time series examined are generated either by a random walk or by a first order autoregressive process, with first order autocorrelation close to but not equal to one. They argue that such processes are

¹ Evidence that mergers occur in waves has also led to the development of theoretical models generating wave like behaviour in equilibrium (see, for example, Fauli-Oller, 2000; Toxvaerd, 2004).

not consistent with the wave hypothesis.² Golbe and White (1987) respond to Shughart and Tollison's claim by applying a nonparametric 'runs' test to examine if the US merger time series are random. They conclude that there is dependence between consecutive terms in that series, and argue that this means merger waves are a real phenomenon. Ravenscraft (1987) identified four prominent merger waves in the US economy. To this end, he regressed measures of merger activity on four dummy variables, each representing one of the four major merger waves and concluded that merger activity in wave years is significantly higher than non-wave years. Furthermore, Golbe and White (1993) offer a direct test of a wave hypothesis describing the time series of US merger activity. Using regression analysis, they estimate a set of sine curves for the period 1919 – 1979. The authors find that the coefficient estimate for the amplitude of the sine wave, which is critical for the wave hypothesis, is statistically significant and thus, conclude that the fitted model adequately describes merger activity. A different approach in testing the merger wave hypothesis is the two-state Markov regime switching model. Town (1992) estimates such a model using different time series for US and UK mergers, and compares it against an ARIMA model. He argues that linear models fail to capture all of the structure of the data. Further, he concludes that the underlying pattern in merger data can be characterized by switches between high and low levels of activity, confirming the wave-like behaviour of the series. In addition, Linn and Zhu (1997), using US merger series for the period 1895-1994, conclude that a two-state regime process, in which there exist two distinct AR(1)

² However, they do not provide any justification for their belief that a first-order autoregressive time series cannot display "wave" behaviour.

processes, explains merger activity well. Finally, Resende (1999) investigates the behaviour of mergers in the UK at the sectoral level for the period 1971-1989. He estimates a Markov switching model with no autoregressive dynamics and constant transition probabilities, and finds that the data are consistent with such a specification. These results indicate that mergers would occur in waves. He also finds evidence of co-movements in sectoral merger wave patterns by using factor analysis. In an another study, Resende (1996) investigates time series properties of mergers in the UK for the period 1971-1989, and finds that the degree of persistence to shocks is uniformly low across sectors; merger tends to react to shocks that are predominately aggregate. Barkoulas et al. (2001) propose a fractionally integrated process to model the wave-like behaviour of US merger series. The authors provide an alternative characterization of US merger activity as a strongly autocorrelated process, and suggest that the observed non-periodic cycle in the series can be attributed to the presence of long-memory dynamics.

In summary, the existing literature examines statistical properties of merger series by using standard time domain techniques; both linear and nonlinear models suggest that mergers occur in waves (with the exception of the study of Shughart and Tollison, and Barkoulas et al. for the US). The UK has received considerably less attention in these studies.

2.2.2 Aggregate and Macro-determinant of Mergers

2.2.2.1 Expectation and Capital Market Conditions Theories

The two basic theories of aggregate merger activity are the expectations theory and the capital market conditions theory. The expectations theory suggests that expectations of future economic growth and current growth such as business failures, growth in industrial production and other proxies of the business cycle and stock prices influence merger activity. Optimistic expectations about the future and strong current growth would increase mergers. The capital market theory hypothesizes that increased interest rates and a tighter capital market may decrease mergers. Steiner (1975) claims that both theories may have some effect on merger intensity, indicating that a multi-cause model of merger activity is preferable.

The first empirical study³ on macroeconomic determinants of merger activity was performed by Nelson (1959), who found a positive correlation between quarterly changes in US mergers and changes in stock prices for the periods 1895-1920 and 1919-1954.

Melicher et al. (1983) employ a multiple time series approach to compare aggregate merger activity in the US economy against components reflecting business conditions (industrial activity, and business failures), and capital market conditions (stock prices, and bond yields) for the period 1947-1977. They conclude that there is a weak relationship between merger activity and business

³ Early studies using US data include Weston (1961), Eis (1969), Maule (1968), and Markham (1955).

conditions, with changes in merger activity being a leading indicator for industrial production and business failures. However, substantial support is found for viewing changes in aggregate merger activity as a capital market conditions phenomenon. Specifically, their results indicate that changes in mergers are related to current and prior changes in stock prices and bond yields.

Geroski (1984) uses Granger causality tests to investigate the relationship between stock market prices and mergers. He uses four different samples: monthly or quarterly for the US or the UK which differ in length and time period covered. Results from all four samples suggests that such correlations are spurious, reflecting other more fundamental forces which jointly determine movements in both series.

Polonchek and Sushka (1987) analyzed the quarterly number of mining and manufacturing mergers in the US economy with assets over \$10 million during the period 1956-1978. Their regressions indicate that mergers are positively related to "Tobin's q" and fuel prices, and negatively related to the commercial paper rate, and real expenditures on housing investment.

Clark et al. (1988) combined regression with time series analysis on annual US merger data from 1919 to 1979 in order to investigate the relation between mergers and macro-variables. They considered the autoregressive nature of the merger series along with other macroeconomic variables in their regressions and concluded that the change in stock prices was positively related to the changes in mergers. However, the relationship between industrial production and mergers was ambiguous.

A similar study is that conducted by Benzing (1991), who used regression analysis to determine the significance of factors in aggregate merger activity in the US before and after 1950. He also included past merger activity as an independent variable, along with other macroeconomic variables in the regression model. He found that stock prices were positively related to merger activity both before and after 1950. However, interest rates were positively related to merger activity prior to 1950, and negatively related to merger activity after 1950. The unemployment rate was negatively related to mergers before 1950, but significantly related to mergers after 1950. He suggested that the above results mean that tightened regulation after 1950 may have caused businesses to take a longer view of mergers and to reduce the business cycle effect. In a later study, Benzing (1993), using the same methodology and US merger data for the period 1963-1986, concluded that a high level of current economic activity (as measured by the unemployment rate) stimulates mergers, while interest rates appear to have no effect. The results on a stock market variable, which was used to proxy market expectations of future economic growth, was inconclusive.

Guerard (1989) examined the casual association of US mergers with stock prices and industrial production for the period 1895-1979 (two different merger series were used). His results suggest that stock prices series or industrial production do not aid in explaining mergers

Crook (1996) used the 'net present value' approach to merger decisions to select variables expected to explain changes in the aggregate number of mergers in US manufacturing and mining firms during the period 1930-1979. Using cointegration techniques, he concluded that there is a long run or equilibrium relationship between the annual number of mergers and the level of

manufacturing production and the level of the nominal bond yield, the equilibrium values being positively related to both variables. Over the period, the predicted equilibrium values of the number of mergers was rising and throughout much of the period, the actual number of mergers was greater than the corresponding equilibrium value. Annual changes in the number of mergers can be explained by changes in the nominal bond yield in the current year and in the two previous years, by changes in Tobin's Q in the current year and in years lagged 1, 2, and 4 years, and by the difference between the actual and equilibrium value in the previous year.

Clarke and Ioannidis (1996), using a Granger causality approach and UK merger data during the period 1971-1993, investigated the relationship between stock market prices and mergers. In contrast to previous studies, stock prices are measured in real terms and mergers are measured either by number or real value. Their results suggest that stock market prices 'Granger' cause mergers.

In summary, most academic studies have indicated that stock prices are positively related to merger activity. In contrast, there is less unanimity concerning the effects of interest rates and production on mergers. The UK has received little consideration in these studies.

2.2.2.2 Market Timing Models

Recently, theoretical models have been developed to capture the relationship between merger activity and stock prices suggested by the empirical evidence described above.⁴ These models are based on a concept dating back⁵ to Hickman (1953), which suggests that in hot⁶ markets, investors may be overly optimistic. Since managers are able to time their actions, they profit from investors' optimism. A small and growing body of literature applying the timing concept to merger activity has emerged.

Shleifer and Vishny (2003) propose a theory based on an irrational stock market and self-interested target managers who can cash out quickly. They suggest that financial markets are irrational which means that they tend to overvalue stocks in the short-run, and the degree of overvaluation varies significantly across industries, sectors or group of firms. If a bidder is overvalued, it takes the opportunity to buy the real assets of a less overvalued target firm using their own overvalued equity. Assuming that target managers maximize their own short-term benefits, their model can explain why the target is willing to accept an all-equity bid even, if it is to the detriment of target shareholders. In other words, Shleifer and Vishny suggest that short-run market perceptions may lead at least in part, to a merger. In fact, if the market believes

⁴ Business history indicates that periods of high market to book ratios coincide with periods of intense M&A activity, especially for stock-financed deals (Maksimovic and Phillips, 2001).

⁵ That concept was more developed by the literature on initial public offerings (IPOs) and seasoned equity offerings (SEOs). For example, Bayless and Chaplinsky (1996) suggest that periods of relatively high issue volume should correspond to periods of reduced information costs. They find evidence of over-optimism in hot markets.

⁶ Hot markets are defined as periods of high equity issue volume (Bayless and Chaplinsky, 1996).

that the merger can drive positive synergy without being over-optimistic, bidding shareholders can realize some gain from its higher valuation. These gains will be diluted in the long-run, when the long-run prices return to the efficient level.

Rhodes-Kropf and Viswanathan (2004) propose a rational theory of mergers based on correlated misinformation. This theoretical model yields parallel empirical predictions on the link between misevaluation and mergers with an economically very different model from Shleifer and Vishny. They suggest that errors in valuing potential takeover synergies are correlated with overall uncertainty in the market. Targets accept all-equity bids because they tend to overvalue potential takeover synergies as a consequence of overpricing in a soaring equity market. The number of misvalued bids is expected to increase with booming financial markets, when uncertainty about the true value of firms is especially pronounced, and better-informed bidders can exploit their informational advantage at the expense of less-informed targets.

Morellec and Zhdanov (2005) develop a theoretical model of takeovers based on stock market valuations of merging firms. The model incorporates competition and imperfect information, and determines the terms and timing of takeovers by solving exercise games between bidding and target shareholders. The model predicts that the probability of negative abnormal returns to the merging firm increases with the dispersion of beliefs regarding the synergy created by the takeover. In addition, abnormal returns to shareholders increase with the volatility of stock returns, and decrease with the correlation between the returns of merging firms.

2.2.2.3 Industry Shocks

Gort (1969) suggests that the “economic disturbance” induced by surprises triggers a wave of mergers when it becomes cheaper to “buy than to make”. Gort holds that industry shocks alter the mean and variance of investors’ assessments of intrinsic value for firms. Such shocks are derived from unexpected changes in demand, changes in technology, movements in capital markets, and general changes in entry barriers within industries.

The theory of industry shocks is appealing because it is capable of rationalizing not only the merger waves caused by large-scale shocks, but also the clustering of merger activity within industries or regions (for example, merger activity caused by more focused shocks). This theory embraces a wide range of possible drivers, including globalization, trade liberalization, changes in tax, accounting, government regulation, and antitrust policy (see, for example, Ravenscraft, 1987).

Several empirical studies support the notion that industry shocks drive M&A activity. Mitchell and Mulherin (1996) find that industry shocks contributed to the extensive takeover and restructuring activity of the 1980s in the US. They show that takeover activity clusters in industries that experienced fundamental economic shocks such as deregulation, technological innovation, demographic shifts, and input price shocks.

Schoenberg and Reeves (1999) examine the factors determining merger activity by using UK mergers over the period 1991-1995. Their findings suggest that exposure to deregulation is the most important single discriminator between

industries with high and low acquisition activity. They also find supporting evidence for industry concentration and industry growth rate as determinants of the takeover rate within an industry.

Jovanovic and Rousseau (2002) claim that large technological change and merger activity are associated. They studied the waves of the 1890-1930 and 1971-2001 periods in the US, concluding that the former was significantly associated with the diffusion of electricity and the internal combustion engine, and latter with the diffusion of information technology.

2.3. The Extent and Character of UK Merger Activity

The point of departure for a study of merger activity is one that examines the aggregate activity over the long-term: the past 100 years. There are two ways to consider deals activity: in terms of the number of transactions, and in terms of total expenditure.⁷ Focus on the number of transactions gives equal weight to all deals - this is an implicit measure of the “breadth” of merger activity in the UK. Conversely, focus on the value of all transactions helps distinguish those episodes dominated by large deals - this might be regarded as a measure of the “depth” or materiality of sizeable deals.

Ideally, a time series on mergers and acquisitions should be comprehensive and consistent, and should contain data that covers a long period of time. Unfortunately, none of the available series meet these criteria, and compromises must be made; any study of merger waves involves a trade-off between internal consistency of the data series and the length of the series. Empirical studies for the US have merged series produced by different institutions⁸ in order to produce a single long series, but this kind of procedure is problematic. There have been a few attempts in the UK to construct a mergers series.

Hannah (1974) compiled a merger series for the period 1880-1918, which included mergers between companies in the manufacturing industry. The major

⁷ Alternative measures of merger activity could be the sum of the assets sales or employment of companies disappearing through merger. Although it is possible to construct series on each of these bases for parts of the economy, especially for industrial and commercial companies, or manufacturing and distribution, there is no long-run comparable series on any of them for the whole economy.

⁸ Research on aggregate mergers and acquisitions in the US has made use of four merger series (for a description, see Golbe and White, 1988).

sources from which mergers were identified were business histories, histories of individual industries, reports of the Monopolies Commission, and the Stock Exchange Year Book. Despite covering quite an early period, there are some omissions in that series. Hannah claims a merger with a value of £1 million or more is likely to have been picked up by at least one, and probably several, of the sources used, and mergers of smaller companies may have been omitted in significant numbers. Utton (1971) compiled a complete record of mergers between quoted companies for the period 1954-1965, where the acquirer belonged to manufacturing industry. Gribbin (1974) reported successful merger proposals considered by the Board of Trade's internal and inter-Departmental Mergers Panel in the broad definition of industrial, commercial and financial sectors for the period 1966- 1972. Gribbin explains that this series only covers takeovers where the gross assets acquired exceeded £5 million, or where the acquisition could create or intensify a monopoly, as it is based on referrals by the Mergers Panel to the Monopolies Commission, in accordance with the 1965 Monopolies and Merger Act. Hannah (1983) presents two series by the Board of Trade based on an analysis of company accounts (1954-1959 and 1960-1968). Unfortunately, the timing of takeovers in these series is based on the accounting year.

Mergers and Acquisitions magazine provides information about UK domestic and foreign mergers and acquisitions. It records the numbers and value of mergers and acquisitions where at least 5% of controlling interests has changed hands for the entire UK economy since 1972.

The longest time series for the UK mergers and acquisitions is provided by the Office of National Statistics (ONS), which covers the period from 1969 to 2005.

Contained in the *Business Monitor MQ7* prior to 1986, it reports the number and value of domestic and cross-border mergers and acquisitions for all industrial and commercial companies. Moreover, it has no lower limit on the nominal pound size of the transactions reported. From 1995, financial institutions are also included. It pertains to all UK companies, both quoted and unquoted.

Finally, *Thomson ONE Banker* and *DataStream* databases list all completed and pending transactions and provide, among others, the names of buyers, sellers, value and types of transaction and sector on all UK domestic and cross-border mergers since the 1980s. There is no explicit size inclusion criterion, and it covers all sectors in the UK economy. Although these series include the UK merger experience since the 1980s, they do not extend back far enough to provide an adequate historical perspective.

In this study, the merger series provided by the *ONS* and *Thomson ONE Banker* is used for empirical analysis at the aggregate and sector levels, respectively ⁹ (see Chapter 3).

2.3.1 The Early Wave of the 1910s-1920s

Reliable evidence about mergers in the UK is only available from the late 1960s. Nevertheless, the lack of data and empirical studies about UK takeovers

⁹ A number of previous studies on mergers have used ONS data (see, for example, Hughes, 1993; Clarke and Ioannidis, 1996; Resende, 1996, 1999).

prior to 1960s does not necessarily mean that merger activity was not present in that period.

Hannah (1974) suggests that the first UK merger wave started approximately in 1880 and ended in 1918, parallel with the first US¹⁰ wave, although the UK wave was smaller than that of the US. UK merger activity in that period was fuelled by radical changes in technology and the industrialization process. A high proportion of the mergers were in two sectors - textiles and brewing - whilst many industrial sectors remained untouched. The horizontal form of merger was overwhelmingly dominant in this period, accounting for 87 per cent of large mergers.

2.3.2 The Waves of the 1960s and 1970s

The worldwide economic depression of the 1930s and the subsequent Second World War prevented the emergence of a new takeover wave for several decades. The second takeover took off in the late 1950s and early 1960s (Brooks and Smith, 1963; Moon, 1968). Table 2.1 provides data on the annual expenditure upon, numbers of, domestic UK and cross-border acquisitions, financing of domestic acquisitions, and sales of subsidiaries between groups during the period 1969-2005.

¹⁰ For a discussion of US merger waves, see Scherer (1980), Golbe and White (1988) and Bruner (2004) ch.4, while for European merger activity see Franks and Mayer (1993), Geroski and Vlassopoulos (1993).

Fairburn (1989) suggests that the industrial policy adopted in the UK during the 1960s was responsible for the high frequency of horizontal mergers in the 1960s. In 1964, the British government introduced a new policy promoting the creation of 'national champions' which would be able to compete on world markets. The Industrial Reorganization Corporation (IRC) was founded to assist mergers of firms in the same line of business. The IRC could exempt merging firms from the antitrust scrutiny. In the following decade, 1970, the policy to promote national champions was abandoned and the focus was on conglomerate integration. Thus, during the 1960s, around 90 percent by value and 80 percent by number of the mergers that were examined by the competition policy authorities were horizontal, while in the 1970s, horizontal mergers were around 70 percent by number and 65 percent by value (Gribbin, 1974; Graham, 1979). In the 1970s, extensive activity occurred in engineering, vehicles, food, drink, textiles, paper printing and publishing, and distribution (Cowling et al., 1980, Cosh, Hughes, and Singh, 1980).

In the 1970s, the average value of mergers by the financial sector was more than double that of mergers by industrial and commercial companies (Aaronovitch and Sawyer, 1975). Lye and Silberston (1980) claim that in the 1960s and 1970s, only a small number of mergers were of high value, i.e. principally those in which independent companies were taken over. There were only a few subsidiaries sales of large dimensions. During this period the level of cross-border acquisitions was very low.

Table 2.1: Expenditure upon, Numbers of, and Financing of UK Domestic and Cross Border M&A, 1969-2005

Period	Domestic M&A				Cross Border M&A			
	Total Expenditure (£m)	Sales of subsidiaries (percentage of total M&A) Number	Total Expenditure (£m)	Percentage of expenditure accounted for by	Inward	Outward	Number	Expenditure (£m)
				Cash	Issues of ordinary shares	Issues of fixed interest securities	Number	Expenditure (£m)
Annual Averages *								
1969-73	1,388	22%	13%	31%	49%	20%	66	95
1974-81	947	26%	16%	62%	33%	5%	50	341
1982-5	4,278	31%	22%	49%	43%	8%	73	726
Years								
1986	15,370	26%	20%	26%	57%	17%	54	1,552
1987	16,539	22%	28%	35%	60%	5%	61	2,701
1988	22,839	25%	24%	70%	22%	8%	99	5,690
1989	27,250	33%	20%	82%	13%	5%	168	12,130
1990	8,329	44%	35%	77%	18%	5%	143	10,958
1991	10,434	42%	28%	70%	29%	1%	146	6,667
1992	5,941	46%	31%	64%	36%	1%	210	4,139
1993	7,063	36%	58%	81%	17%	3%	267	5,187
1994	8,269	31%	31%	64%	34%	2%	202	5,213
1995	32,600	41%	21%	78%	20%	2%	131	12,817
1996	30,742	42%	24%	64%	36%	1%	133	9,513
1997	26,829	24%	16%	41%	58%	1%	193	15,717
1998	29,525	24%	18%	53%	45%	2%	252	32,413
1999	26,163	19%	15%	62%	37%	1%	252	60,860
2000	106,916	21%	6%	37%	62%	1%	227	64,618
2001	28,994	35%	27%	42%	57%	1%	162	24,382
2002	25,236	25%	33%	69%	27%	4%	117	16,798
2003	18,679	30%	41%	86%	90%	5%	129	9,309
2004	31,408	22%	27%	63%	33%	4%	178	29,928
2005	25,134	21%	35%	87%	11%	2%	242	50,280

Note: The data for activity of domestic mergers are principally based on analysis of press reports. From 1969 to 1985 this is also true for cross border mergers. From 1986, however, the latter are based on enquiries to companies as well as press reports and arise from exercises conducted to compile inward and outward investment flow data for the Balance of Payments tables in the national accounts. Cross border acquisitions which are made indirectly via an existing subsidiary abroad are excluded. Acquisitions by UK firms of the subsidiaries of companies abroad of the UK are counted as domestic acquisitions, as are acquisitions of UK companies by UK subsidiaries of firms abroad.

* The first three are annual averages for the periods shown

Source: Office of National Statistics

2.3.3 The Wave of the 1980s

The fourth takeover wave in the UK started in 1981, when the stock market had recovered from the preceding economic recession, and ended in 1989. It was characterized by an unprecedented number of divestitures, hostile takeovers, and management buyouts / buyins (*Thomson ONE Banker*).

As Table 1 shows, in the period 1982-1985, average acquisition expenditure rose significantly. By 1986, expenditure in real terms increased sharply, while there was no corresponding increase in numbers acquired. The first phase of the 1980s merger wave was the product of relatively few massive mergers (Hughes, 1993). After 1986, the numbers as well as the expenditure in real terms rose significantly. Of the independent companies acquired in 1986, 10 per cent accounted for over 85 per cent of total expenditure (*Business Monitor MQ7*, 1987 Q1).

As depicted in Table 1, in the late 1980s, acquisition expenditure in the UK was primarily funded by the use of cash and equity. The use of debt fell significantly after the wave of 1970s. In addition, during this period, a number of very large sales of subsidiaries between groups occurred. Thus, in 1984, the six largest independent company acquisitions had an average value of around £100 million, while the three largest sales of subsidiaries between groups averaged £90 million (Hughes, 1993).

Over 45 per cent by value and 28 per cent by number of all acquisitions by UK companies took place abroad in the period 1986-9. Table 1 reveals a steady increase in the numbers of acquisitions abroad by UK companies and in total acquisition expenditure in the period 1986-90, with activity apparently peaking

in 1989. The US and Canada were the most important destinations for this activity, especially in value terms. The UK was a target for increasing cross-border mergers from both the EC and North America (Hughes, 1993).

2.3.4 The Wave of the 1990s

In the early 1990s, merger activity increased briskly in all segments of the UK economy and all firm size categories. The magnitude of the fifth wave was unprecedented in terms of the takeover value of merger deals. The sale of subsidiaries between groups as a proportion of all domestic acquisitions was similar to the previous takeover wave. As Table 1 shows, in the late 1990s, acquisition expenditure in the UK was primarily funded by the use of cash and equity, with the use of debt reaching its lowest level in relation to previous acquisition waves. Sectors exhibiting more intense merger activity are the financials, consumer products and services, industrials, media, high technology (*Thomson ONE Banker*).

A striking feature of the fifth takeover wave is the significance of 'strategic buyers' who seek to combine with targets who are related along business lines, and with whom synergy value might be created. Strategic combinations dampen somewhat the influence of financial buyers. Another important feature is its international nature. As shown in Table 1, in the late 1990s, cross-border mergers increased remarkably in value, reflecting the growing globalization of product, services, and capital markets.

The number of hostile bids in the UK fell significantly in the 1990s compared to the takeover wave of the 1980s, according to the Thomson Financial Securities Database. This decline in hostile takeover activity can be attributed to the bull markets, as target shareholders are more prone to accept a takeover bid when their shares are overpriced. In addition, hostile takeovers are no longer needed as a corporate governance device, given that there are a sufficient number of alternative governance mechanisms (for example, stock options) that encourage management to focus on shareholder value, and to voluntarily restructure when necessary (Holmstrom and Kaplan, 2001).

2.3.5 A New Wave?

Since mid 2003, takeover activity (including a large number of cross-border deals) has again picked up in the UK. A number of very large sales of subsidiaries between groups has occurred. Acquisitions are still financed mainly through cash and equity, although the use of debt has started to increase.

The increase of merger activity in the UK has been accompanied by a similar increase in US and Europe, continuing the international industry consolidation of the 1990s. Since the beginning of 2002 until the middle of 2005, cross-border acquisitions have accounted for more than 43% of the total value of all mergers by European bidders, and 13% of the total value of all mergers by US firms. The European acquirers seem to prefer friendly negotiations to aggressive bidding.

Since the beginning of 2002, the total number of hostile bids in Europe has amounted to 32, 17 of which have been in the UK (*Thomson ONE banker*).

Although it is too early to draw conclusions about whether a new merger wave is forming, some trends are already emerging; international mergers are playing an important role in merger activity of the early 2000s.

2.3.6 Summary of UK Merger Activity

In the broadest of terms, we may sum up this section as showing that the UK has experienced periods of intense merger activity, followed by low transaction periods. Data suggests that five distinctive merger waves may have been present in the UK economy during the last century. Merger activity exhibits different characteristics in each of them, suggesting the presence of different sets of underlying motives for each wave.

A number of common factors can, nonetheless, be found. First, all waves occur in periods of economic recovery (following a market crash and economic depression caused by war, an energy crisis, etc). Second, the waves coincide with periods of booming stock markets. It is notable that all five waves ended with the collapse of stock markets. Third, takeover waves have been presented by industrial and technological shocks often in the form of technological and financial innovations, supply shocks (such as oil price shocks), deregulation, and increased foreign competition. Finally, takeovers often occur in periods when

regulatory changes (for example, those related to anti-trust or takeover defense mechanisms) take place.

Such conclusions about common factors are however, based on casual observation. A more formal and explicit analysis is needed to ascertain whether such factors are statistically significant. Thus, in Chapter 3, we investigate the relation of aggregate UK merger activity¹¹ and such macroeconomic and financial factors by using frequency domain techniques.

¹¹ Although cross-border mergers play an important role in UK merger activity (see, for example, Conn et al. 2003), domestic mergers only will be considered in this study. An examination of UK cross-border merger is left for future research.

2.4. The Role of the UK Authorities in Merger Activity

Takeovers are regulated through a number of institutions and mechanisms. In the UK takeovers are regarded as a central function of the stock market.¹² The Stock Exchange may influence takeovers by listing requirements for new companies and rules for existing companies which wish to raise new funds such as equity, and requirements for buyers to make full bids once shareholdings reach 30 per cent. On the other hand, any UK mergers which do not fall under the European Community Merger Regulation,¹³ and which meet the jurisdictional tests in the Enterprise Act 2002, falls under the regulation of two UK authorities: the Office of Fair Trading and Competition Commission. In the following section, a brief description of their respective roles is presented.

¹² The takeover process acts as a discipline on firms allowing control to be transferred from inefficient to efficient management and encouraging a convergence of interests between management and shareholders. For a discussion of the relation between capital markets and takeovers in the UK and European countries, see Franks and Mayer (1993).

¹³ Under the EC Merger Regulation, the European Commission has exclusive competence, subject to limited exceptions, to regulate certain large scale mergers, defined as 'concentrations having a Community dimension'. In particular, the EU Commission will consider investigating any merger involving world-wide turnover greater than €5,000 m, or where EU turnover of at least two of the companies concerned exceeds €250 m. As a consequence, subject to limited exceptions, mergers which exceed the relevant turnover thresholds set out in the EC Merger Regulation are not subject to the OFT's jurisdiction under the Act.

2.4.1 The UK Competition Policy

The UK introduced its competition regime in 1948 with the establishment of the Monopolies Commission.¹⁴ In 1965, its remit was widened to inquire into mergers as well as monopoly markets (Wilks, 1999). Under the Competition Act 1998, the Monopolies and Mergers Commission (MMC) became the Competition Commission (CC), and the powers of the Commission and the government responsible for administering competition law, the Office of Fair Trading (OFT), were amended.

Prospective mergers are voluntarily notified to the OFT, which screens all merger proposals¹⁵ and carries out preliminary investigations of markets where competition problems are thought to be present. If further investigation is deemed to be necessary, it sends the case to the CC for a full investigation.¹⁶ A merger (whether in the form of acquisition of assets, the purchase of shares, public bid, joint venture, management/leveraged buy-out or buy-in, or a similar transaction) will qualify for investigation where either one or both of the following criteria is satisfied:

¹⁴ For a discussion of UK competition policy and its evolution, see Parr et al. (2005), Clarke et al. (1998), and Fairburn (1993).

¹⁵ In sectors such as media, water and sewerage, electricity and gas, telecoms and communications, rail, aviation, and financial services, mergers are governed by different approval mechanisms or sector-specific rules either instead of, or in addition to, the general jurisdiction of the OFT under Enterprise Act.

¹⁶ The OFT also has some powers of its own, and it can, and does, carry out its own investigations.

- a) As a result of the merger, a share of at least 25 per cent of the supply of goods or services of any description in the UK, or in a substantial part of it is created or enhanced (the 'share of supply' test);
- b) The value of the turnover in the UK of the company being taken over exceeds £70 million (the 'turnover' test).

It is implicit in these criteria that at least one of the companies concerned must be active within the UK. Table 2.2 presents statistics on cases considered by the OFT.

Table 2.2:¹⁷ UK Mergers Considered by the Office of Fair Trading

Year	Qualifying mergers	First Release data on mergers of UK companies*	Qualifying mergers as % of First Release cases
1998	269	887	30%
1999	254	714	36%
2000	192	765	25%
2001	200	554	36%
2002	194	502	39%
2003	190	531	36%
2004	117	642	18%

Source: OFT annual reports for 2000, 2001, 2002, 2003, 2004

* "First Release" is an Office for National Statistics publication giving data for the number of acquisitions of UK companies

After a reference has been made, the CC considers a series of questions; first, whether a relevant merger situation has been, or will be, created; and secondly, if so, whether the creation of that merger situation has resulted, or may be expected to result, in a substantial lessening of competition within any market or market in

¹⁷ 'First Release' includes the number of acquisitions of domestic UK companies and the number of UK companies acquired by foreign ones (inward acquisitions).

the UK for goods or services. There is no obligation for the firms involved in a merger to demonstrate that positive benefits arise from the merger, and although in practice, firms may often seek to do so, the Commission will clear a merger if it finds that it will not result in a substantial lessening of competition, even if no positive benefits may be expected to arise.¹⁸

Consistent with the practice in the US under the FTC, it is likely that only a small proportion of mergers qualifying for investigation will be referred to the Commission. Table 2.3 presents statistics on mergers examined by OFT and references to CC over time.¹⁹ Confidential guidance cases refer to cases where companies obtain formal confidential advice in relation to a proposed but unannounced merger. Before a planned acquisition becomes public knowledge, the OFT is prepared to give guidance in confidence as to whether it is likely that the transaction, once announced, will be referred to the Commission. Pre-notified cases refer to publicly announced but uncompleted merger cases, where companies fill a statutory Merger Notice setting out details of the proposal and the market it will affect and ask clearance from the OFT.

As set out in Table 2.3, the OFT reviewed 270 cases in 2003/2004, of which 117 were qualifying mergers, along with a further 153 which did not qualify for investigation (this category includes mergers which were found not to qualify, merger proposals which were abandoned and informal advice cases). These figures are lower than in previous years. (In 1998 the OFT reviewed 425 cases.) The reduction in cases may be due, in part, to a merger cycle, and in part, to the change in jurisdictional thresholds under the Act, which has reduced the

¹⁸ For a discussion, see Parr et al. (2005) Ch.1, and Lyons (2001).

¹⁹ For a statistical history of MMC (now CC) reports, see Clarke et al. (1998) Ch.1.

proportion of mergers qualifying for investigation (Parr et.al., 2005). That justification can also apply to data in Table 2.2.

Table 2.3: Mergers Examined by OFT and References to Competition Commission

Year	Number of cases examined by OFT	Found not to qualify, proposals abandoned and informal advice cases	Change		Confidential guidance cases	Prenotified cases	Qualifying cases less confidential guidance	Total references	Total references as a percentage of	
			Qualifying cases						Qualifying cases less confidential guidance	Qualifying cases less confidential guidance
1998	425	156	269		45	45	224	8	3.0%	3.8%
1999	415	161	254	-5.2%	35	62	219	10	3.9%	4.9%
2000	315	123	192	-24.4%	21	60	171	14	7.3%	8.2%
2001	356	156	200	24.0%	27	40	173	10	5.0%	5.8%
2002*	355	161	194	-3.0%	30	52	164	14	7.2%	8.5%
2002/2003*	318	128	190		28	51	162	13	6.8%	8.0%
2003/2004	270	153	117	38.4%	13	29	104	12	10.3%	11.5%

Adapted from Parr et al (2005)

Original Source OFT annual reports for 2000, 2001, 2002/2003, and 2003/2004

* Report for 2002/2003 covers 15 months from Jan 2002 to March 2003 data is shown for full year 2002 and for 12 months from April 2002 to March 2003

Companies have the right to appeal to the Competition Appeal Tribunal (CAT) against the use of the powers given to the OFT by the Competition Act. In the old regime, decisions made by the CC were merely recommendations to the Secretary of State, but in the new regime put into place by the Enterprise Act 2002, the CC's decisions – both in the identification of adverse effects arising from a substantial lessening of competition and in the remedies designed to deal with these effects - became determinative, that is to say, they became final subject only to legal appeal to the CAT.

2.4.2 Interaction between the UK Competition Commission and the Economic Consequences of Mergers

Academic studies have pointed to possible significant costs to the economy arising from state regulation²⁰. These costs take the form of administrative costs of operating the regulatory system and the compliance costs to the company resulting from a competition inquiry, in the form of legal and other advisory expenses and management time. However, these costs can be expected to be *de minimis* in relation to a company's value; typically, such costs in the UK amount to between £500,000 to £2 m per merger (Arnold and Parker, 2006).

A potentially much more important impact results from shareholders value from a revaluation of the share prices during an inquiry. Frank and Harris (1993)

²⁰ For a review, see Blundell and Robinson (2000)

use event study methodology and data from a sample of 159 UK mergers referred to the MMC between 1965 and 1990 to examine shareholder value changes to bidder and target companies from a merger. They show that those proposed mergers eventually referred to the Commission are viewed at the bid date as value-creating for shareholders. However, the market's capitalization of those gains is likely to be attenuated by the perception of a relatively high probability of the mergers not taking place (compared with those mergers that are not referred). Value gains are eroded on the referral date by approximately 8 per cent to targets and 1 per cent to bidders. There is significant further erosion to targets when the bid is rejected, and a small positive gain to targets upon acceptance. Value changes to bidders are small in both the referral and report months, and are generally not significantly different from zero.

Forbes (1994) investigates the value impact for bidding companies only of MMC references, using event study methodology and data from a sample of 53 mergers in the period 1976 to 1990. He compares abnormal returns among the initial announcement of the merger, announcement of referral to MMC and the Commission's decision. The value effects are found to be broadly consistent with those in Franks and Harris; bidder returns are small and not statistically significant.

More recently, Arnold and Parker (2006), using 50 merger cases referred to the MMC/CC during 1989-2002, look at the impact on shareholder value of UK competition regulation. The study confirms the finding from earlier studies of greater gains to shareholders in target than bidding companies, but does not find evidence supporting overall loss of shareholder value to target company shareholders when a merger is prohibited. It finds evidence that when the

regulatory regime is stable and well understood, the capital market behaves efficiently in response to new information. However, for a sub-group of mergers involving companies with a new regulatory regime, where the industry and the stock market has little or no experience with respect to mergers, the capital market operates less efficiently.²¹

A few studies have examined the consequences of the enforcement of UK competition law on industry structure and the conduct of firms.²² In an early study, Shaw and Simpson (1986) establish a significant decrease in market shares by leading companies after a UK Monopolies and Mergers Commission (now the CC) investigation over a time horizon of 14 years. The authors derive the conclusion that 'intervention by the MMC in reducing barriers to entry did not fail'. Davies et al (1999), also determine the probability of an adverse finding against firms investigated by the UK Monopolies and Mergers Commission on the basis of data from 1973 to 1995 collected from MMC reports. They find that the larger the share of the market leader, the more likely the MMC is to judge a monopoly practice to be against the public interest. It is most (least) inclined to judge against exclusive dealing (other vertical restraints). They also suggest that the MMC was less inclined to reach adverse findings in the 1990s than it was in earlier years.

²¹ The relevant studies for the EU are those of Brady and Feinberg (2000) and Duso et al (2003). They look for evidence of regime effects and individual case effects (relating to cases grouped by EU member State and by industry sectors) of regulatory decisions on shareholder value. They find that the regime effects are weak. However, for individual cases, enforcement of the merger regulations could have a substantial effect on individual company share prices. They also suggest that findings by the European Commission of 'serious doubts', or the announcement of a 'suspension' decision adversely affect the share price.

²² For similar studies concerning the EU competition policy, see Harding and Gibbs (2005).

2.5. Concluding Remarks

This chapter presented research on mergers within an economy-wide perspective. It reviewed studies examining the statistical properties of merger series. Such studies suggest that there is dependence between consecutive terms in that series, and argue that this means merger waves are a real phenomenon. Furthermore, studies examining the macro-determinants of mergers indicate that stock prices are positively related to merger activity, whilst there is less unanimity concerning the effects of interest rates and production on mergers.

The historical overview of UK mergers and acquisitions presented in this chapter demonstrates that mergers have played a major role in the structural transformation of the UK economy during the last 100 years. However, the patterns of UK merger activity have received little research attention, mainly because there are no available merger series that are consistent and contain data that cover a long period of time. Casual inspection of available data and existing studies suggest that five merger waves have occurred in the UK during the last century, each of which may be characterized by different features. Although some authors accept the wave hypothesis based on casual empiricism, it is necessary to test the idea formally, to provide evidence that appearances are not somehow deceiving. This is the objective of Chapter 3.

In order to complete the picture of the UK merger environment, the chapter closed with description of the regulatory context and the main institutions involved in shaping merger outcomes.

CHAPTER 3: UK MERGER WAVES¹?

3.1. Introduction

Although we have talked of merger waves in the UK in the context of existing research, in this chapter we explore more formally whether this is appropriate.

The phrase merger cycle itself may be questioned by some researchers who prefer the more agnostic term fluctuations. Of course, it is obvious that merger series do not punctually follow a sine or cosine wave. However, they do display what Hillinger (1992) calls a *quasi-cycle*, meaning that: “*the length of the period and also the amplitude [is] to some extent variable, their variations taking place, however, within such limits that it is reasonable to speak of an average period and an average amplitude*”.

Empirical literature on merger waves, as discussed in Chapter 2, has confined itself to characterizations of the stochastic process behind mergers either by focusing on linear and/or non-linear time series models, or by devising tests for the stationarity of merger series. However, linear models such as ARIMA models are poor approximation of the merger series, as a linear representation of the data is unable to capture all of the structure that exists in available merger series

¹ I am pleased to acknowledge insightful suggestions from the participants of seminars at the Warwick Business School as well as the 2006 EARIE meeting in Amsterdam, especially Denis Mueller and Eileen Fumagalli, on early versions of this chapter.

(Town, 1992). In particular, analysis based on ARIMA models may be misleading if such models are not consistent with the stochastic properties of the data, and may also be misleading if chosen primarily on grounds of parsimony (see, for example, Harvey and Jaeger, 1993). Although a non-linear, Markov switching - regime model is better for describing aggregate merger behavior, it cannot characterize the quasi-cyclical dynamics of merger series-periodicity, explanatory power, and regularity. Such a model also fails clearly to distinguish movements at different frequencies. Finally, studies examining the stationarity of merger series claim the rejection of “the randomness hypothesis” due to the rejection of a unit root hypothesis. However, they do not provide us with more information about merger cycles.

In this chapter, we employ spectral analysis in order to investigate UK merger cycle regularities within a model free framework. Spectral analysis is an alternative approach which is better suited to describing and analyzing quasi-cyclical fluctuations at different frequencies. It is concerned with the exploration of cyclical patterns of data. The purpose of the analysis is to decompose a complex time series with a cyclical component into a few underlying sinusoidal (sine and cosine) functions of different wavelengths. The term ‘spectrum’ provides an appropriate metaphor for the nature of this analysis. Performing spectrum analysis on merger time series is like putting the series through a prism in order to identify the wave lengths and importance of the underlying cyclical component. As a result, we uncover regular cycles of different lengths, which initially, might have appeared to be simply random noise.

Having identified merger cycles with different durations, we apply methods of multivariate spectral analysis in order to determine whether there is

synchronization of UK aggregate merger cycles with a business or capital markets cycle, as well as synchronization over cycles in different sectors.

Furthermore, frequency domain analysis of the merger cycles helps to overcome the important but controversial issue of detrending, a problem connected with the lack of consensus on of what constitutes cycle fluctuations. Cycle fluctuations are typically identified with deviations from the trend of the process. However, within the empirical literature, there is fundamental disagreement on the properties of the trend and on its relationship with the cyclical component of the series.² Since the issue of what is an appropriate statistical representation of the trend has not been resolved, and since the choice of the relationship between the cyclical and secular components is arbitrary, statistical based approaches to detrending raise questions about the robustness of stylizing facts. We adopt the view that if there is information suggesting that merger cycles are fluctuations within a range of periodicities, a natural definition arises in terms of these fluctuations. It is clear that in this case, the option is to isolate the desired fluctuations (and not detrending), using the wide range of filtering methods available. We will justify our use of the Hodrick Prescott (1997) and Baxter King (1999) filters.

This chapter is organized as follows. Section 3.2 introduces spectral analysis, both univariate and multivariate cases. Section 3.3, gives our justification for

² In the past, the representation and extraction of the secular (and thus, the cyclical component) of a series was handled in a very simple way. The trend was represented with a deterministic polynomial function of time, assumed to be independent of the cyclical component and extracted using simple regression methods. More recently, following Nelson and Plosser's (1982) findings, Beveridge and Nelson (1981), Watson (1986), and Hamilton (1989) have proposed alternative definitions of the trend, different assumptions about the relationship between the trend and the cycle, and novel methods for estimating the two components.

extracting the cyclical component of merger series instead of detrending. It also provides a description and our justification for the use of Hodrick, Prescott and Baxter, and King filters, and the consequences of filtering a time series. Section 3.4 provides a univariate analysis of UK mergers. It first describes the data used, then presents the univariate results and finally discusses the findings. Section 3.5 discusses the synchronization of cycles, and presents data used in multivariate analysis of UK mergers. It presents the results of such analysis and discusses the findings. Finally, Section 3.6 summarizes the results from univariate and multivariate analysis.

3.2. An Introduction to Spectral Analysis³

3.2.1 Univariate Spectral Analysis

Spectral analysis is a modification of Fourier analysis, rendering it suitable for stochastic functions of time. Fourier analysis (see, for example, Priestley, 1981) is the technique of using an infinite number of orthogonal sine and cosine functions $X_t(\omega)$ (representing waves) with frequencies $\omega \in [-\pi, \pi]$ to approximate a stationary process X_t . Frequency is defined as cycle per period. The influence of any given wave $X_t(\omega)$ on the overall movement X_t depends on its amplitude (variance or deviation from the mean of the series), and is called power in spectral analysis. The power spectrum of X_t is given by the Fourier transform of its autocovariance function $\gamma(k)$, $k = 0, \pm 1, \pm 2, \dots$:

$$f(\omega) = \frac{1}{2\pi} \sum_{-\infty}^{\infty} \gamma(k) \exp(-i\omega k), \quad \omega \in [-\pi, \pi] \quad (1)$$

where i is the imaginary square root of -1 , π is a mathematical constant approximately equal to 3.14, and the sine and cosine functions are represented by the complex exponential function given by Euler's formula:

$$\exp(-i\omega k) = \cos(-\omega k) + i \sin(-\omega k) \quad (2)$$

Since $f(\omega)$ is symmetric about $\omega = 0$, it is customary to limit the analysis to the frequency interval $0 \leq \omega \leq \pi$. Consequently, the Fourier transformation maps a time series from the time domain into the frequency domain. By definition, frequency is the reciprocal of periodicity, where the latter measures the time

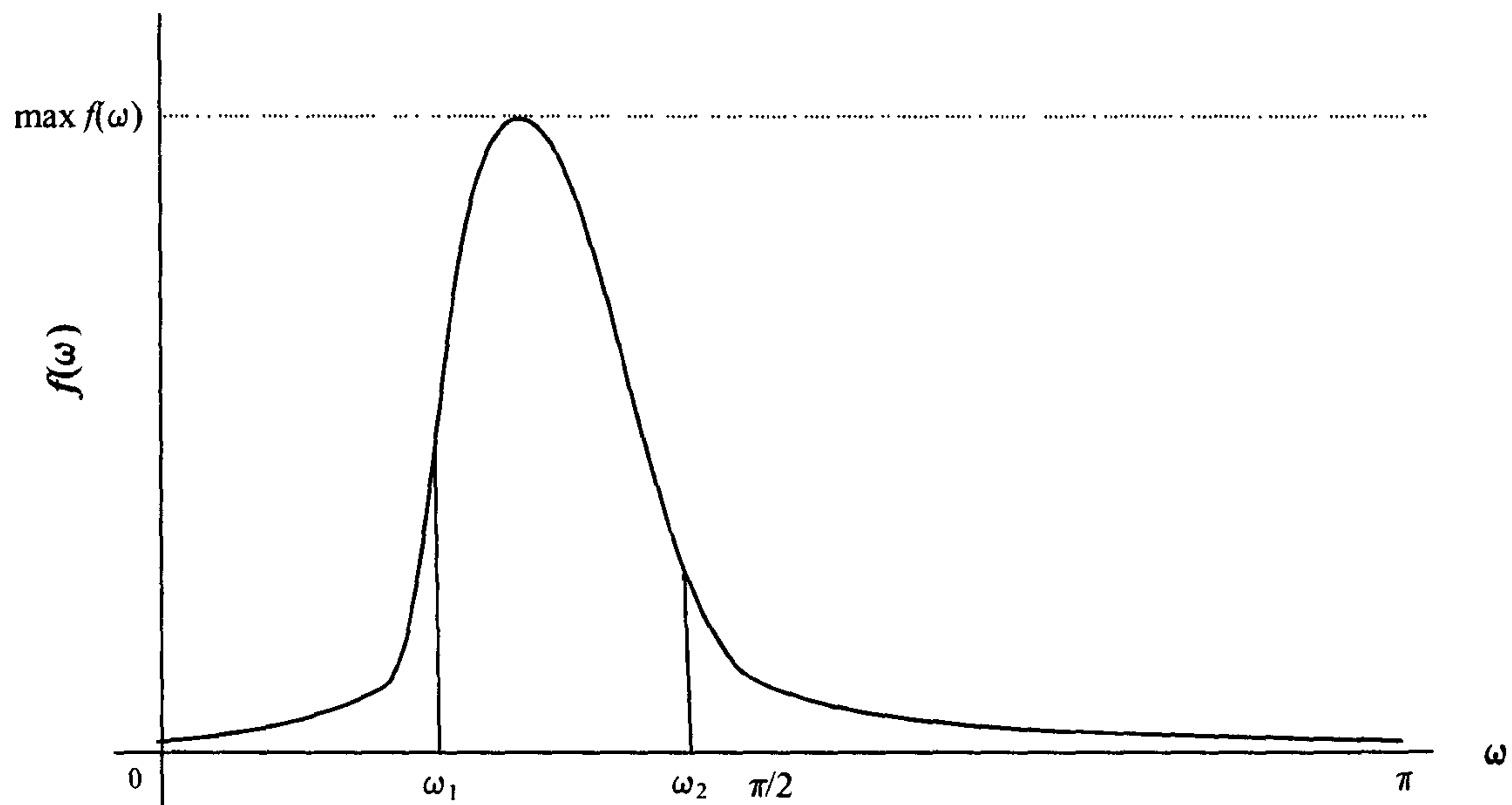
³The classic text on spectral analysis is Bloomfield (1976). However, introductory discussion of spectral analysis can be found in Stoica and Moses (1997) and Chatfield (2004). A more technical analysis is given by Priestley (1981), Brillinger and Krishnaiah (1983) and Canuto et al. (2006). An application of spectral analysis to social sciences is given in Warner (1998).

required for completion of a cycle. Thus, the spectrum of a series decomposes its total variation by the cycle-length of various periodic components.

Figure 3.1 illustrates the plot of a sample power spectrum. The interpretation is quite similar to a probability density function; the total area under the power spectrum equals the process variance, while $f(\omega)d\omega$ is the portion of the total variance of X_t which is due to the component $X_t(\omega)$ with frequencies over the interval $[\omega, \omega+d\omega]$. In other words, if the process X_t contains a coherent cycle at some frequency, ω^* , then the value of the power spectrum, $f(\omega)$, should reach a local maximum at ω^* . If the data contain several cycles with different frequencies, then $f(\omega)$ should have local maxima at each, with the global maximum at the frequency having the largest amplitude. The spectrum in Figure 3.1 has been normalized so that the area under the curve equals one. Hence, the area under the curve from ω_1 to ω_2 is the share of total variance of X_t which can be attributed to the composite of the waves in that range. Furthermore, its quasi-cyclical fluctuation depends on the relative power of its constituent components. When all waves in $[\omega_1, \omega_2]$ have similar power, the composite will display relatively irregular fluctuations. In contrast, when power is concentrated over a very narrow band of frequencies, it will display more regular cycles. This corresponds to a well defined peak in the spectrum in the range $[\omega_1, \omega_2]$, as in Figure 3.1. Accordingly, the steepness of the spectrum peaks can give an indication of the degree of regularity in the corresponding fluctuations. Thus, spectral analysis permits a natural decomposition of a series into quasi-cyclical components defined over frequency bands corresponding to cycles of different

duration. It offers measures of the periodicity, regularity, and explanatory power of fluctuations in these components.

Figure 3.1: Sample Power Spectrum



Note: Horizontal axis measures frequencies (ω) of cycles, while the vertical axis measures the power spectrum ($f(\omega)$)

3.2.2 Estimation of Power Spectrum

Implementing Equation. 1 is problematic, as it requires autocovariances from $-\infty$ to $+\infty$. The classic solution to this problem is to assume that out of sample covariances are zero. This assumption has the disadvantage that, when working with short economic time series, it produces an estimate of the spectrum, called the periodogram, which is inconsistent (see, for example, Chatfield, 2004). However, although the periodogram is itself an inconsistent estimator, smoothing the periodogram gives a consistent estimation procedure. It is clear that the periodogram is the discrete finite Fourier transform of the complete sample autocovariance function. However, the precision of the values of the estimated autocovariance, c_k , decreases as k increases, because the coefficients are based on fewer and fewer terms. Thus, it would seem intuitively reasonable to give less weight to the values of c_k as k increases. An estimator, which has this property, is

$$\hat{f}(\omega) = \frac{1}{\pi} \left\{ \lambda_0 c_0 + 2 \sum_{k=1}^M \lambda_k C_k \cos \omega k \right\} \quad (3)$$

where $\{\lambda_k\}$ are a set of weights called the lag window, and M (<sample size) is called the truncation point. Many lag windows have been suggested in the literature (see, for example, Chatfield, 2004). We smoothed the periodograms

using three different lag windows; Bartlett's, Turkey's, and Parzen's windows.⁴ As all yielded similar results, we report the estimates using Bartlett's window. The truncation point M has to be chosen subjectively so as to balance 'resolution' against 'variance'. The smaller the value of M , the smaller will be the variance of $\hat{f}(\omega)$ but the larger will be the bias. If M is too small, important features of $f(\omega)$ may be smoothed out, but if M is too large, the behavior of $\hat{f}(\omega)$ becomes more like of the periodogram with erratic variation. A useful rough guide is to choose M to be about $2\sqrt{N}$, where N is the sample size (see Chatfield, 2004, p129). The normalized spectrum, $h(\omega)$, is estimated by

$$\hat{h}(\omega) = \hat{f}(\omega) / \sigma_x^2, \quad (4)$$

where σ_x^2 is total unconditional variance of the series given by

$$\sigma_x^2 = \int_{-\pi}^{\pi} f(\omega) d\omega. \text{ Eq. (4) gives the percentage of total variance that is due to}$$

frequency component ω . By definition, $\int_{-\pi}^{\pi} \hat{h}(\omega) d\omega = 1$.

⁴ Parzen window is given by $\lambda_k = \frac{1}{2} \left(1 + \cos \frac{\pi k}{M}\right)$, $k = 0, 1, \dots, M$, the Parzen window by

$$\lambda_k = \begin{cases} 1 - 6\left(\frac{k}{M}\right)^2 + 6\left(\frac{k}{M}\right)^3, & 0 \leq k \leq M/2 \\ 2\left(1 - k/M\right)^3, & M/2 \leq k \leq M \end{cases} \text{ and the Bartlett window by } \lambda_k = 1 - k/M \text{ for}$$

$$k = 0, 1, \dots, M$$

3.2.3 Extension of Spectral Analysis to the Multivariate Case

By means of bivariate spectral analysis, it is possible to describe pairs of time series in frequency domain by decomposing their covariance into frequency components. Cross spectral analysis can be considered as the frequency domain equivalent of correlation analysis. The definition of the (smoothed) cross spectrum, analogous to that of the (smoothed) spectrum, is obtained by substituting the cross covariance function for the autocovariance function (see, for example, Priestley, 1981).

The cross spectrum between time series X_t and Y_t is expressed as

$$f_{xy}(\omega) = \frac{1}{2\pi} \sum_{-\infty}^{\infty} \gamma_{xy}(k) \exp(-i\omega k) \quad (5)$$

with $\gamma_{xy}(k) = \text{Cov}(x_t, y_{t-k})$

The cross spectrum contains all the information concerning the relations between the two series in the frequency domain and it is, in general, complex valued. It can therefore be decomposed into its imaginary and real parts:

$$f_{xy}(\omega) = co_{xy}(\omega) - iqu_{xy}(\omega) \quad (6)$$

Where $co_{xy}(\omega)$ is the cospectrum between the two variables and represents the covariance between X_t and Y_t attributable to the fluctuations determined by ω . It can also be interpreted as the covariance between the 'in phase' components of the two processes, components whose phases are matched in time. $qu_{xy}(\omega)$ is the quadrature spectrum, representing the covariance between the 'out of phase' components of the two processes. Fluctuations of significant importance in the series, as captured by large values of $f_x(\omega)$ and $f_y(\omega)$, may not make an important contribution to the contemporaneous covariance between

the variables, simply because they are in different phases of the implied cycle. The quadrature spectrum searches for these unmatched fluctuations.

In the next step, we introduce a measure which assesses the degree of linear relationship between cyclical components in the two series, frequency by frequency. This measure is the squared coherency and is defined as:

$$C_{xy}(\omega) = \frac{|f_{xy}(\omega)|^2}{\sqrt{f_x(\omega)f_y(\omega)}} \quad (7)$$

Coherency ranges from 0 to 1. If coherency is high at a particular frequency, this means that the components of each series corresponding to that frequency are highly correlated. However, this measure is completely independent of the position in time of the two series. Coherency adjusts the series in time, so that the components' phases match. Thus, if the cycles obtained from two series had exactly the same shape, but one of the cycles series was lagging with respect to the other, coherency would be high for every frequency. What matters is the cyclical behavior. If it is similar, coherency is high. Using coherency and the concept that the area under the spectrum is equal to the variance of the series, the following equation can be derived:

$$\int_{-\pi}^{\pi} f_x(\omega) d\omega = \int_{-\pi}^{\pi} C_{xy}(\omega) f_x(\omega) d\omega + \int_{-\pi}^{\pi} f_u(\omega) d\omega \quad (8)$$

The first term on the right in the equation is the product of squared coherency between X_t and Y_t and the spectrum of X_t (explained variance); the second term is white noise. This equality holds for every frequency band $[\omega_1, \omega_2]$. Thus, total variance of a series equals an explained variance (by some series Y_t) and a remaining unexplained portion. Comparing the area under the spectrum of the explained component to the area under X_t autospectrum in a frequency band

$[\omega_1, \omega_2]$ yields a measure of the explanatory power of X_t , analogous to an R^2 in the time domain.

However, coherency, as previously mentioned, is independent of the position in time of the series. It indicates only whether or not two series have the same pattern.

Another concept that can help characterize much better the relations between the series is the phase effect, which is defined as

$$Ph_{xy}(\omega) = ArcTan\left(\frac{qu_{xy}(\omega)}{co_{xy}(\omega)}\right) \quad (9)$$

It measures the phase difference between the frequency components of the two series: the number of leads (if $Ph_{xy}(\omega) > 0$) or lags (if $Ph_{xy}(\omega) < 0$) of x on y.

The analysis of quantities given by Equations 8 and 9, together with the (auto) spectrum of each series, will give an overall view of the frequency interaction of the two series.

3.3. Requirements for Applying Spectral Techniques

Spectral analysis requires a stationary process, which raises the difficult issue of detrending. Instead of using the usual approaches to test for stationarity and then detrending, we adopt a different view in the spirit of Burnside (1998). Thus, we first extract the cyclical component of the series (this is, by definition, stationary) by using appropriate filtering methods, and then apply spectral techniques to investigate the properties of that cyclical component

3.3.1 Extracting the Cyclical Component of the Series

It is well known that time series can be decomposed into cyclical and trend components.⁵ The cyclical component captures temporary fluctuations around the trend associated with cycles, while the trend component describes long-term growth. Thus, time series, X_t , observed over period $t=1,2,\dots,T$ is decomposed additively into a trend, μ_t , and a cyclical component, ε_t , i.e.

$$X_t = \mu_t + \varepsilon_t \quad (10)$$

Since our aim is to look at stylized facts of merger cycles rather than time series in general, it is natural to treat the data in such a way that all variation outside merger cycle frequencies is filtered out. In other words, our focus is upon extracting the cyclical component of the series and then analyzing its properties using spectral analysis.⁶

Alternative definitions of the trend in an economic time series have been proposed in the literature, each of these definitions having different implications for the statistical properties of both the trend and the residual (commonly referred to as the cyclical component), and the correlation between them. That has led to the development of a variety of methods for estimating trend and cycle components of an economic series.⁷ Since the appropriate method depends on the

⁵ Since only trend and cycle are assumed to exist, the procedures followed in this study implicitly assume that the seasonal and cyclical components of the series are lumped together, and that irregular (high frequency) fluctuations play an inconsequential role.

⁶ The cyclical component of a time series is, by definition, a stationary process and thus, spectral analysis can be applied.

⁷ There have been various attempts to construct trend and cycle estimators that work well in a variety of situations such as first order differencing, unobservable components model, Beveridge and Nelson's procedure, Hodrick and Prescott's filter, band pass filters, cointegration, multivariate frequency domain, common linear (e.g. Mills, 2003).

definition of the trend and the correlation of the trend and the cyclical component, it is difficult to distinguish among these. As Canova (1998) indicates, there is something misleading in the fact that different estimation methods lead to different facts about trend and cycle components.⁸ However, when detrending and extracting the cycle component of a time series are recognized as being distinct exercises, there are many facts about the cycle component which should be accepted as being robust. In other words, it is important at this stage to distinguish between the arguments about the right way to detrend on the one hand, and those about the nature of a cyclical component of interest on the other.⁹ Thus, we proceed by first defining a merger cycle and then describing methods to extract the cyclical component from the merger time series. Empirical evidence (Town, 1992; Linn and Zhu, 1997) on merger waves, as well as conventional wisdom that merger cycles are unlikely to be longer than business cycles define the merger cycle as fluctuations with a range of periodicities from 6 to 32 quarters.¹⁰ Defining the merger cycle as fluctuations with a specified range of periodicities, it is natural to adopt a linear filter as a procedure to isolate the merger cycle component. We compile statistics using two different filters so as to gain information on the behavior of variables at

⁸ The problem of spurious cycles due to inappropriate data transformations is well known in empirical business cycle analysis (King and Rebelo, 1993; Harvey and Jaeger (1993), Osborn, 1995).

⁹ For example, if one is using first difference methods to render stationary an economic time series, it is misleading to argue that by so doing, only the cyclical components of certain frequencies are being isolated. This is because first differencing places strong emphasis on high frequency components. (See the discussion by Burnside (1998) and the reply of Canova (1998).)

¹⁰ Burns and Mithell (1946) define business cycles as cyclical components from 6 to 32 quarters in duration. Similar cut-off points are used by Granger and Hatanaka (1964), Lucas (1980), and Levy and Dezhbakhsh (2003).

different cycle frequencies in the spirit of Burnside (1998). We choose Hodrick and Prescott, and Baxter and King filters, which emphasize different cycle concepts and which appear to be the most reliable tools for measuring cycles (Canova, 1994). These two filters provide different windows through which the data can be examined.

3.3.2 Filtering Techniques

When a series is filtered, the relative importance of its components is changed so that only the component of interest is retained. Thus, the characteristics of a cycle can be identified by retaining only the desired frequencies and totally eliminating the remaining while inducing no phase shift, i.e. no alteration in the timing relationships between series at any frequency (ideal filters). In other words, the objective is to obtain a filter that eliminates the low frequencies (slowly evolving components of that series or trend) in the series and preserves the components that account for the short-run major fluctuations; fluctuations that have been defined as lasting from 6 to 32 quarters (1.5 to 8 years).

The Hodrick and Prescott (HP) filter retains high frequency components and attenuates fluctuations at low frequencies. This was originally developed as the solution to the problem of minimizing the variation in the cyclical component of an observed time series, $\varepsilon_t = X_t - \mu_t$, subject to a condition on the 'smoothness' of the trend component, μ_t . In this way, the two components are identified. The assumption that the trend is smooth is imposed by assuming that the sum of squares of the second differences of μ_t is small. The smoothness condition

penalizes acceleration in the trend, so that the minimization problem becomes that of minimizing

$$\text{Min}_{\{\mu_t\}_{t=1}^T} \left[\sum_{t=1}^T \varepsilon_t^2 + \lambda \sum_{t=2}^T \left[(\mu_{t+1} - \mu_t) - (\mu_t - \mu_{t-1}) \right]^2 \right], \lambda > 0 \quad (11)$$

where λ is a Lagrangean multiplier that can be interpreted as a smoothness parameter i.e. one that penalizes the variability of trend. As λ increases, the penalty imposed for large fluctuations in the trend component increases and the path for $\hat{\mu}_t$ becomes smoother, so that in the limit, as $\lambda \rightarrow \infty$, μ_t becomes a linear trend. Optimizing the smoothness parameter is an issue that has fuelled considerable research.¹¹ Setting the smoothing parameter to $\lambda = 1,600$ produces a frequency response function that is very close to that of the ideal high-pass filter with lower pass $\pi/16$ cycles per period,¹² if quarterly data is being used (Hodrick and Prescott, 1997; Ravn and Uhlig, 2002). Thus, this choice produces a filter that is close to optimal for passing the cyclical component having periods of 32 quarters or less. However, this optimality result is based on application of the filter to an infinitely long time series, or from a practical viewpoint, to the

¹¹ Although most researchers have followed Hodrick and Prescott and used the value of 1,600 for the smoothing parameter when using quarterly data, there is less agreement in the literature when moving to other frequencies. Backus and Kehoe (1992) use a value of 100 for annual data, whereas Cooley and Ohanian (1991) suggest a value of 400 and Baxter and King (1999) a value of 10.

¹² The transfer function of HP filter is $H(\omega) = \frac{4\lambda(1 - \cos(\omega))^2}{1 + 4\lambda(1 - \cos(\omega))^2}$. Thus, the cyclical component of the HP filter places zero weight on the zero frequency ($\hat{H}(\omega) = 0$), and close to unit weight on high frequencies ($\hat{H}(\omega) = 16\lambda / (1 + 16\lambda)$). Thus, for $\lambda = 1,600$, this filter looks remarkably like an approximate high pass filter with cut-off frequency $\omega = \pi / 16$ cycles per period or cut-off periodicity of 32 quarters per cycle.

midpoints of series of typical length. The optimality conclusion does not apply at, or close to, series endpoints (Mise et al., 2005; Kaiser and Maravall, 1999). A solution to this problem, proposed by Kaiser and Maravall (1999), is application of the filter to series extended with proper optimal forecasts (obtained with the appropriate ARIMA model for the series). However, this solution would require to render the series stationary. The most appropriate procedure, one which renders a series stationary without simultaneously distorting its cyclical structure, depends on the type of non-stationarity in the data. As already discussed, in practice, such a procedure is difficult to find. Weak reliance on the power of the unit root test seems hazardous in this context, so we adopt another approach, proposed by Baxter and King (1999). Since the optimality of HP is improved as we move towards the midpoints of the series (especially after the twelfth observation), it would seem natural to drop twelve observations from the beginning and end of the sample period.

Baxter and King develop the theory of band pass filters and propose an alternative to the Hodrick –Prescott filter. Roughly speaking, the band-pass filter is a linear filter that takes a two-sided weighted moving average of the data, where cycles in a ‘band’, given by a specified lower and upper bound, are ‘passed’ through, or extracted, and the remaining cycles are ‘filtered’ out.¹³ The Baxter-King (BK) filter has the following two-sided moving average representation:

¹³ At quarterly frequencies, the desired band is 6 to 32 quarters per cycle, which means a frequency band of $\pi / 16 \leq |\omega| \leq \pi / 3$. Thus, the transfer function of the ideal band pass filter takes the form:

$$W^*(\omega) = \begin{cases} 1 & \text{if } \frac{\pi}{16} \leq |\omega| \leq \frac{\pi}{3} \\ 0 & \text{otherwise} \end{cases}$$

$$\alpha_K(L) = \sum_{k=-K}^K \alpha_k L^k \quad (12)$$

Where the lag operator L is defined so that $L^k X_t = X_{t-k}$ for positive and negative values of k . In addition, symmetry (weights are such that $\alpha_k = \alpha_{-k}$ for $k=1, \dots, K$) is imposed so that the filter does not induce a phase shift. It approximates the ideal filters by choosing the filter weights so as to minimize:

$$Q = \frac{1}{2\pi} \int_{-\pi}^{\pi} |W^*(\omega) - W_K(\omega)|^2 d\omega \quad (13)$$

Where $W^*(\omega)$ is the frequency response function of the ideal filter, $W_K(\omega)$ is the frequency response function of the filter described by (7) and K denotes the maximum lag length of the resulting two-sided moving average.

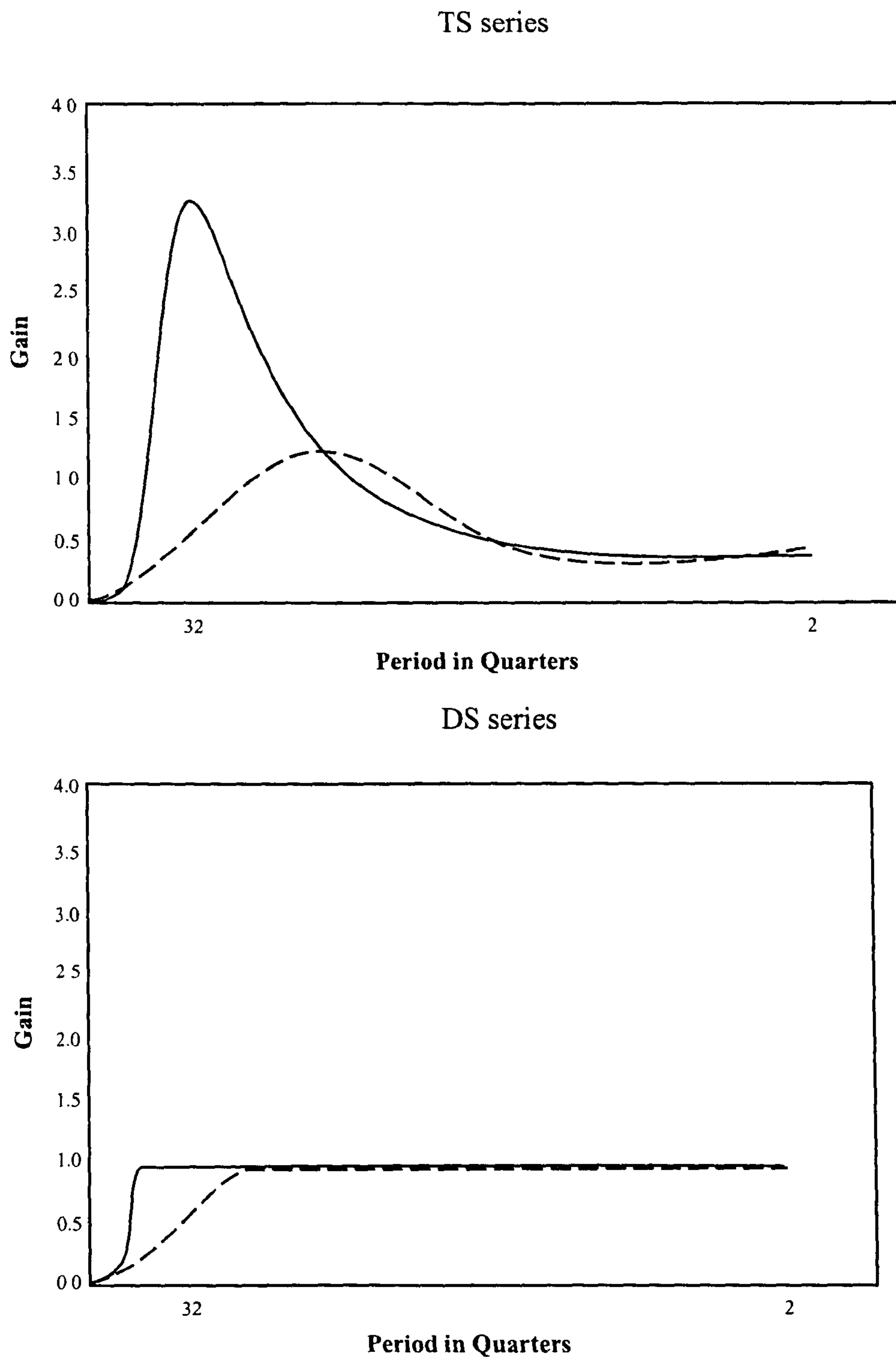
HP and BK filters are good and justified attempts to approximate the ideal filters. However, each filter fails to retain perfectly the desired frequencies (*compression* and/or *exacerbation* effect), and frequencies that should suppress also pass the filter (*leakage* effect).¹⁴ In Figure 3.2, the transfer function¹⁵ plots the squared gain (change in amplitude) of HP and BK filters for both trend stationary (TS) and difference stationary (DS) series. The ideal filter would eliminate permanent fluctuations (those at period ∞) and irregular fluctuations (those at periods less than 6 quarters-only in the case of BK filter) and leave all others untouched, implying a squared gain of one. In other words, the ideal filter extracts fluctuations within the desired band of periodicities (or until the upper band, in case of HP filter). If the squared gain is higher than one in a range of

¹⁴ For a more technical analysis on distortionary effects of the Hodrick-Prescott filter, see Ehlgren (1998), Cogley and Nason (1995), Singleton (1988), and of the Baxter and King filter, see Murray (2003).

¹⁵ The transfer function indicates the extent to which the filter alters the spectrum of the original time series.

frequencies within the desired band (from 6 to 32 quarters) or below the upper band in the case of HP filter (32 quarters), the fluctuations corresponding to those periodicities are expanded relative to the original series (*exacerbation*). Others are attenuated (*compression*), in which case, the squared gain is lower than one. Leakage effect exists when periodicities outside the band (or above the upper band in the case of HP filter) are not completely eliminated. Unfortunately, there is no ideal filter for all processes. The HP filter is quite close to ideal for a trend stationary series but has a tendency to induce spurious power when applied to the wrong type of data. The BK is an alternative that minimizes the risk of introducing spurious cyclical structure in the data when the type of non-stationarity in the data generating process is unknown (Baxter and King, 1999). The danger of spurious cycles can be minimized by careful comparison across filters, bearing in mind the transfer function in Figure 3.2. Thus, we compare results with the known potential distortions induced by the filter used, and compare across filters to judge robustness. Confidence is justified if the BK and HP filtered data both display cycle peak at or below a period of 28 quarters.

Figure 3.2: Transfer Function for the HP and BK Filters



Note: Dash line refers to while BK filter while the dark line refers to HP filter

3.4 Univariate Analysis of UK Mergers

3.4.1 Data Description

One difficulty in the time series analysis of mergers is the need for relatively long data series. Any study on merger waves involves a trade-off between internal consistency of the data series and the length of the series. Empirical studies for the US have merged series produced by different institutions in order to produce a single long series, but this kind of procedure is problematic.

We consider the longest consistent series available for the UK mergers provided by the Office of National Statistics (see Chapter 2). Specifically, we consider the number of completed domestic mergers quarterly over the period from 1969 to 2005. Ideally, one would measure merger activity by the real value of merged firms. However, this measure is subject to huge errors, since the price paid for the acquired firm is often not disclosed. In these cases, the value of the acquisition would be estimated from publicly available information, which generally understates the true value of the transaction. This bias would represent a simple shift in the mean of the series.

At the sectoral level of analysis, the data source is the *Thompson ONE Banker* database; the most extensive resource for merger transactions around the world. We consider the number of completed domestic mergers by sector (as defined by the *Thompson ONE Banker*) quarterly for the period from 1985 to 2005. The two different sources of the different levels of analysis provide a more complete picture of mergers than using just one source. Series have not been merged in order to construct longer series. Summary statistics for the merger data at the aggregate and sector level are given in Table 3.1.

Table 3.1: Mergers and Acquisitions in the UK– Summary Statistics

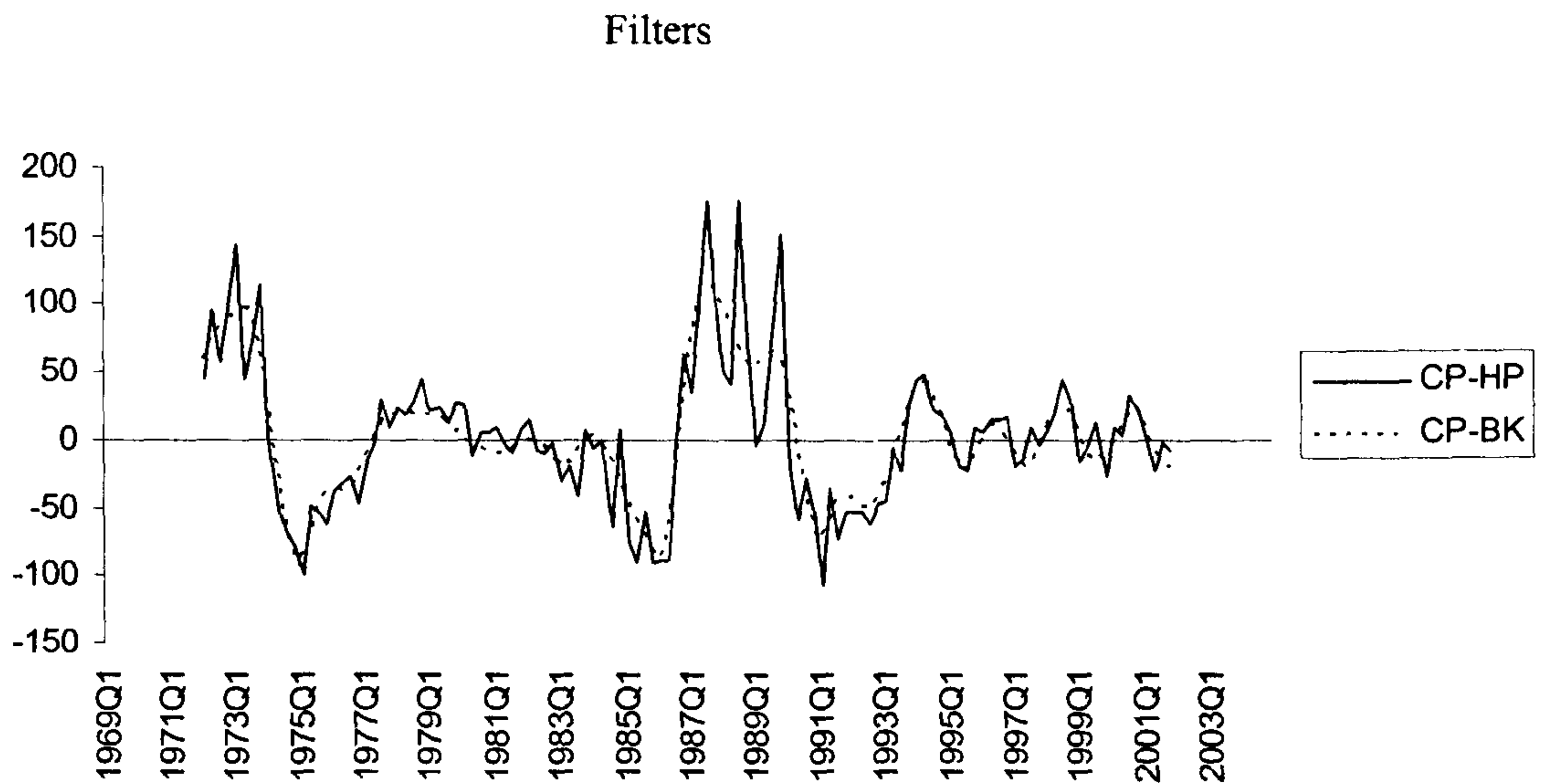
	Mean	Std.Dev.	Minimum	Maximum
Aggregate Mergers	168	82.49	56	464
Sectors				
Telecommunications	14	4.38	0	19
Consumer Staples	67	11.98	3	61
Retail	73	16.44	3	71
Real Estate	57	24.24	2	131
Media & Entertainment	106	25.08	0	109
Materials	74	16.17	0	74
Industrials	144	27.25	2	121
High Technology	74	26.09	0	139
Consumer Product & Services	123	31.80	1	127
Energy and Power	36	7.98	0	33
Financials	89	18.95	6	100
Healthcare	28	8.10	0	36

Note: Data for aggregate mergers cover the period from 1969-2005 quarterly and are sourced by *Office of National Statistics* while those for different sectors cover the period from 1985-2005 quarterly and are sourced by *Thomson ONE Banker*

3.4.2 Univariate Results : Cyclical Component of UK Mergers

Figure 3.3 displays the results of applying HP and BK filters to the aggregate number of mergers. There is a very close correspondence between the cycles isolated by the HP filter and those generated by the BK filter, although the HP filtered series is somewhat less smooth. The maximum and minimum of that series are the same for both HP and BK filters, with the former occurring in 1987 Q3 and the latter in 1991Q1. Other peaks occur in 1973Q1, 1978Q4, 1989Q3, 1994Q2, (also in 1988Q3, but only if using the HP filter), while troughs exist in 1975Q1, 1985Q1. The above results are an indication of quasi-cyclical behaviour of the aggregate mergers with different amplitudes and regularities. The cyclical component of sector mergers also exhibits the same pattern, regardless of the filter used.

Figure 3.3: Cyclical Component of Aggregate Mergers Series using HP and BK



Note: The horizontal axis measures period in quarters, while the vertical measures the deviations from the mean of the series (merger numbers). The common sample period for these graphs is 1969.1-2005.4, but since $K=12$ is used, (BK filter), three years of data (12 observations) is lost at each end of the plots. In addition, as the HP filter is close to optimal only at the midpoints of series, the same number of observations is dropped in order to avoid spurious cycles towards the end of the series (see Section 3.3.2, pp: 59-60)

These cyclical components are further studied using the spectrum estimation, in order to analyze duration, regularity, and explanatory power. Figure 3.4 presents the estimated spectrum for the BK and HP filtered data of aggregate mergers (the correspondent spectrum of mergers by sector are presented in Appendix A). Since these are point estimates of the power spectrum function, they give no indication of their likely accuracy. Thus, we also calculate the

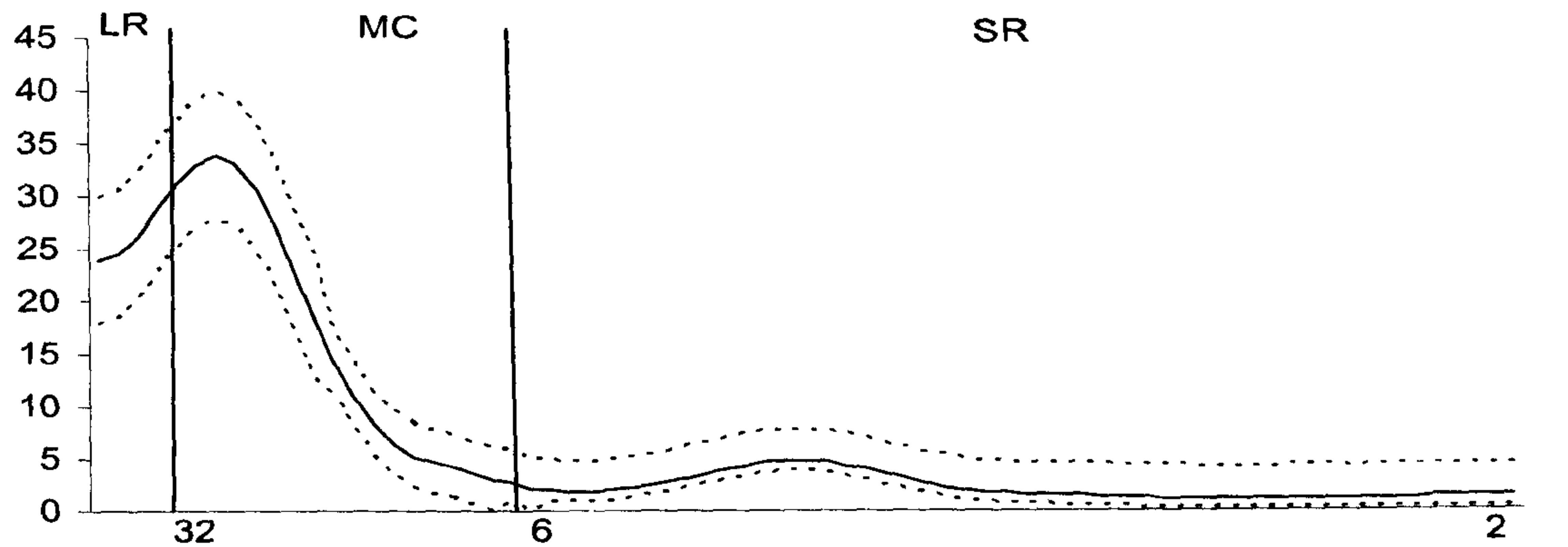
corresponding 95 percent confidence intervals.¹⁶ Based on the fact that each frequency component, ω , corresponds to a particular periodicity (cycle length), the horizontal axis measures cycle lengths in quarters, in order to make conclusions more straightforward. Thus, the area in the plot is divided into three segments: the long run periodicity band (LR), which corresponds to cycles of 32 quarters or longer, the merger cycles band (MC), which corresponds to cycles of 6-32 quarters, and the short run (SR) periodicity band, which corresponds to cycles of 2-6 quarters. Note that as we move to the right along the axis, the cyclical period falls. This also implies that the first half interval covers cycles with periods from infinity down to 5 quarters, while the second half covers only periods from 5 down to 2 quarters (the smallest cycle observable with quarterly data).

¹⁶A $100(1-\alpha)\%$ confidence interval for $f(\omega)$ is given by $\frac{\hat{v}f(\omega)}{\chi^2_{\nu, \alpha/2}}$ to $\frac{\hat{v}f(\omega)}{\chi^2_{\nu, 1-\alpha/2}}$, where

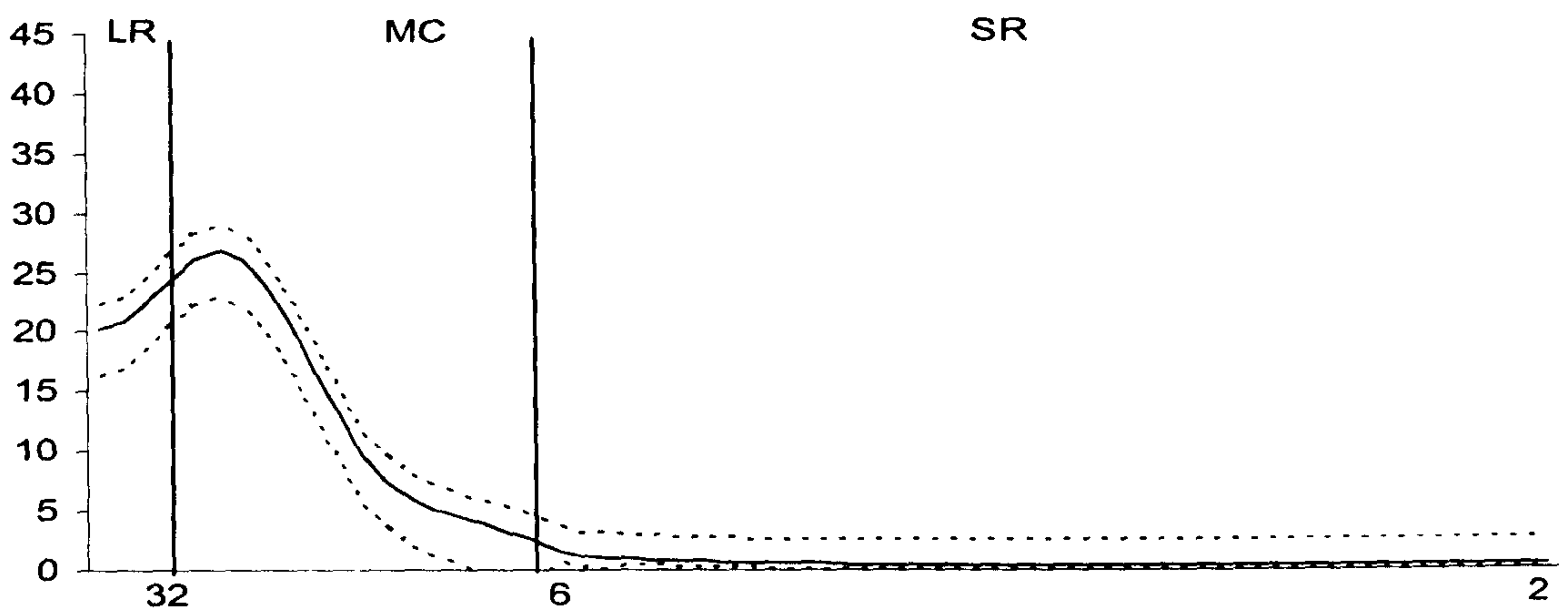
$\nu = 2N / \sum_{k=-M}^M \lambda^2$ is the number of degrees of freedom of the lag window (see Chatfield, 2004

p:139).

Figure 3.4: Univariate Estimated Spectrum of Aggregate Mergers using HP and BK Filtered Data.



HP Filtered Data



BK Filtered Data

Note: The dashed line gives the 95% confidence interval. The horizontal axis measures the cycle length in quarters, while the vertical measures the power of spectrum of mergers series (variance of merger series).
 MC=merger cycles periodicity band, LR=long run periodicity band,
 SR=short run periodicity band

3.4.3 Discussion of Univariate Results

The estimated spectrum provides clear evidence of cyclical structure for aggregate mergers. In addition, for every sector, the estimated spectrum displays at least one identifiable peak (see Appendix A). Table 3.2 reports the periods at which maximum power is obtained with HP and BK filtered data. As peaks imply strong periodicity in the data, the presence of a peak in the spectrum is an indication of a predictable component in the corresponding series. In aggregate mergers, and also in all sectors, a peak is found within the merger cycle band, suggesting that merger cycle fluctuations have a predictable component.

Table 3.2: Duration of Regular Cycles by Sector, and of Aggregate Mergers using HP and BK Filtered Data (period in quarters)

	Cycle duration	
	HP filtered data	BK filtered data
Aggregate Mergers	24	24
Sectors		
Telecommunications	16	16
Consumer Stample	28	20
Retail	20	20
Real Estate	20	20
Media & Entertainment	20	18
Materials	20	20
Industrials	20	20
High Technology	16	16
Consumer Products & Services	20	20
Energy and Power	12	12
Financials	20	20 (8)
Healthcare	20	20

Note: The apparent difference between the overall cycle length of 24 quarters and the average cycle length of 20 quarters will affect small differences in phases.

Since sectors exhibit a regular cycle of 20 quarters or less, it is the (slightly) lead/lag relation among them that may create a cycle of 24 quarters in aggregate level.

Can we be sure these peaks are not a spurious product of the filter used? For aggregate mergers, as well as for sectors such as Consumer Products and Service, Healthcare, Industrials, Real Estate, High Technology and Materials, the answer is yes. For these sectors, and also for aggregate mergers, regardless of how the data are filtered, not only is a cycle peak identified in the merger cycle band, but each one is also below that in the transfer function for both HP and BK filters. For sectors such as Energy and Power, Media and Entertainment, Retail, and Telecommunication, again, it is the case that a spectrum peak in the merger cycles band is found in data filtered by both methods, though the variation of the series which occurs within the short run band when the HP filter is applied is higher than that for the BK filter (especially in Telecommunications). Since the two filters have different transfer functions, it is not surprising that when they are applied to the same time series, the resulting filtered series display different properties. Remember that both filters eliminate high periodicity (or trend), but while BK extracts the cyclical component within the band of 6 to 32 quarters smoothing low periodicity irregular variation, the HP filter imposes only an upper bound in the periodicity of the isolated fluctuations and does not remove the irregular variation in the series. Thus, the existence of high variation in the spectrum of these sectors is just the consequence of the dominant role played by the low periodicities in the spectrum. In other words, merger activity in these sectors may contain important low periodicity components that are passed by HP filter, but that are removed by the BK filter. Thus, confidence in the spectrum is justified. The remaining sectors, Consumer Staples and Financials, are more

questionable. Regarding the former, the peak in the HP filtered data is roughly consistent with spurious cycles induced by the filter. Thus, there is no confidence regarding cycles in that sector. For Financials, BK filtered data display two different peaks within the merger cycles band, while HP filtered data for the same sector exhibit only one peak within the same band. Thus, on the basis of BK filtered data, we can conclude that Financials exhibits two different merger cycles of 20 and 8 quarters duration, while on the basis of HP filtered data, that sector exhibits only one cycle of 20 quarters duration. Consequently, only the cycle of 20 quarters duration is consistent with both filters, and we can be confident that this cycle is a true feature of the data.

For a more rigorous assessment of the spectrum mass distribution across the three bands, Table 3.3 reports the results of variance decomposition of the normalized spectrum (for both filters) of mergers at aggregate and sector level. By doing so, we can check whether most of the spectrum mass is concentrated in the merger cycle periodicity band. Although that is obvious in the case of BK filtered data, it is questionable in the case of HP filtered data. The first column of the table contains the proportion of the variance due to the long run periodicity component, while the next two columns report the proportion of the merger variance due to merger and short run cycles, respectively. As expected, variance decomposition when BK filtered data are used suggests that the merger cycle periodicity component explains most of the merger variance. Cyclical variation ranges from 67 percent to 83 percent. However, in HP filtered data, the estimated distribution of mergers variance across long run, merger cycle, and short run periodicities suggests that for 10 out of the 13 sectors (with the exception of Financials, Consumer Staple, and Telecommunications) in our sample, and also

for aggregate mergers, the merger cycle component is larger than the other two components. Aggregate mergers exhibit proportional cyclical variation of 54 percent, indicating that the bulk of the spectrum mass is concentrated in the merger cycle periodicity band. Among sectors, Energy and Power exhibits the highest cyclical proportional variation of 73 percent, followed by high Technology, Real Estate, and Media and Entertainment. The merger series of Consumer Products and Services, Industrials, Materials, Healthcare, and Retail have merger cycle periodicity components of less than 50 percent, but higher than the other two cyclical components. Finally, Financials, Consumer Staples, and Telecommunications display a short run variation which is higher than that of the merger cycle band. Indeed, their short run periodicity band accounts for most of the variance in the series. This means that irregular cyclical fluctuation in these sectors is more important than longer cycles (cycles from 6 to 32 quarters). Overall, these results suggest that the bulk of the spectrum mass is concentrated in the merger cycle band for the majority of the sectors and aggregate mergers.

Table 3.3 Variance Decomposition of Merger Activity by the Periodicity Component

Variance decomposition -HP filtered data			
	LR	MC	SR
Aggregate mergers	0.26	0.54	0.20
Sectors			
Telecommunications	0.09	0.35	0.57
Consumer Staples	0.12	0.33	0.55
Retail	0.09	0.46	0.46
Real Estate	0.18	0.52	0.30
Media & Entertainment	0.12	0.50	0.37
Materials	0.16	0.48	0.38
Industrials	0.15	0.48	0.38
High Technology	0.13	0.59	0.29
Consumer Products & Services	0.19	0.48	0.33
Energy and Power	0.08	0.73	0.19
Financials	0.10	0.39	0.51
Healthcare	0.13	0.46	0.42
Variance decomposition -BK filtered data			
	LR	MC	SR
Aggregate mergers	0.30	0.68	0.01
Sectors			
Telecommunications	0.18	0.69	0.13
Consumer Staples	0.18	0.67	0.15
Retail	0.11	0.83	0.06
Real Estate	0.20	0.76	0.04
Media & Entertainment	0.16	0.77	0.08
Materials	0.20	0.77	0.03
Industrials	0.18	0.77	0.05
High Technology	0.13	0.78	0.08
Consumer Products & Services	0.22	0.74	0.05
Energy and Power	0.08	0.73	0.19
Financials	0.21	0.75	0.04
Healthcare	0.19	0.76	0.04

Note: MC=merger cycles periodicity band, LR=long run periodicity band,
SR=short run periodicity band

So far, we have identified cycles with peaks in the spectrum of aggregate and sector level merger series. In order to assess the significance of these peaks and consequently, the significance of cycles, we test formally for cyclical structure in the data following a procedure developed by Canova (1996) and modified by Reiter and Woitek (1999). The test statistic is given by

$$D = \frac{\int_{\Omega_{MC}} I_N(\omega) / \|\Omega_{MC}\|}{\int_{\Omega_R} I_N(\omega) / \|\Omega_R\|}, \quad (9)$$

where Ω_{MC} defines the merger cycle periodicity range, while Ω_R defines the short plus the long run periodicity ranges ($R = SR \cup LR$). $I_N(\omega)$ is the sample periodogram and $\|\cdot\|$ represents the number of periodogram ordinates in the interval. Thus, the numerator measures the average power of the series inside the merger cycle periodicities, while the denominator measures the power outside the referred band.

Table 3.4 presents the value of the test statistic (D) for the HP and BK filtered data. If D is significantly greater than one, there is cyclical structure at merger cycle periodicities in the data.¹⁷ Table 3.4 shows that when the data are filtered by BK filter, aggregate mergers and mergers in all sectors exhibit cyclical behavior. However, when the HP filter is used, the results are not so clear. Thus, for aggregate mergers and for sectors such as Energy and Power, Financials, Consumer Products and Services, Healthcare, Industrials, Materials, Media and Entertainment, Real Estate, Retail, and High Technology, the results strongly support the presence of merger cycles in the 6-32 quarters range (1.5-8 years).

¹⁷ Canova (1996) shows that $\|\Omega_R\| \cdot D$ follows the $\chi^2(2\|\Omega_{MC}\|)$ distribution

For the two remaining sectors (Consumer Staples and Telecommunications), the test statistic is not significant, although it is greater than one. Thus, the hypothesis of a merger cycle in these sectors can not be accepted. That conclusion is further supported by the spectrum (see Appendix A) and variance decomposition, Table 3.3 (HP filtered data), which shows that short run cyclical fluctuations tend to be more important than merger cycle fluctuations. Thus, for Consumer Staples and Telecommunications, we do not find a robust cyclical structure. The case of Financials, however, is the most controversial. Although the D test supports the notion of merger cycles in Financials, variation decomposition indicates that short run fluctuations explain more than the merger cycle fluctuations (HP filtered data). Furthermore, spectrum with HP and BK filtered data (see Appendix A) indicates a cycle of 20 quarters or two cycles of 20 and 8 quarters, respectively. Consequently, we can be confident only about a merger cycle of 20 quarters (5 years) duration in Financials, although strong lower periodicity also exists.

Overall, the above results suggest that aggregate mergers occur in cycles of 24 quarters (6 years), although there are some less regular periodicities. That conclusion is consistent with the cyclical component of the merger series (Figure 3.3) where the hidden periodicities are shown. At the disaggregate sector level, most UK industries exhibit cyclical merger activity of approximately 20 quarters (5 years).

Table 3.4: Canova Test (D) for UK Merger Cycles

	HP filtered data	BK filtered data
Aggregate mergers	2.69	6.78
Sectors		
Telecommunications*	1.23	4.57
Consumer Staples*	1.11	4.01
Retail	1.93	6.35
Real Estate	2.50	5.73
Media & Entertainment	2.35	4.63
Materials	1.62	6.98
Industrials	2.10	7.44
High Technology	3.13	7.09
Consumer Products & Services	2.14	5.82
Energy and Power	1.84	8.47
Financials	1.47	4.18
Healthcare	1.96	6.04

Note: *Average spectrum in the merger cycle periodicity band is not significantly higher than at other periodicities bands at 5 per cent significance level

3.5 Is there a Synchronization of Cycles?

Since we have identified the power and the duration of merger cycles in aggregate and at the sector level, an interesting question is whether there exists the synchronization of cycles; in particular, synchronization over cycles in different sectors, and synchronization of the aggregate merger cycles with a business or capital markets cycle.¹⁸ As regards the former, relevant literature (see Chapter 2, Section 2.2.3) argues that merger waves result from shocks to an industrial sector's economic, technological or regulatory environment. If these shocks are common to sectors, they will lead to a synchronization of sector merger cycles. If there are different shocks, a lead / lag relation among sectors will be observed.

On the other hand, with regard to the latter question, we take the view that merger is an investment decision and as such, management uses information to develop estimates of future cash flows, to discount those cash flows with the appropriate cost of capital, and to evaluate whether the net present value of the merger is positive. Such evaluation is sensitive to expectations of current and future economic and financial market conditions. (For empirical evidence, see relevant literature in Chapter 2, Sections 2.2.1 and 2.2.2).

As a result, an important determinant of mergers is the real business cycle because high levels of economic activity generate higher expected cash flows from a merger and a greater need for additional real capital. Thus, when an

¹⁸ A number of studies suggest the existence of business cycles, and the cyclical behaviour of interest rates and stock prices in the UK, (see, for example, Roma and Torous, 1997; Andreou et al, 2001).

economy is in expansion, it is expected to encourage merger activity. The real GDP growth will be used to proxy the business cycle and the current economic activity. Thus, real GDP growth and merger activity move together.

Secondly, stock prices would have two effects on merger activity. Stock prices have an important influence through the mechanism of the cost of capital. High stock prices reduce the firm's estimate of its cost of capital, raising the net present value of the future economic benefits available from a merger. On the other hand, Fama (1981) shows that current stock prices are statistically significant predictors of the future rate of change in economic activity. As a result, higher stock prices indicate the market's assessment of favourable future economic conditions, which in turn, means higher future cash flows associated from a merger. In this case, more mergers should become positive net present value investments. In contrast to most existing studies, we use the real stock market prices, since high stock prices can simply imply that the nominal value of stocks is higher as a result of inflation (see, for example, Clarke and Ioannidis, 1996; Polonchek and Sushka, 1987). Thus, stock prices are expected to move together with merger activity.

Finally, many mergers are financed with borrowed capital, and would be influenced by the current real interest rate. Higher interest rates would indicate higher cost of capital and tighter monetary conditions, which would be expected to discourage merger activity. Consequently, movements of real current interest rates and merger activity are expected to be in the opposite direction.

The above hypotheses are empirically investigated by applying concepts of cross spectral analysis.

3.5.1 Data Description

In addition to data on merger activity used in univariate analysis, we use quarterly data on UK stock market prices, GDP growth, and interest rates from 1969 to 2005. In accord with the literature, the Financial Times Stock Exchange 100 Price Index (FTSE 100) is chosen as the measure of stock market prices, taken from *DataStream*. The nominal short term interest rates are measured as the 3-month Treasury-bills taken by the *International Monetary Fund* (IMF) database. In addition, real GDP is taken by the *International Monetary Fund* (IMF) database and its growth rate is calculated as the proportionate change in real GDP levels. The FTSE 100 and short term interest rates are deflated by the gross domestic product deflator (at market prices). In the rest of the study, when discussing the above variables, we refer to their value in real terms.

3.5.2 Multivariate Results

In this section, we present the main empirical results, based on estimation of coherency, phase effect, and quadrature spectrum and univariate spectra.

Table 3.5 presents the significant relations across sectors with the correspondent phase value. It is obvious from the table that there is synchronization across most sectoral cycles. Only cycles in Financials and Healthcare do not have a significant relation with any other. Thus, we are able to conclude that sector specific shocks are responsible for merger cycles in these two sectors.

Table 3.5: Coherence and Phase Difference over Different Sector Cycles

	Energy & Power	Financials	Consumer Products & Services	Healthcare	Industrials	Materials	Media & Entertainment	Real Estate	Retail	Consumer Staples	High Technology	Telecommunications
Energy & Power					X (-)	X (-)	X (+)			X (-)		X (+)
Financials												
Consumer Products & Services					X (-)	X (-)	X (-)	X (-)	X (-)	X (-)		X (+)
Healthcare												
Industrials						X (-)	X (+)	X (-)	X (-)	X (-)		
Materials							X (-)	X (-)	X (-)	X (-)		
Media & Entertainment									X (-)	X (-)	X (-)	
Real Estate									X (-)			
Retail										X (+)	X (-)	
Consumer Staples												
High Technology												X (-)
Telecommunications												

Note: An "X" indicates that a significant relationship exists between the two associated variables. "+", "-", and "~" indicates a lead, lag, and synchronization relation, respectively. Phase values are calculated with respect to sectors in the first column.

The cyclical component of aggregate mergers, interest rates, GDP growth, and the stock prices are presented in Figure 3.5.¹⁹ Figure 3.5 shows that aggregate merger cyclical fluctuations lead that of interest rates by approximately 2 years. This means that interest rates are procyclical indicators of merger activity. Thus, interest rates do not reach their peak until some time after merger activity has reached its trough, a point that is not reached until a recovery in merger activity is well underway. Although this relation is constant over time, the amplitude of these cyclical patterns differs according to the time period analyzed. Thus, during 1969-1984, interest rates are more volatile than mergers, while after 1984, they both exhibit very similar amplitude.

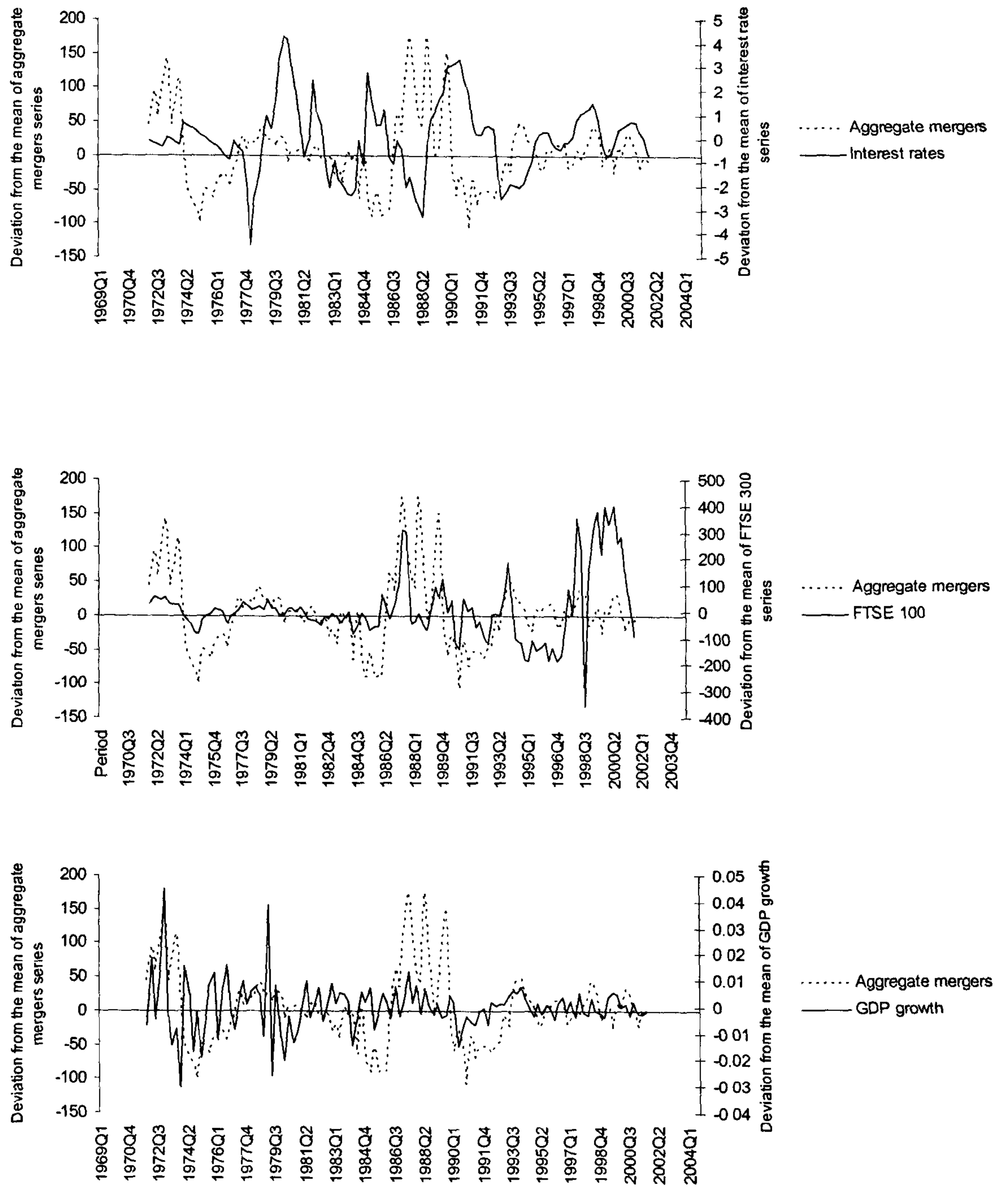
On the other hand, aggregate mergers and business cycles move together with similar amplitudes, although during the 1980s, the amplitude of the former is much higher than that of the latter.

Mergers cycles are not similar in amplitude to stock market cycles, with the exception of some periods (1977-1981 and 1986-1990). During 1996-2001, the amplitude of the stock market cycle is higher than that of mergers. The relation of these cyclical components is further studied by spectral methods.

¹⁹ As HP and BK filters give similar results, in this section, we present only results from HP filtered data.

Figure 3.5: Cyclical Component of UK Aggregate Mergers, Interest Rates, Stock

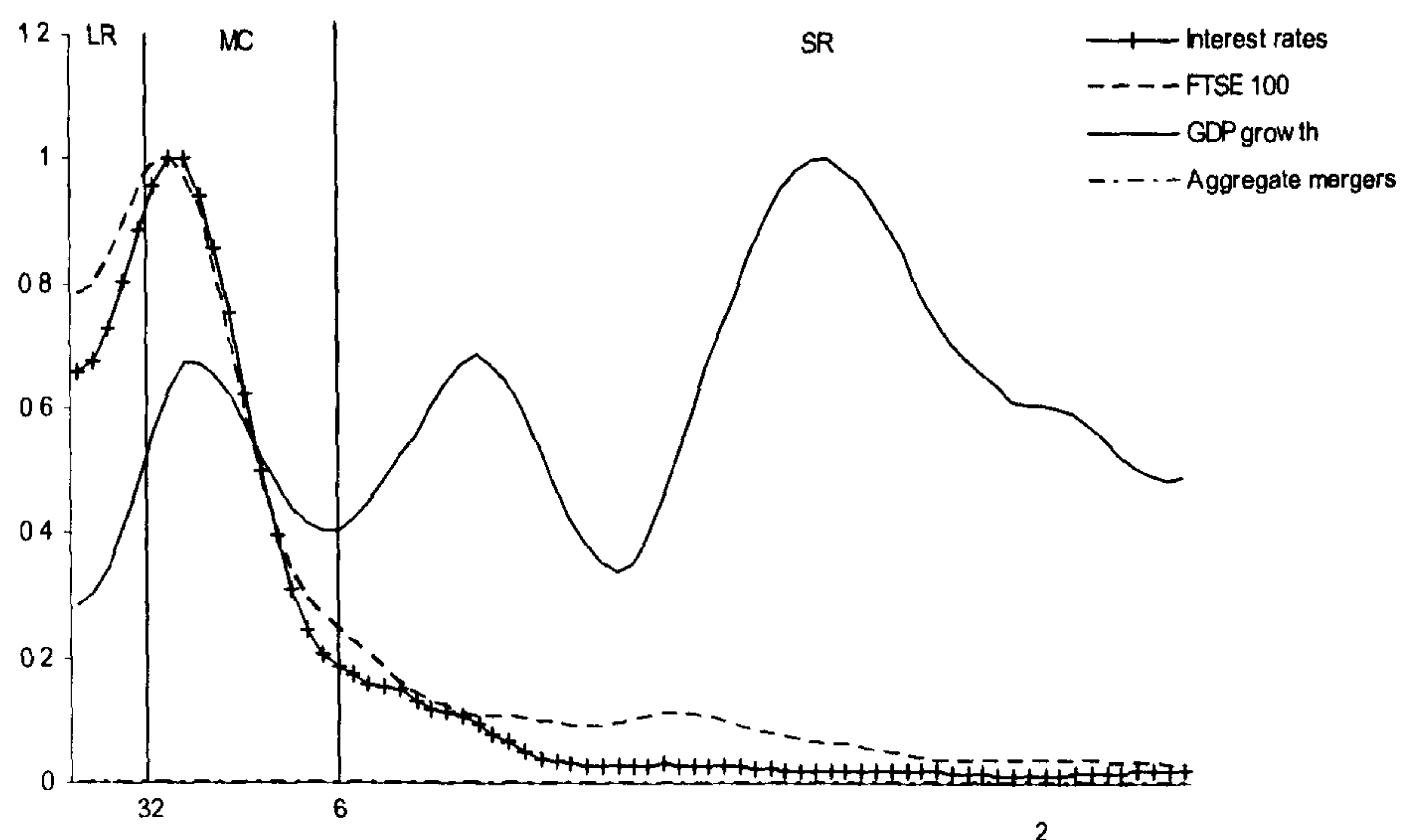
Prices, and GDP Growth using HP Filter



Note: The common sample period for these graphs is 1969.1-2005.4, but since we use $K=12$ (BK filter), we lose three years of data (12 observations) at each end of the plots. In addition, with the HP filter, we drop the same number of observations in order to have robust results (see Section 3.3.2).

Figure 3.6 shows the univariate spectrum of interest rate, GDP growth, stock prices, and mergers. We notice that the mass of the spectrum for all of the variables is concentrated in the periodicity band 10 to 32 quarters, with a peak at 24 quarters. That means that all the variables exhibit a regular cycle of 24 quarters, the only exception being GDP growth, which exhibits higher variation. More specifically, it presents three different peaks corresponding to three different cycles, the first with 24 quarters duration, the second with 6 quarters duration and the third cycle with about 4 quarters duration (the third one may be due to seasonality, as the series are not seasonal adjusted; seasonal variations are regarded as very small cycles). Thus, all the variables have in common a 24 quarters (6 years) cycle.

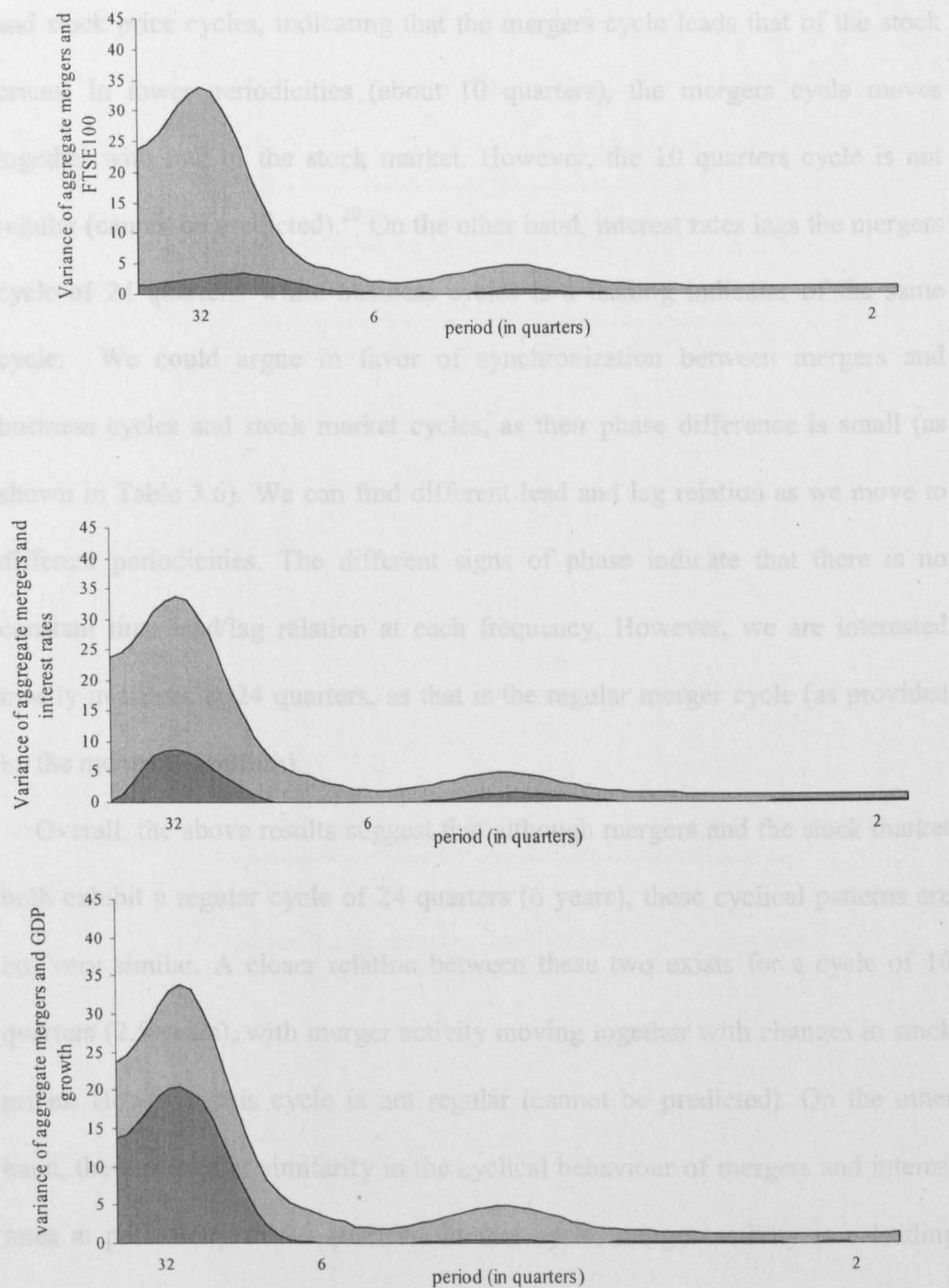
Figure 3.6: Univariate Spectrum of Interest Rates, Stock Prices, GDP Growth, and
Aggregate Mergers



Note: The spectrums are normalized (divided by their maximum value)

In order to have a clearer view of the relation between these variables, we present some estimates from cross spectral analysis. Figure 3.7 shows the explained variance of merger activity in terms of interest rates, GDP growth, and stock prices. Explained variance is the ratio of the heavy grey area relative to the sum of the high and heavy grey area. Here, we find that in a merger cycle of 24 quarters, 53% of the mergers variance is explained by the GDP growth, while interest rates and stock prices can explain 26% and 9%, respectively. However, in a smaller but not regular merger cycle of 10 quarters, the GDP growth can explain 6% of the mergers variance, while interest rates and stock prices can explain 2% and 28%, respectively. Thus, long, regular merger cycles can be explained by business cycles, while smaller, irregular ones can be better explained by stock price fluctuations. In both cases, however, there is a portion of aggregate mergers that is not explained at all by these macroeconomic and financial variables. That portion is bigger in the case of a smaller cycle.

Figure 3.7: Explained Variance of Aggregate Mergers in terms of Stock Prices, Interest Rates, and GDP Growth



Note: The heavy grey area measures the portion of aggregate mergers that is explained by stock prices (FTSE 100), interest rates, and GDP growth, while the sum of heavy and light grey gives the aggregate mergers.

Finally, Table 3.6 reports phase values between mergers and interest rates, business cycle, and stock prices only for the periodicity band 6 to 32 quarters. Table 3.6 shows that there is a phase difference of 0.1 radians between mergers and stock price cycles, indicating that the mergers cycle leads that of the stock prices. In lower periodicities (about 10 quarters), the mergers cycle moves together with that of the stock market. However, the 10 quarters cycle is not regular (cannot be predicted).²⁰ On the other hand, interest rates lags the mergers cycle of 24 quarters, while business cycles is a leading indicator of the same cycle. We could argue in favor of synchronization between mergers and business cycles and stock market cycles, as their phase difference is small (as shown in Table 3.6). We can find different lead and lag relation as we move to different periodicities. The different signs of phase indicate that there is no constant time lead/lag relation at each frequency. However, we are interested mostly in values at 24 quarters, as that is the regular merger cycle (as provided by the mergers spectrum).

Overall, the above results suggest that although mergers and the stock market both exhibit a regular cycle of 24 quarters (6 years), these cyclical patterns are not very similar. A closer relation between these two exists for a cycle of 10 quarters (2.5 years), with merger activity moving together with changes in stock prices. However, this cycle is not regular (cannot be predicted). On the other hand, there is greater similarity in the cyclical behaviour of mergers and interest rates at periodicity of 24 quarters. In that cycle, merger activity is a leading indicator of the interest rates cycle. The closest relation exists between mergers

²⁰ Periodicities in the area around 10 quarters contribute equally to the aggregate mergers univariate spectrum.

and business cycle in their sharing of a common cycle of 24 quarters, these two cycles synchronizing.

Table 3.6: Phase Differences between Aggregate Mergers and Interest rates, Stock Prices, GDP Growth along Cycles with Different Periodicities.

Period	Interest rates	FTSE 100	GDP growth
29	1.9	0.1	-0.4
24	2.0	0.1	-0.4
21	2.1	0.1	-0.3
18	2.2	0.1	-0.3
16	2.3	0.1	-0.3
14	2.4	0.0	-0.2
13	2.4	0.0	-0.2
12	2.5	0.0	-0.2
11	2.5	0.0	-0.1
10	2.5	0.0	-0.1
9	1.2	-0.1	-0.1
8	0.7	-0.2	-0.1
7	2.8	-0.2	-0.1
6	-1.4	0.2	-0.1

Note: Period is measured in quarters, and phase values in radians

3.5.3 Discussion of Multivariate Results

Multivariate spectral analysis suggests that there is synchronization over most of the UK sector mergers (notable exceptions being Financials and Healthcare, which are cycles that do not seem to cohere with those of any other sector). This result is consistent with that of Resende (1999). Thus, we can conclude that mergers in the UK spread through all sectors at the same time.

There is evidence of synchronization between the UK merger cycle and the business cycle with a duration of six years, there being a strong coherency between these two cycles. On the other hand, mergers and interest rates cycles exhibit a less strong coherency; both exhibit a cycle of six years, while the mergers cycle leads that of interest rates. The above results suggest that until expansion in the UK economy, as firms become optimistic about future prospects, they engage in merger activity. As mergers are sometimes financed with borrowed capital, the demand for credit may well increase. Thus, mergers may be a factor, among others, influencing interest rate increases during expansion. These results are consistent with studies that suggest that interest rates are procyclical, lagging economic indicators (see, for example, Friedman, 1986; Blanchard and Watson, 1986).

On the other hand, although mergers and stock prices both exhibit a regular cycle of six years, these cyclical patterns are not very similar. A closer relation between these two exists for a less regular cycle of 2.5 years, where the two cycles synchronize. From the above results, we can conclude that stock price fluctuations move together with small, less regular merger cycles, while over longer regular merger cycles, stock prices do not seem to cohere with merger activity. The above results may explain why empirical studies give mixed results

regarding the relation between merger activity and stock prices (see, for example, Geroski, 1984; Guerard, 1989; Benzing 1993; Clarke and Ioannidis, 1996). These studies apply time domain techniques that do not distinguish between cyclical fluctuations of different duration. Results of the present study show that the relation between merger activity and stock prices is different over cycles of different duration.

3.6 Concluding Remarks

Using well-known concepts from spectral analysis, we have described the properties of merger cycles in the UK.

We concluded that Energy and Power have the smallest merger cycle of 12 quarters (3 years), followed by High Technology, with a merger cycle of 16 quarters (4 years). Most industries have merger cycles of 20 quarters (5 years). Only Consumer Staples and Telecommunications do not exhibit a regular merger cycle. In addition, there is synchronization of merger cycles for most of the sectors, while only Financials and Healthcare cycles do not cohere with any other. Furthermore, aggregate mergers exhibit a regular cycle of approximately 6 years. Cycles with lower periodicities also exist but they cannot be regarded as regular. These results suggest that past merger activity may influence current merger activity. There may be a bandwagon effect to merger activity that influences most sectors in the UK economy.

Furthermore, we examined the synchronization of aggregate mergers with interest rates, stock prices, and business cycle, all exhibiting a cycle of 6 years. There is clear evidence of a strong coherence between aggregate mergers and business cycles. These two cycles synchronize, although the amplitude of the former is much higher than that of the latter. A less strong coherence exists between aggregate mergers and capital markets cycles. Aggregate mergers and interest rates exhibit a similar cyclical pattern, with the former leading the latter by 2 years, while the aggregate mergers cycle has an even weaker coherence with the stock prices cycle of 6 years. On the other hand, a stronger relation between aggregate mergers and stock prices exists in smaller cycles of about 2.5 years.

However, within this cycle, the coherence of interest rate and business cycle is very small.

These results suggest that aggregate mergers synchronize with the business cycle. As the economy expands, it would seem that business becomes more optimistic and confident about the future, and when excess capacity is exhausted, they may borrow to finance merger and acquisition activity, triggering the interest rate cycle. Based on the weak relation between aggregate mergers and long stock market cycles, the observed relation between high stock market valuations and merger cycles may have been misattributed to expectations about the future economic conditions (see, for example, Benzing 1991). On the other hand, the stronger relation of stock prices and merger activity over a small, less regular cycle of 2.5 years may be attributed to behavioural misevaluation factors (see, for example, Morellec and Zhdanov, 2005; Rhodes-Kropf and Viswanathan, 2004). Rapidly changing stock prices are indicative of pervasive disequilibria in equity markets, and in such situations, the changes are so great, that market valuations do not accurately reflect long term profit opportunities. Thus, when financial markets overvalue stocks in the short run, a bidder takes the opportunity to buy the real assets of a less overvalued target firm using their own overvalued equity. These opportunities will be diluted in the long run, when the stock prices return to the efficient level.

However, results show that a large portion of an aggregate mergers cycle cannot be explained by the business cycle, interest rate or stock price fluctuations. Although evidence suggests that a merger cycle of 6 years synchronizes with the business cycle, only 53% of the merger fluctuations can be attributed to the business cycle. On the other hand, fluctuations in the interest

rates and stock prices can explain 26% and 9%, respectively. These effects of business cycle, interest rates, and stock prices on merger cycle may be overlapping. Since the largest portion of a merger cycle that can be explained by macro factors is 53%, there is a need to search for complementary driving forces of merger activity at the micro-level. Macro-environmental forces create receptive conditions for the development of merger activity. By examining firms' motives for mergers, we provide an indication of the micro-forces that feed into, and further reinforce, merger activity.

The next chapters provide such an analysis at the micro-level. First, we review the most profound motives for mergers, as suggested by industrial organization and finance perspectives. A theoretic-decision model is then constructed to explain the timing of mergers based on different micro-forces. And finally, the model is empirically tested.

PART 3: MICROECONOMIC ANALYSIS

CHAPTER 4: MERGER ACTIVITY – THE FIRM LEVEL PERSPECTIVE

4.1. Introduction

Research on the causes of merger activity at the firm level has received growing attention from both the industrial economics and financial perspectives over the last two decades. Extensive theoretical and empirical literature has explored both the motives and consequences of mergers.¹

Industrial organization literature is based on both the efficiency-increasing power of mergers, be it by the exploitation of synergies, or growth opportunities, and on the market power hypothesis, which perceives the struggle for market shares and price-setting power as the dominant motive behind mergers. On the other hand, finance literature focuses on the corporate control hypothesis, which considers the control of firms as a valuable asset traded in a market for corporate control. That market facilitates the dismissal of managers who are not acting in

¹ Although there is a large body of literature on the welfare effects of mergers, a review of it lies beyond the objectives of this study (see, for example, Farrell and Shapiro, 1990; Hay and Werden, 1993; Spector, 2003). There is also evidence of difficulties associated with mergers. Organization research points to the role of cultural clashes. The human resource management literature indicates that acquired firm employees may react unfavourably to mergers. For a survey and synthesis of these literatures, see Larson and Finkelstein (1999).

the shareholders' best interests.² The misvaluation of firms is another motive for merger stressed by finance literature.

Both approaches have yielded some useful insights into merger activity. Rather than reviewing the entire extensive literature on the topic, we concentrate on the more important theoretical and empirical conclusions, in order to indicate that such an analysis at the micro-level can be utilized in developing explanations of merger waves.

This chapter is organized as follows: Section 4.2 reviews the main models of merger drivers from an industrial organization perspective. Section 4.3 reviews studies explaining mergers from a finance perspective. Finally, Section 4.4 concludes by proposing a marriage of the main conclusions of the industrial organization and finance perspectives in order to explain merger waves.

² There are also theories that point towards the managers' interest in mergers, be it that they incorrectly believe themselves to be better able to manage the target (hubris hypothesis), or that they act for personal advantage (empire-building hypothesis). However, we focus on merger theories that are based on the assumption of shareholders' wealth maximization.

4.2. Industrial Organization Perspective in Analyzing Mergers

The industrial organization literature on mergers assumes that managers are rational and maximize the profit of shareholders. Under these assumptions, early theoretical studies analyzed static oligopoly models to examine the incentives to merge in the presence of either Cournot or Bertrand competition. A central postulate is that the pre-merger and the post-merger situations are represented as either Cournot or Bertrand equilibrium points involving different market structures, with the merged firm being treated as a single player in the post-merger game. It is asked whether firms participating in a merger benefit from merging their business instead of staying independent. The early industrial organization literature assumes that a group of firms has an incentive to merge if the profits of the participating firms increase relative to their combined profits in the status quo equilibrium. This is the ‘traditional criterion’ for merger incentives in industrial organization literature. However, more recent literature indicates that gains from concentration often do not satisfy the traditional criterion. Thus, theoretical models allowing the merger decision to be made endogenously emerged in an attempt to provide a clearer picture of the merger process.

Another view of the merger phenomenon is one that allows for the interdependence of merger decisions. Theoretical literature on sequential mergers has been developed in order to examine whether merger incentives are influenced by future mergers.

Finally, a theory of pre-emptive mergers has been developing in order to provide explanations of why unprofitable mergers occur.

In the next subsections, we first present the main theoretical models of merger incentives in a static framework where a merger is seen in isolation, followed by models of sequential mergers, and then pre-emptive merger models.

4.2.1 Theoretical Models of Mergers within a Static Framework

Stigler (1950), in a highly influential model, stresses the problem of enforcing an agreement between competitors. Enforcement depends on being able to detect cheating, and he shows that detection is easier with fewer firms.³ Stigler's model predicts that increased concentration from mergers can lead to collusion and the identification of factors facilitating collusion.

On the other hand, Stigler (1950) argues that firms which do not participate in a merger (outsiders) may benefit more than participants (insiders). When a merger occurs, the merged firm has an incentive to reduce its production to a level below the combined output of its constituent firms, leading to an increase in industry price (if the cost reductions associated with the merger are not too large). Outsiders will then expand output and profit from the higher industry price. Thus, insiders do not capture all the profits resulting from their merger. Such externality of a merger may increase total industry profits, but may not be profitable for the merged firm.

³ Models of repeated games, however, indicate that tacit collusion is possible, even with very large numbers of firms, and predict that collusion is one of many possible equilibria (see e.g. Shapiro, 1989, pp: 364-6).

Salant et al (1983) raise again the possibility that some exogenous mergers may be unprofitable, by examining a Cournot oligopoly model where identical firms with constant marginal costs sell homogenous products to consumers with a linear demand curve. They consider Cournot equilibrium, in which a subset of the firms merges while the other firms remain independent. After the merger, the insiders have an incentive to contract production for any given output by outsiders, prompting outsiders to respond by expanding their own production. However, as the outputs of the outsiders increase, the profits of the insiders decrease. Hence, the possibility arises that the increase in production by outsiders following the merger will reduce insider profits by more than the increase in profits that would have occurred had outsider production remained constant. They show that a merger is unprofitable, even if it creates efficiency gains because these gains are not great enough to compensate for the profit reduction induced by the reaction of outsiders. They indicate that a merger is unprofitable unless the merging coalition consists of more than 80 per cent of all firms in the industry.

However, by assuming that the merged firm does not differ from the others, Salant et al. understate the incentive to merge. Perry and Porter (1985) consider a model which addresses the industry asymmetries caused by the merger of subsets of firms. They suggest that a merged firm faces a different maximization problem because of its altered cost function and new strategic considerations. They assume that demand and marginal cost are linear functions of output, and focus on the incentive to merge that arises solely from firm size and behaviour in an imperfectly competitive environment. They model industry as consisting of oligopolists and a competitive fringe. By assuming that the competitive fringe

capacity is constrained, profitable opportunities remain for the oligopolists. Thus, as firms from the competitive fringe merge and form a new oligopolist, the fringe will contract but not vanish. The competitive fringe becomes a smaller fraction of the industry, so that on balance, the industry behaves less competitively. The new oligopolist (merged firm) supplies less than did its component firms of the fringe prior to merger, and as a result, prices increase (in this case, firms from the competitive fringe cannot react to a merger by increasing production due to capacity constraints). Without this price effect, there would be no incentive for fringe firms to merge. Therefore, the profits of the merged firm can exceed those of its constituent firms only if the merger results in a price rise sufficient to offset the lower output level. They show that when the number of merged firms is small, the competitive fringe is large, so that the residual demand facing the firms in the fringe considering merger is relatively flat. Thus, an output contraction has a small price effect and the profitability of merger is reduced. However, when the number of merged firms is large, the residual demand is relatively steep, so that additional merger can more readily increase the price.

Rothschild (1990) employs a variant of Perry and Porter's oligopoly-fringe model to analyze the incentives for horizontal merger. They consider three different ways that merger may take place: between firms which remain in the fringe, between firms within the oligopoly, and across the boundary of fringe and oligopoly. They show that if merger takes place in the oligopoly, then the profits of outsiders in both oligopoly and fringe are increased. A merger in the fringe which produces no synergies leaves unaffected the profits of all outsiders, irrespective of their location in the industry. If a merger in the fringe is synergy-producing, then the profits of the outsiders in the fringe are reduced, while those

of the outsiders of the oligopoly are increased only if demand is sufficiently large.

On the other hand, Deneckere and Davidson (1985) investigate the incentive to merge when firms produce differentiated products and engage in price competition. They assume constant and identical cost and a symmetric demand. They show that mergers are always beneficial to existing members and become more profitable as the size of the merger increases. The resulting industrial concentration confers positive externalities on other industry members.

Some other studies examine whether profitability of a merger depends on the linearity of demand. Cheung (1992) shows that for demands satisfying the criterion that the marginal revenue of the industry decreases, the minimal market share for a merger to be profitable is 50% of industry output. Fauli-Oller (1997) explains why Cheung's threshold was lower than that of Salant et al. for a merger to be profitable. He shows that the profitability of mergers depends on the degree of concavity of demand; the greater the degree of concavity, the lower the profitability of a merger. Therefore, Cheung's threshold is lower than that of Salant et al. because he allows for strictly convex demands.

Huck et al. (2001) suggest that profitability of a merger in markets with quantity competition depends on the market structure and on the merging firms' exogenous given 'strategic power'. They consider a Stackelberg market with homogenous products and linear costs. Leaders independently and simultaneously decide on their individual supply and the remaining followers decide upon their quantity after learning about the total quantity supplied by the leaders. It is shown that two leaders rarely have an incentive to merge, nor do

two followers. However, if a leader merges with a follower, this increases the joint profit of the two firms by lowering total industry production.

A more recent alternative point of view investigates the pattern of mergers that can be expected to occur, by endogenizing the merger decision.⁴

Horn and Persson (2001a) proposes an approach to modeling endogenous merger formation by employing ideas on coalition formation from cooperative game theory in order to study the determinants of mergers. They show that the free-riding problem mentioned above (see, for example, the study of Salant et al.) is not as pervasive in their approach under fairly general assumptions regarding technology and demand. They suggest that while the free-riding problem might be descriptive of markets with a larger number of firms, it seems less plausible that, in a concentrated industry, a limited number of firms who can communicate and sign binding agreements would forego the gains from merger as a result of indefinitely trying to become even more profitable outsiders. If the parties can communicate and sign binding contracts, the outcome should also be efficient.

Rodrigues (2001) uses a two-stage game to model endogenous mergers. In the first stage of the game, firms decide whether or not to merge, and in the second, they compete on the product market. They show that three factors interact to determine whether or not firms will merge: the initial number of firms in the industry, the expected competitive intensity, and the possibility of economizing on fixed costs through merger. The model shows that the equilibrium market

⁴ Gowrisankaran (1999) develops a model that endogenizes the merger process, but in a dynamic framework. In this model, mergers, investment, entry, and exit are endogenous variables rationally chosen by firms to maximize expected future profits. This model indicates that in addition to increased concentration in the industry, mergers serve as a relatively quick way for the industry to adjust when needed, compared to entry, exit, and investment.

concentration, and firms' propensity to merge, is decreasing in the first of these factors and increasing in the other two.

Inderst and Wey (2004) present a model in which both the gains of insiders and those of outsiders are important to predict the likelihood of a merger. They model the takeover of a designated target as an auction in which the target chooses an optimal reserve price. At the heart of their analysis is a free-rider problem among potential acquirers. They show that even if there are substantial gains to insiders, the target's optimal reserve price always create a free-rider problem. An acquirer is worse off than any of the remaining independent firms.

In summary, although the above studies use different set-ups, they all stress the importance of the number of merged firms already in the industry in explaining merger activity.

4.2.2 A theory of Pre-emptive Mergers

A growing body of literature on pre-emptive mergers has been developed. In a theoretical piece, Colangelo (1995) studies whether, and under which circumstances, pre-emptive merging occurs in vertically related industries. He shows that when either vertical or horizontal merger, but not both, are possible, vertical mergers often pre-empt horizontal mergers. The overall gains from a vertical merger are often greater than that from a horizontal one. Upstream (downstream) firms are therefore often prepared to bid more for a downstream (upstream) target than other downstream (upstream) firms. The pre-emptive role

of vertical merger is linked to the fact that horizontal mergers are largely detrimental for the vertically related non-merged firms. While pre-emptive merging can take place, even with a large number of firms, the larger the number of firms, the larger the number of the merging parties necessary for a merger to be so detrimental for the non-merged firms to call for a pre-emptive reaction.

A pre-emptive merger mechanism has also been demonstrated by Horn and Persson (2001b), using a cooperative game theory model. They study an international oligopoly and the so-called tariff-jumping argument, according to which international mergers are more likely than domestic mergers, since the former saves on trade costs. They show, however, that domestic firms may agree to a profitable merger to pre-empt international mergers that would stiffen the competition in the home market.

Using a spatial competition model, Brito (2003) proposes that firms may have clear incentives to be insiders in a merger, even when efficiency gains do not exist and market power is the only reason the merger is profitable. When the number of mergers is limited, firms may decide to merge with the purpose of pre-empting other mergers. This behaviour is based on the fact that some outsiders may gain less than the participating firms when products are not symmetrically differentiated. The existence of pre-emptive mergers depends crucially on the asymmetric profile of post-merger pay-offs and on the number of mergers being limited by the antitrust authorities. Therefore, such mergers are more likely to arise in concentrated markets where firms sell non-symmetrically differentiated products.

In a related study, Fauli-Olier (2000) discusses the strategic value of an early merger by modelling a five-staged sequential game of merger formation. The

main assumptions are cost asymmetries and Cournot competition of independent firms. Before Cournot competition occurs, efficient firms are allowed to bid sequentially for inefficient firms, so that market structure can be altered. Profits depend on the number of inefficient firms having been previously bought, but not on who carried out the takeover. Demand also influences the realization of profits. Inefficient firms will accept any offer assuring them, at least, their opportunity cost, that is, the profits they would obtain if they stayed in the market. The opportunity cost of one firm accepting an offer when no one else does depends on whether by deviating, it will be bought in later or remain independent. In the former case, the opportunity cost is the profits determined by zero mergers, while in the latter, the opportunity cost is the profits determined by the number of mergers already taken place. In other words, inefficient firms are no longer symmetric, because they obtain different pay-offs when they refuse offers. A firm that moves fast and buys an inefficient firm first obtains more profits because it pays less for its target. By buying first, a firm can exploit the competition between inefficient firms. Finally, he indicates that mergers are prompted by two different factors. Firstly, a low realization of demand increases the profitability of takeovers; and secondly, takeovers raise the profitability of future takeovers.

On the other hand, Akdogu (2003a) considers a reduced form model with exogenous targets and extends it to study a situation where multiple targets are available sequentially. If multiple targets are available, the pre-emption motives are attenuated by the possibility of imitation. In an empirical paper, Akdogu (2003b) finds empirical evidence for pre-emption in the telecom industry in the US.

The above studies illustrate that strategic motives, and pre-emption in particular, are important merger incentives. There are studies that emphasize the fact that strategic motives may be so strong as to induce firms to agree to unprofitable mergers.

Thus, Fridolfsson and Stennek (2005) develop an endogenous merger model based on coalitional bargaining, where the merger is expected and only the identity of the winner is unknown. The intuition of their model is that firms will compete not to be left out from the merger. It explains how mergers can reduce profits and raise share prices by using pre-emption theory. Demand and cost shocks are the main reasons for these mergers. In their model, target receives their reservation values and the buyer takes the whole surplus, which is at odds with the empirical evidence.⁵

In addition, Molnar (2005) proposes and tests a pre-emption theory for mergers. He indicates that it can be optimal to overpay for a target firm and decrease the acquiring firm shareholders' value if the loss is less than in the alternative case when the merger is undertaken by one of the product market rivals. His model is based on synergies, market power as the main motive for mergers, and competitive bidding for targets. The empirical results do not reject the pre-emption theory as an explanation of mergers.

Pre-emption theory is also applied to a different stage of the merger process, namely, takeover bidding.⁶ Fishman (1988) explains why bidders offer targets such a high premiums, by examining 'pre-emptive' bidding strategies. He

⁵ For a review of empirical studies on M&A performance, see Goergen and Renneboog (2004).

⁶ Angwin (2004) also stresses the importance of speed in acquisition integration.

develops a model of strategic bidding among competitors in an environment of asymmetric and costly information. In the scenario of two-bidders for the same target model, after observing the first bidder's initial offer, a second bidder updates his prior beliefs about the first bidder's valuation. Then, on the basis of these beliefs, the second bidder decides whether to acquire information and bid for the target. This gives the first bidder the ability, through his initial offer, to affect this decision. This is the strategic interaction between bidders. In the model, the higher the valuation of the first bidder, the lower is the second bidder's expected profit from entering the competition. In equilibrium, the first bidder may make a high-premium, 'pre-emptive' bid that signals a high valuation and deters a second bidder from competing. Otherwise, he makes a low-premium bid that signals low valuation, in which case, a second bidder competes. Thus, it is not the bid itself that pre-empts the second bidder, but rather the information conveyed by the bid.

In summary, pre-emptive theory of mergers is based on synergies, market power and competition for targets. It suggests that merger is a rational response of value-maximizing managers to some market shocks. These shocks could include deregulation, technological innovation, negative demand or negative cost shocks occurring in the acquiring firms' product market.⁷ These shocks have the effect of creating synergies or cost savings, rendering some mergers profitable. When several potential acquiring firms achieve these large cost savings, they

⁷ Mitchell and Mulherin (1996) find evidence consistent with major economic changes shaping the merger and restructuring markets. Jovanovic and Rousseau (2002) argue that mergers reallocate capital to more productive purposes and to more productive managers.

compete for the opportunity to merge if the available targets are limited.⁸ The winning firm that acquires the target could become a lower cost producer and will be able to increase its product market share if the costs savings are large enough. If the merged firm increases its market share, rivals are worse off. Intuitively, if a firm expects that one of its rivals will gain large cost savings or efficiencies by taking over some other firm, then it can be rational for the first firm to pre-empt this merger with a takeover attempt of its own. By pre-empting the rival firm's merger, the first firm avoids the larger loss of profits it would have suffered had its rival been successful. However, its post-merger profit could still decrease relative to its pre-merger profit. This pre-emption can be optimal, even if it requires the first firm to overpay relative to the increase in the joint profits of the combined firms. In this case, the merger itself may reduce the acquirer's value because of the high price paid for the target.

4.2.3 Theoretical Models of Sequential Mergers

The theoretical literature is mostly focused on a single merger seen in isolation. There is, however, a small body of literature on sequential mergers.

Pioneering work on sequential mergers has been done by Nilssen and Sorgard (1998). They analyze the interdependence of merger decisions over time. They discuss the strategic motive for merger in terms of the taxonomy of business

⁸ An important issue in the pre-emptive theory of mergers is the notion that targets are limited. Socorro (2004) highlights the importance of firms fitting well for stable mergers to arise.

strategies introduced by Fudenberg and Tirole (1984). In particular, they investigate whether firms will be more likely or less likely to carry through their own merger when they take into account any possible future merger of the rivals. They denote the effect that such considerations have on the profitability of firms' own mergers as the strategic motive for merger, which is determined by two factors. The first is whether own merger will encourage or discourage a rival's merger. If rivals' gains from merging alone are less than gains from merging after own merger has occurred, then own merger will encourage rivals' merger. The second factor is whether a rival merger will increase or decrease own profit. They find that the prospects of a subsequent merger decision have an ambiguous effect on the profitability of the first merger.

Matsushima (2001) considers sequential mergers using Nilsen and Sorgard's method. However, they demonstrate a different mechanism of sequential mergers; they do not allow cost savings effects from a merger. They adopt a spatial model and demonstrate that cost savings are derived from transferring output from the distant firm (inefficient firm) to the near firm (efficient firm). They show that if transportation cost per length is large relative to market size, a sequence merger occurs. The intuition is that the production (transportation) technology of each firm is the same. At each location, however, these firms are asymmetric with regard to their transportation costs; the larger the transportation cost per length, the larger the asymmetry at each location. The cost savings obtained from transferring output from the distant firm (inefficient firm) to the near firm (efficient firm) become greater at each location, triggering a sequence of mergers to occur. On the other hand, if the transportation cost per length is small relative to market size, a merger sequence does not occur, even though

firms would be better off with the sequential merger. Given that the first merger is completed, the non-merged firms free ride on the first merger and do not merge because the cost saving is not great. The first pair anticipates it and they do not merge.

Motta and Vasconcelos (2003) models a sequential merger formation game with endogenous efficiency gains in which every merger has to be submitted for approval to the antitrust authority. They consider a model in which firms operate in a market with linear demand, and what distinguishes firms is the amount of capital they own. The total supply of capital is assumed to be fixed to the industry. They assume that each firm operates with constant marginal costs of production, but that the level of its marginal costs is a decreasing function of its share in the industry capital. That assumption embraces the fact that a merger brings the individual capital of merging firms into a single larger resulting firm and, therefore, it gives rise to endogenous efficiency gains by decreasing marginal costs. It also assumes that there exist plant-specific fixed costs. That means that by creating a larger firm, a merger has the effect of increasing fixed costs proportionally. According to their model, a merger increases a firm's capacity, which in turn, leads to scale economies. They show that, using Cournot competition, when such efficiency gains are very small, there will be no merger. When they are of intermediate importance, firms outside the merger lose competitiveness but continue to operate profitably, resulting in a more efficient market outcome. If a merger provides important cost savings, then it will be followed by a merger of the rivals. In other words, if there are efficiency gains to be reaped from a merger, outsiders will respond by merging as well. This

‘defensive’ merger will allow the outsiders to match the efficiency gains of the first merger partners.

Kamien and Zang (1990) explore the possibility of endogenous monopolization of an oligopoly through one firm’s acquisition of the others, by using a homogenous good Cournot oligopoly model. The main assumptions are that firms’ unit production costs are constant and identical, and that entry into the industry by new firms is infeasible. The first of these assumptions implies that merger is solely for the purpose of reducing competition, while the second assumption determines the limits of monopolization through acquisition without the impediment of entry by new firms. Two possible mechanisms of monopolization are analyzed as three-staged non-cooperative games. In both, each original owner possessing a single firm, independently and simultaneously makes bids for each of the other firms. Furthermore, they have an asking price for their firm. A firm is sold in its entirety to the highest bidder whose bid exceeds the firm’s asking price. After this stage an owner may possess more than one firm. In ‘the centralized version of [the] monopolization’ mechanism, as Kamien and Zang call it, an owner of several firms operates only one of them to avoid internal competition, as that merger yields no economies of scale. In the so-called ‘decentralized version of monopolization’, an owner of several firms may choose to operate more than one in competition with the others. The operated firms engage in Cournot competition. Both models indicate that an owner of a firm, when considering the possibility of selling out, takes into account the fact that the merged entity that can be formed without its participation will increase the merged entity’s profits by reducing competition. This increases the cost of buying out firms. As a result, an equilibrium analysis

of the above two mechanism discloses that monopolization through acquisition is possible only when there are just a few firms in the industry.

Later, Kamien and Zang (1991) analyze monopolization by acquisition under the assumption that firms' total cost functions are strictly convex. This assumption provides an additional incentive for merger, by providing a merged firm with a cost advantage over an unmerged one. That is, a merged firm will have a lower cost of producing any given quantity than one that is unmerged. Despite the double incentive for merger, reduction of cost and number of competitors, their analysis discloses that monopolization is more feasible than in the linear total cost case. It still is limited to industries with a relatively small number of firms.

In another paper, Kamien and Zang (1993) examine whether the number of firms in an industry can be whittled down through successive rounds of mergers to a number at which complete monopolization is possible. They suggest that while sequential acquisition makes it easier to monopolize an industry, there may still be some limits to monopolization. They consider a sequential non-cooperative game in which the Kamien and Zang (1990) centralized game is played over and over, each time with possibly fewer firms due to purchase in previous rounds. They analyze two possible scenarios. In the first, they consider a single buyer seeking to acquire all the other firms from the outset, and find that monopolization, if demand is linear, can be accomplished only when there are three or fewer firms to begin with. In the second scenario, they allow for the possibility of the industry being whittled down by permitting every owner in the industry to be a potential buyer. In this case, they find that sequential monopolization becomes easier, as compared to the case of a single buyer.

However, this model indicates that if the number of initial firms is sufficiently large, then a monopoly cannot be attained as equilibrium within a given number of iterations. Also, monopoly cannot be attained if the number of firms that can be purchased in any single round is uniformly bounded.

In summary, the above studies stress the interdependence of M&A decision over time. A merger may trigger another merger, as firms are likely to imitate rival actions in order to reap similar benefits.

4.2.4 Interim Summary

The main conclusions of the industrial organization literature on M&A incentives can be categorized into three groups. The first refers to static models on M&A where mergers are seen in isolation. Using different oligopoly models, it is investigated whether firms participating in a merger benefit from merging their business instead of staying independent. A factor that determines, among others, whether or not firms will merge is the number of merged firms already in the industry. In industries with a large number of firms, it seems more likely that firms will remain independent. In such industries, the benefits to outsiders are greater than those to insiders and as a consequence, firms free-ride to merger. Since the benefit to the marginal merger increases as the number of previous mergers increases, the propensity of firms to merge increases with the number of merged firms. We label such conclusion as the stock effect of M&A. After a certain concentration has been reached, a merger may take place and as it does

so, further mergers may occur. That means that such an effect may reinforce merger activity and amplify a wave. We argue that stock effect may be utilized to partially explain merger waves (see Chapter 5, Section 5.2.1).

The second group of merger explanations refers to the pre-emptive motive of merger activity. If a firm anticipates a merger of one of its rivals, it can be rational for the first firm to pre-empt this merger with a takeover attempt of its own. By pre-empting the rival firm's merger, the first firm avoids the larger loss of profits it would have suffered had its rival been successful. However, its post-merger profit could still decrease relative to its pre-merger profit. We name such pre-emption as the order effect of merger. When several firms adopt such behaviour that attempts to pre-empt a rival's merger, a sequence of mergers may be triggered, with firms attempting to be in the early stages of that order. We argue that order effect may be utilized to partially explain merger waves (see Chapter 5, Section 5.2.2).

The third group of merger explanations stresses the interdependence of merger decision over time. If a merger provides important gains, then it will be followed by a merger of rivals; that is, when a merger provides gains to insiders, outsiders will respond by merging as well. This 'defensive' merger may allow outsiders to match the gains, if any, of the first merger partners. On the other hand, if these gains are small, a sequence of mergers may not occur, even though firms would be better off with the sequential merger. Given that the first merger is completed, the outsiders free-ride on the first merger and do not merge because the gains are not great; the first pair anticipates it and do not merge. We label such behaviour, where a merger triggers another merger, as the herd effect of merger. That effect stresses the fact that once the bandwagon gets rolling, firms choose to merge

because other firms are merging. Mergers stop occurring when industry has been concentrated and mergers are not profitable anymore because targets have become too expensive or are not allowed by antitrust authorities. We argue that the herd effect can be utilized to partially explain merger waves. (see, Chapter 5, Section 5.2.3).

4.3. Finance Perspective in Analyzing Mergers

The finance literature on mergers and acquisitions stresses that an active market for corporate control exists, and merger and acquisitions are probably the result of the successful workings of this special market. The market for corporate control concept is based on the neoclassical tradition and treats mergers as a market process of allocating spare resources to their most effective use via the best management. Manne (1965) indicates that the control of firms may constitute a valuable asset that exists independent of any interest in either economies of scale or monopoly power. Control of firms is traded in this market, as managers who believe they can run firms better than incumbent management seek some way of realizing the gains potentially available either through taking over the inefficient firm or through merging with it.⁹ In the absence of any internal methods of control, or where such methods are not successfully implemented, the market for corporate control facilitates the dismissal of low quality management.

Thus, if managers are pursuing goals other than value maximization, or if they are simply poor quality managers, then we would anticipate that a firm's financial performance, as measured by profitability, would be lower than that in value-maximizing firms. If the market for corporate control is operating to discipline non-value-maximizing managers, then lower profitability should be associated with a higher probability of takeover. However, lower profitability

⁹ In theory, optimal contracts can be designed to ensure that managers act in shareholders' interests and, in this case, no takeovers will be observed in equilibrium. However, practical problems of implementing such contracts can arise because information imperfections are often more severe than these can allow for and contracts become non-optimal when some change to firm performance occurs (Morck et al., 1988)

could lead to an increased probability of takeover not only for disciplinary reasons, but because lower profitability could financially constrain a firm; both internal funds are lower and access to external funds may be more difficult. Firms with many profitable investment opportunities but no available funds could be expected to become the targets of firms without financial constraints.

Jensen (1986, 1988) provides a specific type of non-value-maximizing activity on the part of managers, namely, the inappropriate use of a firm's free cash flow.¹⁰ According to Jensen's free cash flow theory, value maximizing managers should distribute the free cash to shareholders in the form of higher dividends (or alternatively, they could use it in order to repurchase their own shares). The free cash flow theory of mergers can be interpreted as suggesting two additional channels through which the market for corporate control might exert its influence. Higher dividends paid out by firms with no investment opportunities will signal that managers are not squandering shareholders' assets and thus should be related to a lower probability of takeover in such firms.¹¹ At the same time, any increase in investment by firms with no profitable investment opportunities will necessarily be value-reducing, and the market should discipline such over-investment behaviour by a takeover. Thus, Jensen's theory of takeover indicates a role for both investment and dividend policy in influencing the probability of takeover, at least among firms which have no profitable investment opportunities.

¹⁰ Free cash flow is the cash available to a firm in excess of that required to finance the firm's profitable investment opportunities.

¹¹ The idea that managers use dividends as a signal to convey information about their intentions or about the future performance of the firm is one which has been much investigated in the literature (see, for example, Miller and Rock, 1985).

Empirical literature attempts to reveal the characteristics of acquired firms using market, financial and accounting data.

Early empirical studies for the UK by Singh (1971, 1975) for the periods 1954-1966 and 1967-1970, Kuehn (1975) and Cosh et al. (1984) for the period 1961-1967 and late 1960s, respectively, do indeed suggest that acquired firms are more likely to be less profitable. Empirical studies using US data include that of Hayes and Taussig (1967) for the period 1954-1966 and Hindley (1970) for the period 1957-1969 using US data. In general, these studies tend to support the market for corporate control hypothesis, although that support is relatively weak. Empirical studies by Palepu (1986) and Schwartz (1982), using US data and covering mergers in the 1980s, produce results that are also consistent with the market for corporate control hypothesis. Thus, the general conclusion of studies covering the 1950s, 1960s and 1970s is that acquired firms tend to be less profitable and generally sluggish.

A study by Hasbrouck (1985), covering the early 1980s in the US, attempts to assess differences in the financial characteristics of target and non-target firms. The results indicate that unregulated non-financial target firms are characterized by low valuation ratios and to a lesser extent, high current financial liquidity.

On the other hand, findings from Hannan and Rhoades (1987), also covering the US in the 1980s, do not indicate that poorly managed firms are more likely to be acquired than those that are well managed. Specifically, the results suggest that firms with large market shares and operations in urban areas are relatively more likely to be acquired, but not firms with low profits or low growth. Meador, et al. (1996) examine the accounting, financial and market characteristics of target firms for the period 1981-1985 of the US economy. The results are also in

direct contrast to the theory that firms with inefficient management are likely targets for merger. The significance of sales growth suggests that firms seeking to expand their market share choose to merge with firms whose sales are increasing. In addition, smaller firms are more likely candidates than larger firms.

Asquith et al. (1983) have also observed that acquired firms tend to be smaller than acquirers, suggesting a negative relationship between takeover likelihood and size. Firm size role may arise as an induced effect stemming from transaction costs and barriers to takeover. Transaction costs include the costs associated with the absorption of the target into the acquirer's organizational framework as well as the costs associated with finding a prolonged battle that a target may wage to defend itself. Successful takeover is contingent on acquisition of a proportion of the outstanding equity at a price reflecting market value plus a premium. With credit rationing, potential bidders may face limitations on the absolute size of their outlay and hence, limitations on the size of the firm they may reasonably expect to acquire (Rege, 1984; Machlin et al, 1993).

Financial leverage is another characteristic that makes a firm an attractive target; unused debt capacity may be considered attractive. Managers inclined to minimize the risk of bankruptcy have incentive to underlever the firm. If, however, low leverage is viewed as a sign of managerial incompetence, this will lead to a firm-specific relationship between this variable and takeover likelihood. As an alternative justification, it may be noted that firms with low leverage offer the combined firm the opportunity of raising funds by borrowing externally (Hasbrouck, 1985).

The role of financial liquidity in takeover behaviour is less straightforward. Firms may hold financial assets in excess of normal transaction requirements for a number of reasons. For example, the tax consequences of distributing cash to the shareholders may be unfavourable (Rege, 1984). If firms are short of finance, then more liquid firms may be attractive targets.

In a more recent study, Dickerson et al. (2002), using UK data for the period 1970-1991, find evidence that some takeovers can be interpreted as having disciplinary motivations; low profitability was found to be associated with a higher probability of takeover, although this effect was weaker in the latter half of the study period. Furthermore, firms without investment opportunities (as indicated by Tobin's q ratio) did not experience a significantly increased takeover probability if they increased investment or reduced dividends.

Rhodes-Kropf et al. (2005) suggest that undervalued firms are considered as cheap buys and are more likely to become targets.¹² They use market to book value ratio as a valuation measure of a firm. In particular, they break down the market to book value ratio into three components: firm specific pricing deviation from short-run industry pricing, short-run deviations from firms' long-run pricing, and long-run pricing to book value. The first two components track misvaluation at the firm and sector levels, and the third tracks long-run growth opportunities. They find that acquirers with high firm-specific overvaluation use stock to buy targets with relatively lower firm specific overvaluation at times when both firms benefit from an over-heated sector or market. Cash targets are

¹² The misvaluation argument has also been used to explain the relation between stock market and aggregate merger activity (for a discussion, see Chapter 2, Section 2.2.2). In addition, Gugler et al. (2005) provide supporting evidence of the q theory of mergers and misvaluation hypotheses as possible explanation of merger waves at the firm level.

undervalued relative to stock targets, while cash acquirers are less overvalued than stock acquirers. After controlling for firm-specific and sector or market-specific misvaluations, they find that firms with low long-run growth opportunities actually merge with those with high long-run growth opportunities.

In summary, the above literature examines financial, accounting and market characteristics of firms in order to distinguish between acquired and non-acquired firms. Factors such as profitability, investment opportunities, dividends, growth prospects, size, liquidity, leverage and undervaluation seem to play an important role in determining a target firm. We label these firm-specific characteristics as the rank effect of merger. We argue that as firms develop, these characteristics change and may create 'attractive' targets. As a result, the gains from a merger may also change, which generates different preferred dates for merging. Thus, rank effect can be utilized in order to provide a partial explanation of merger waves (see Chapter 5, Section 5.2.4).

4.4. Concluding Remarks

This chapter has reviewed the most prevalent theoretical explanations for, and empirical evidence on, mergers as depicted in the industrial organization and finance literature. Literature on mergers tends to focus on the effects of acquisitions on profitability as the main incentive for acquisitions. A merger is more likely to result in an increase in profitability for the merged firm when the number of outsiders is small. Thus, the propensity of firms to merge increases as the number of merged firms increases (a labelled stock effect of merger). The pre-emption theory of acquisitions states that firms that acquire another firm early, gain more than late movers (a labelled order effect of merger). In addition, a merger may trigger another merger as firms attempt to imitate the action of their rivals and match the efficiency gains of the first merger partners (a labelled herd effect of merger). Finally, firm-specific characteristics play an important role in an acquisition decision (rank effect of merger).

An analysis of the existing literature suggests that attempts to explain merger activity (with the exemption of literature on sequential mergers) refer to merger seen in isolation; that is without taking into consideration the interdependence of mergers over time. We propose that this research on mergers can be combined to provide an explanation of the dynamics within merger waves.

We propose a model, as explained in Chapter 5, which is tied closely to the explanations suggested by the existing literature in an attempt to shed some light on merger waves. Specifically, we construct a decision-theoretic model that simultaneously incorporates stock, order, herd, and rank effects of mergers. The prime objective of doing so is to obtain a model that may be used to assess empirically which, if any, of these effects plays an important role in explaining

merger activity. We then consider whether the model would generate merger waves.

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CHAPTER 5: A THEORETICAL MODEL OF MERGER TIMING

5.1. Introduction

In this chapter, we construct a decision-theoretic model of merger timing. The merger decision is analyzed from the target's perspective, which provides an alternative approach in analyzing the merger process.

This model differs from previous analyses in that it incorporates different merger motives simultaneously within a dynamic framework and endogenizes the merger process. Merger literature has shied away from a dynamic endogenous merger process¹ because of the complexity of modelling an endogenous process. The reason for the complexity is that in a merger environment where any firm can merge with any other, it is hard to sort out which mergers will occur from among the many conflicting possibilities. Instead of endogenizing the merger process, most studies have picked particular mergers and checked whether they are profitable relative to no mergers occurring. However, the criterion of 'profitable relative to no merger' is not a valid guide to whether a merger will occur. For instance, a merger between two firms A and B that is profitable relative to no merger might not occur because A will wait for B and a third firm, C, to merge, knowing that it will be much better off than with no merger, due to the decreased competition. In general, because the future always

¹ A notable exception is Gowrisankaran (1999).

holds the possibility of mergers, which, in turn, affects the reservation prices from not merging, a merger that is profitable in relation to no merger will not necessarily occur. Furthermore, it is not certain that a merger that is not profitable relative to no merger will not occur. If a firm expects that one of its rivals will gain large cost savings or efficiencies from taking over some other firm, then it can be rational for the first firm to pre-empt this merger with a takeover attempt of its own. By pre-empting the rival firm's merger, the first firm avoids the larger loss of profits it would have suffered had its rival been successful.

Our model exploits such dynamics of merger process by assuming that potential targets should have different preferred takeover dates, or, in other words, at any given date, only some of the potential targets will wish to actually be acquired by another firm. Literature, as discussed in Chapter 4, suggests four effects of merger: stock, order, herd, and rank effects. We argue that these effects may also influence the timing of merger activity (for a similar analysis on technological diffusion, see Karshenas and Stoneman, 1993). By encompassing these four effects, the model provides explanations of the nature of merger activity and the dynamics of a wave at the micro-level of analysis.

The chapter is organized as follows: Section 5.2 constructs a deterministic model of merger timing while Section 5.3 describes the stock, order, herd, and rank effects. Section 5.4 presents a stochastic model of merger timing. Section 5.5 outlines the empirical approach taken to estimate the theoretical model. Section 5.6 discusses the incorporation of herd effect into the empirical model. Finally, Section 5.6 summarizes.

5.2. A Deterministic Model of Merger Timing

Consider a firm, i , that is a potential merger target with stand alone market capitalization, $V_i(t)$. It is subject to a continuous series of bids $P_k(t)$ over time from k bidding firms ($k=1\dots n$). Assume two-sided information asymmetry, i.e. the bidders and the target each has private information about their respective values. The management of both firms maximizes shareholder wealth. In addition, both bidder and target are assumed to be risk neutral.

In an intertemporal decision model it is usual to consider two criteria that have to be met for a purchase to occur – the profitability criterion and the arbitrage criterion. The former says that the sale must be profitable to the seller and the second says that it would not be more profitable for the seller to wait for a higher future bid. In this context however it is argued that, via the market mechanism, the valuation of the target firm in time t , $V_i(t)$, will reflect potential future selling possibilities and prices and as such if the profitability criterion is met then so will be the arbitrage criterion.

Define $Max(P_k(t)/V_i(t))$ as the highest bid to market value offered at time t and assume that if a merger is to proceed the target will sell to that bidder offering this highest bid. To make this approach operational it is necessary to consider the determinants of $Max(P_k(t)/V_i(t))$. The argument proceeds upon the basis that a main determinant of $Max(P_k(t))$ will be the value of the merged entity that results and thus the discussion considers this issue. It should however be stated that, as it is the ratio of this to the stand alone value of firm i , i.e. the ratio of $Max(P_k(t)/V_i(t)$ that matters, factors that equally affect market values of merged and stand alone entities will tend to cancel out. It is for this reason that we have not pursued the more common macroeconomic based approach, arguing in fact

that macro factors will most likely affect bidders and targets equally and thus will provide little insight into merger timing and determination. Similarly, as we are only interested in the maximum of $P_k(t)/V_i(t)$ the characteristics (and thus identity) of the actual buyer are of little interest to us, for such characteristics in a bidding war will primarily determine only who is the bidder rather than the bid being made.

5.3. Determinants of bidding by potential acquirers

Four different mechanisms have been suggested in the literature (see Chapter 4) that should affect $Max(P_k(t)/V_i(t))$, here labeled as stock, order, rank and herd effects

5.3.1 Stock Effects

Stock effects result from the assumption that the benefit to the marginal merger increases as the number of previous mergers increase. This assumption is derived from the industrial organization literature on mergers (see, Chapter 4, Section 4.2.1, for example, Salant et al. (1983), Horn & Persson (2001a)). Based on this stream of literature, the incentive to merge depends upon a complex resolution of two forces. First, a merger results in a price increase. However, second, the output of the merged firm declines relative to that of its partners prior to the merger. Although the price increase benefits all firms, the question is whether that price increase can be sufficient to compensate for the output reduction of the merged firm and, thus, increase merged firm profits. It has been suggested (Perry and Porter, 1985) that when the number of merged firms is small, the number of remaining firms in an industry is large, so that the residual demand facing remaining firms considering merger is relatively flat. Thus, any output contraction has a small price effect, so the profitability of a merger is reduced. However, when the number of merged firms is large, the residual demand is relatively steep, so that an additional merger can more readily increase the price. Consequently, there is an incentive to merge when there is a large number of merged firms but not when the number is small. A merger is related to

previous mergers because of the strategic interaction between firms in an industry through the product market.

The model is made operational by arguing that $Max(P_k(t)/V_i(t))$ will be large when there is a large number of merged firms but not when the number is small.

5.3.2. Order Effects

Order effects result from the assumption that firms engaging early in merger activity can reap first mover advantages (see relevant literature in Chapter 4, Section 4.2.2). The theory of pre-emptive mergers claims that when several potential acquiring firms achieve cost savings or market power, they will compete for the opportunity to merge if the available targets are limited. Targets may be limited by antitrust authorities or by geographic markets, or simply by firm-specific characteristics which make certain firms attractive targets (see Section 5.2.4).

The winning firm that acquires the target could become a lower cost producer and increase its product market share if the cost savings are large enough. If the merged firm increases its market share, rivals are worse off. Intuitively, if a firm expects that one of its rivals will gain large cost savings or efficiencies from taking over another firm, then it can be rational for the first firm to pre-empt this merger with a takeover attempt of its own. By pre-empting the rival firm's merger, the first firm avoids the larger loss of profits it would have suffered had its rival been successful. Its post-merger profit could still decrease relative to its pre-merger profit. However, the market value of the pre-emptive firm increases.

The model is made operational by arguing that, via an order effect, $(Max(P_k(t)/V_i(t)))$ may increase as the expectation of merger bids by other firms increase. For simplicity it is here assumed in the empirical work that expectations of mergers can be measured by realized mergers one period ahead

5.3.3 Herd Effects

Herd effects result from the assumption that merger decisions are interdependent over time. Literature (see Chapter 4, Section 4.2.3) suggests that a merger may trigger a sequence of mergers. The rationale behind this is that if a merger provides important efficiency gains or cost savings, then it will be followed by a merger of the rivals. In other words, merging gives a signal that efficiency gains can be reaped from a merger, so rivals will respond by merging as well. This 'defensive' merger will allow outsiders to match the efficiency gains, if any, of the first merged firms. On the other hand, if cost savings are small, firms are less likely to carry through their own merger because they anticipate that rivals will free ride (as it is more profitable to remain independent) and no merger will occur. This suggests that the very act of trying to use the information contained in the merger decisions made by others may create a bandwagon phenomenon, which once rolling, prompts firms to merge because others are merging.

However, merger sequence in an industry may not lead to a monopoly because of antitrust authorities. Furthermore, when the number of merged firms is very large and the industry has been concentrated with only a few firms, a merger may be privately unprofitable. A firm, when considering the possibility of selling out, takes into account the fact that the merged entity that can be formed without its participation will increase the merged entity's profits by reducing further competition. This increases the reservation price of a target and thus, the cost of buying out firms. Therefore, the benefits of firms participating in a merger may be less than those of remaining outside. This creates a free rider

problem that limits the development of a monopoly and dissipates merger activity.

The model is made operational by assuming that if a merger occurs that will encourage a rival's merger, then that, in turn, will lead to a sequence of mergers. Mergers stop occurring when industry has been concentrated and merger activity is no longer profitable.

5.3.4 Rank Effects

These effects result from the assumption that potential targets have different inherent characteristics, and as a result, the fit with a certain bidder will be different; thus, different gains are obtained by the merged firm. As these different inherent characteristics may change through time as firms develop, gains from a merger change, too, generating different preferred merger dates. The model is operationalized by ranking potential targets in terms of their attractiveness, from highest to lowest. Attractive targets will attract more/larger bids while those that are less attractive will attract less/lower bids.

There are numerous firm-specific factors influencing the merger decision, some of which may not be even observable or quantifiable. The factors that will be considered in this model are those which, in the finance literature, are believed to exert a systematic influence on the merger decision (see Chapter 4, Section 4.3). As the market for corporate control theory suggests, managers of efficient firms believe that they can run inefficient firms better than incumbent management, and seek some way of realizing the gains potentially available by taking over the inefficient firm. These inefficient firms are regarded as attractive targets.

Literature suggests different mechanisms through which the market for corporate control can operate, the main channel being the profitability of the firm. However, corporate finance theory indicates lower profitability could lead to an increased probability of takeover not only for disciplinary reasons, but because lower profitability could financially constrain a firm (both internal funds are lower and access to external funds may be more difficult). In this case, firms with many profitable investment opportunities could be expected to become the

targets of firms without financial constraints. By conditioning on investment, leverage and liquidity, we can take into account financial constraints as far as possible (see, for example, Meador, et al., 1996; Dickerson et al., 2002).

Furthermore, an application of the Tobin's q-theory to takeovers would imply that a takeover bid of a low q-firm is an attempt to acquire valuable resources at a cost below that of *de novo* investment. Since q ratio measures returns on a firm's existing assets,² as long as there are firms with q less than one, any firm desiring to enter the market will prefer acquisition to *de novo* investment, and *ceteris paribus* one would expect to find more acquisitions of such firms (see, for example, Jovanovic and Rousseau, 2002).

The 'free cash flow' theory (Jensen, 1988) suggests that if a larger share of profits is distributed in the form of dividend payments to shareholders (which implies that the free cash flow is not used to invest in unprofitable projects, but instead, is allocated to shareholders), this acts as a signal to the market that the firm's managers are acting prudently. It is this fact, according to the free cash flow interpretation, which explains why high dividends are related to low takeover likelihood. An alternative view suggests managers use dividends in an attempt to minimize probability of takeover. In this case, high dividends are aimed at inducing shareholders' loyalty, even though they might be a source of short-termist behaviour.

Finally, low leveraged or more liquid firms are more likely to be acquired. It has also been observed that target firms tend to be smaller than bidders, suggesting a negative relationship between takeover likelihood and size. Firms seeking to expand their market share choose to merge with firms that exhibit

² q ratio equals the ratio of market to replacement value of a firm.

high growth. Finally, undervalued firms are considered cheap buys and are more likely to be acquired (for a discussion, see Chapter 4, Section 4.3).

5.4. A Stochastic Model of Merger Timing

Any modeling process necessarily abstracts from various real-life factors which, although possibly known with certainty by the individual players, cannot be incorporated into the model. These factors are introduced into the model through a stochastic error term ϵ . Assume that the distribution, $F(1+\epsilon)$ is independent of payoffs and remains invariant across firms and time. The criterion for firm i to be sold (merged in time t) is then given by $Max(P_k(t)/V_i(t)) \geq (1+\epsilon)$ i.e. when the maximum bid (over k) received in the time period is greater than the value of the firm by an amount reflecting firm specific stochastic factors. The probability of a target i being acquired in the small interval $\{t, t + dt\}$, conditional on not having being acquired by time t , the hazard rate, $h_i(t)$, is then given by:

$$h_i(t) = Pr[Max(P_k(t)/V_i(t)) \geq 1 + \epsilon] = F(Max(P_k(t)/V_i(t)) \quad (1)$$

Section 5.3 indicates that $Max(P_k(t)/V_i(t)$ is a function of rank ($R(t)$), stock ($S(t)$), and order ($O(t)$) effects. Thus, Equation 1 can be written as:

$$h_i(t) = J[a_1R(t), a_2S(t), a_3O(t)] \quad (2)$$

Hypotheses regarding the existence of rank, stock, and order effects can then be tested by considering the significance of coefficients a_1, a_2 , and a_3 in Equation 2 (see Chapter 6).

5.5 The Empirical Approach

The empirical approach taken in this study is a survival or duration analysis³. Survival analysis is concerned with analyzing the time to the occurrence of an event. For survival analysis, we need methods that directly account for the sequential nature of the data, and are able to handle censoring and incorporate time-varying covariates. The solution is to model survival time (duration time of firm before being acquired) or time to acquisition indirectly, via the so - called 'hazard rate', which is a concept related to chances of a firm being acquired at each instant (or time period) conditional on survival up to that point.

Specifically, let the dependent variable of interest be the, survival time or the time to acquisition. Let this continuous random variable be denoted T . The basic building block in duration modeling is the acquisition rate or hazard function at some time t , commonly denoted $h_i(t)$, which represents the instantaneous acquisition rate at time t . In continuous terms, the probability that a firm, i , who is independent until time t , is acquired in a short interval of length dt after t is:

$$h_i(t) = \lim_{dt \rightarrow 0} \frac{Pr(t \leq T \leq t + dt / T \geq t)}{dt} = \frac{f(t)}{S(t)} \quad (3)$$

Where $f(t)$ is probability density function $f(t) = Pr(T = t)$ and $S(t)$ is the survivor function which is nothing more than the reverse cumulative distribution function of T :

³ For a discussion, see Appendix B. Furthermore, classic texts on survival analysis is that of Cox and Oakes (1984), Lancaster (1990), Kalbfleisch and Prentice (2002). An introductory discussion is given by Cleves et. al. (2004) while a more mathematical one by Lawless (2003).

$$S(t) = 1 - F(t) = Pr(T \geq t) \quad (4)$$

The survivor function reports the probability of surviving beyond time t . Said differently, it is the probability that there is no acquisition prior to t .

The probability density function $f(t)$ summarizes the concentration of duration lengths (acquisition times) at each instant of time along the time axis. The hazard function summarizes the same concentration at each point of time, but conditions the expression on survival (no acquired) up to that instant, and so can be thought of as summarizing the instantaneous *transition intensity*.

The hazard rate (or function) can vary from zero (meaning no risk at all) to infinity (meaning the certainty of acquisition at that instant). Over time, the hazard rate can increase, decrease, remain constant, or even take on more serpentine shapes. There is a one-to-one relationship between the probability of survival past a certain time and the amount of risk that has been accumulated up to that time. The hazard rate measures the rate at which risk is accumulated.

In this study we make use of models belonging to the accelerated failure time (AFT) family of survival time models. Specifically, we estimate three different models from AFT family: log-logistic, log-normal, and generalized gamma:

1) Log-logistic model

The log-logistic model is specified as :

$$h(t, X) = \frac{\psi^{\frac{1}{\gamma}} t^{\left(\frac{1}{\gamma}-1\right)}}{\gamma \left[1 + (\psi t)^{\frac{1}{\gamma}}\right]} \quad (5)$$

Where $\psi \equiv \exp(-\beta X)$ and γ is a shape parameter, $\gamma > 0$.

In specific, $\beta X \equiv \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_k X_k$ which means that we define a combination of k explanatory variables for each firm while β s are parameters, later to be estimated. The hazard rate is monotonically decreasing with survival time for $\gamma \geq 1$. If $\gamma < 1$, then the hazard rate first rises with time and then falls monotonically.

2) Log-normal model

This model has hazard rate:

$$h(t, X) = \frac{\frac{1}{\sigma\sqrt{2\pi}} \exp\left[-\frac{1}{2}\left\{\frac{\ln(t)-\mu}{\sigma}\right\}^2\right]}{1 - \Phi\left(\frac{\ln(t)-\mu}{\sigma}\right)} \quad (6)$$

Where $\Phi(\cdot)$ is the standard Normal cumulative distribution function and characteristics are incorporated with the parameterization $\mu = \beta X$. The hazard rate is similar to that of log-logistic model for the case $\gamma < 1$; that is first rising and then declining.

3) Generalized Gamma model

This model has a rather complicated specification involving two shape parameters: they are the shape, k , and scale, σ , parameters. The hazard function is quite flexible in shape, even including the possibility of a U shaped. The Generalized Gamma model incorporates several of the other models as special cases. If $k = 1$, we have the Weibull model; if $k = 1$, $\sigma = 1$, we have the Exponential model. With $k = 0$, the Lognormal model results. And if $k = \sigma$,

then we have the standard Gamma distribution. These relationships mean that the generalized Gamma is useful for testing model specification. By estimating this general model, we can use a likelihood ratio test to investigate whether one of the nested models provides a satisfactory fit to the data.

There are at least two advantages in using survival analysis over alternative static models for investigating the timing of a takeover. Firstly, there is the issue of unobserved firm heterogeneity. Suppose that a firm characteristic, unobservable to us, is positively related to the probability of takeover (call it “attractiveness”). Then, those firms which have more of it will be taken over first (at a younger age), leaving the firms with less attractiveness still in the sample, getting older. The consequence for the estimates is that the probability of takeover will be seen to fall with age, but this is spurious because it is simply the fact that these firms are less attractive that prevents them from being taken over, not the fact that they are older per se. The biases induced affect the age (duration) variable as well as all other coefficients, as long as other covariates are correlated with age. Survival analysis can be used either to mitigate the effect of unobserved firm heterogeneity or to incorporate explicitly the unobserved heterogeneity directly into the functional specification.

The second advantage of our approach is that observations are assumed to be time-dependent. We allow firms to develop, to be dynamic entities, not just random clusters of characteristics at any point in time. Survival analysis recognizes that certain observations come from the same firm and places these observations in the correct chronological order. Our framework explicitly allows for dependency over time, in that the hazard methodology estimates the

conditional probability of takeover. It is ideally suited to our main question, since it allows us to investigate whether, given that a firm has survived up to a certain point in time, changes in stock, order, and rank effects will lead to a change in the timing of takeover.

5.6. Herd Effect

Thus far, herd effects have been ignored in the modelling. In this section, we discuss the empirical model, in order to analyze herd effects. As discussed, we adopt models from AFT family of models. The hazard function of these models in a general form is :

$$h(t / X_t) = h_o(t\psi_t)\psi_t, \quad \psi_t \equiv \exp(\beta X_t) \quad (7)$$

Where X is a vector of explanatory variables incorporating all the variables discussed above (rank, stock, order effects), β is a vector of parameters, and $h_o(\cdot)$ gives the relationship between the hazard rate for a firm with characteristics X and the hazard rate for the case when $X = 0$, i.e. the 'baseline' hazard $h_o(\cdot)$.

The effect of the explanatory variables is to change the time scale by a factor equal to ψ_t . If explanatory variables equal zero, we get the baseline hazard rate; the hazard rate that depends only on time t (see, for example, Jenkins, 2005). The baseline hazard summarizes the pattern of 'duration dependence', i.e. whether hazard rate increases or decreases with time, assumed to be common to all firms.

Herd effects, as discussed, are based on imitation, due to informational asymmetries. Such an endogenous process can be introduced by specifying the hazard function⁴ as

$$h(t / X_t) = h_o(t\psi_t)\psi_t\Phi(t) \quad (8)$$

Where Φ incorporates the imitation process. We assume a nonparametric form for Φ , as theory suggests no unique parametric specification of the herd effects.

⁴ For a similar application in technological diffusion process, see Karshenas and Stoneman (1993).

Equation 8 gives a general model that incorporates rank, stock, order, and herd effects. However, it is apparent that it is not possible to separately identify the baseline hazard from the herd effect in this equation. Thus, the herd effects are absorbed into the baseline hazard, and in the empirical analysis, we estimate Equation 8 with no explanatory variables and examine the pattern of duration dependence (see Chapter 6).

5.7 Concluding Remarks

Studies in M&A follow a pre-selected point of view, which is either an industrial organization or finance perspective, and tend not to combine approaches. In this study, we have set up a general model of M&A timing that simultaneously incorporates rank, stock, order, and herd effects. These four effects represent the main streams in the existing literature. This model differs from previous analyses, as it provides an effective way to analyze merger timing without a pre-selected perspective, and also enables comparison of relative model performance.

In this model, merger decisions are analyzed within a dynamic framework from the target perspective, which provides an alternative point of view in describing the merger process. The target firm plays an important role in merger activity, as it determines the gains of the bidder by setting its selling price.

Finally, the econometric model adopted in this study provides some additional advantages in analyzing merger timing; it deals mainly with issues of unobserved firm heterogeneity and allows for time dependency over time.

CHAPTER 6: DATA AND ESTIMATION

6.1 Introduction

This chapter describes the sample selection and data used in this study. It also presents the results arising from the duration analysis used to empirically examine the impact of time-varying variables (described in Chapter 5) on timing of acquisition in the UK economy.

An important issue in acquisition studies is sampling methodology. The typical procedure used in the acquisition literature is to draw a sample with an approximately equal number of acquired and non-acquired firms; a ‘matched’ sample. Unlike random sampling, in ‘matched’ sampling, a firm’s probability of being selected into the sample is a function of its acquisition status, i.e. whether or not the firm is a target. This may lead to biased and incorrect inferences (Palepou, 1986).

However, there is a valid econometric justification for preferring a ‘matched’ sample over a random sample in the estimation of an acquisition model because the number of acquired firms is very small compared to the number of non-acquired in the population. If a random sample were to be drawn from such a population, the sample would be likely to consist of an overwhelming majority of non-acquired and very few acquired firms. The information content of such a

sample for model estimation would be quite small, leading to relatively imprecise parameter estimates. The sample can be enriched informationally by making the sample proportions of acquired and non-acquired more evenly balanced. Manski and McFadden (1981) show that in a population like the one described above, an appropriately 'matched' sample provides more efficient estimates compared to a random sample of the same size.

We select a sample in which the proportion of acquired firms is the same as the population proportion of acquired firms in the UK during the period 1990-2004. We use maximum likelihood estimation procedure to estimate the model parameters. Note that the maximum likelihood procedure consists of maximizing the sample likelihood. Since the maximization of the sample likelihood yields an unbiased estimate of the probability of a firm being acquired and sample proportion of acquired firms is the same with that of the population, this procedure yields an unbiased estimate of the population acquisition probability.

Before estimating any parametric models, we investigate duration data using non-parametric techniques, in order to provide summaries of the survival times of all the firms in the sample. Having done that, we proceed by estimating appropriate parametric models as suggested by non-parametric analysis. That is a common practice in the literature and helps in identifying the most appropriate empirical model for our research questions.

This chapter is organized as follows: Section 6.2 describes sampling methodology and Section 6.3 discusses survival data structure. Section 6.4 defines dependent and explanatory variables and their measurements. Section 6.5 presents non-parametric analysis of duration data. Section 6.6 discusses the estimation of parametric models. It first discusses estimation issues, such as

endogeneity bias, and then proceeds by estimating different parametric models. The most appropriate model is chosen based on different diagnostics tests. In Section 6.7, a generalization of the preferred model is conducted, in order to test for a heterogeneous population. In Section 6.8, the effects of the explanatory variables are calculated and discussed. Section 6.9 discusses the herd phenomenon in takeover activity. Section 6.10 discusses the results, while Section 6.11 summarizes the main conclusions.

6.2. Sample Selection

We use a large sample of UK quoted companies from all sectors over the period 1990-2004, in order to investigate our research hypotheses. In order to be considered, an acquisition has to meet the following criteria:¹

1. A UK domestic acquisition (acquirer and acquired companies operate mainly in the UK)
2. Listing of both firms on the UK stock exchange
3. Acquisition of an independent firm
4. 50% or higher change of ownership²

We initially identified 616 acquisitions under the above criteria during the sampling period, by using the *Thompson ONE Banker* database (for a description, see Chapter 2, Section 2.3). The next step was to collect financial statements for these firms for at least three years before the acquisition. This ensured that there was a reasonable span of data on each firm and allowed us to observe acquired firms for some time before acquisition. That requirement reduced the acquired firms available to 234 firms.³ We used *DataStream* (for a

¹ We excluded from our study leverage buyouts, buyins / management buyouts, bankruptcy acquisitions, privatizations, minority stake purchases.

² The 50% threshold signifies legal ownership of a company. This is a common criterion for defining takeovers and assigning timing to them. (See, for example, Appendix I in Hannah, 1983, for the existing historic series in the UK, and for criteria for including acquisitions in these series.)

³ It is extremely difficult to collect financial data for firms that have been acquired, as most of them change names or are fully merged with the acquirer and are not listed in the UK stock exchange after the acquisition. However, a t-test on means indicates the elimination of firms is random and it is not associated with specific sectors, firm age or size, type or value of transaction.

description, see Chapter 2, Section 2.3) to obtain information on firms' annual accounts. The information was derived from published annual reports and, along with accounting data, included various descriptive pieces of information on the firms.

We also used the *DataStream* dataset in order to select randomly firms that were not engaged in any acquisition (being neither acquirers nor acquired firms) during the sampling period. These firms had to be listed in the UK stock exchange, and to operate in the UK market. After screening for data requirements, the population meeting the above criteria numbered 2,054 firms, which were then classified into 12 sectors (obtained from *Thomson One banker* dataset classification), with firms in each sector being arranged in alphabetical order. Every sixth firm was selected from these lists (12 lists, one per sector) to generate a random group of 546 firms. Table 6.1 presents the decomposition of the sample into 12 sectors.

Table 6.1: Sector Representation in the Sample used in Survival Analysis

Sector Index	Sectors	Number of acquired firms	Number of firms not involved in any acquisition	Total number of firms per sector	Sector contribution to the sample
1	Consumer Products and Services	35	81	116	14.8%
2	Energy and Power	11	25	36	4.6%
3	Financials	36	85	121	15.5%
4	Healthcare	10	24	34	4.4%
5	High technology	25	59	84	10.8%
6	Industrials	28	66	94	12.1%
7	Materials	11	26	37	4.7%
8	Media & Entertainment	29	67	95	12.2%
9	Real Estate	17	40	57	7.3%
10	Retail	13	31	44	5.6%
11	Consumer Staples	10	24	34	4.4%
12	Telecommunications	7	17	25	3.2%
	Total	234	546	780	100%

Note: when selecting the number of firms not involved in any acquisition for each sector, we followed the proportion of each sector to the total number of acquired firms.

In total, our sample consists of 780 firms. The proportion of companies acquired in our sample (30%) is representative of the population proportion of acquisitions in the UK over the period. The sample is summarized in Table 6.2.

Table 6.2: Composition of the Sample used in Survival Analysis

Year acquired	Number of firms acquired
1990	16
1991	18
1992	6
1993	7
1994	13
1995	22
1996	30
1997	28
1998	32
1999	33
2000	13
2001	7
2002	4
2003	4
2004	1
Total acquired firms	234
Firms not involved in acquisition during 1990- 2004	546
Total number of firms	780

Our sampling methodology contrasts with that usually employed in the literature on acquisitions.⁴ An advantage of our sampling methodology is that we do not artificially choose a sample of firms for which we suspect that the probability of takeover is likely to be particularly influenced by variables investigated in this study. This is in contrast to a number of papers in the literature which either focus on one particular industry where, say, extraneous investment is thought to have occurred, and then test the over-investment hypothesis (Jensen, 1986); or where the market for corporate control hypothesis is investigated by examining only hostile takeovers (Bhagat et. al., 1990). Such approaches have an element of subjectivity.

6.3. Survival Time Data

1990 is selected as the starting point (onset of risk of a firm being acquired) in our study because we seek to incorporate a complete takeover wave in our empirical analysis (recall that early 1990s is the start of the fifth takeover wave; see Chapter 2, Section 2.3 and Chapter 3, Section 3.5.1 for a discussion). We observe firms over time from 1990 until 2004. For much of the time, the beginning of ‘under observation’ period coincides with the onset of risk. However, there is a period of ignorance,⁵ for some firms, extending from on or

⁴ A notable exception is Dickerson et al. (2002), who also follow the population proportion of acquisitions when constructing their sample.

⁵ Mainly because there is no available data during a period

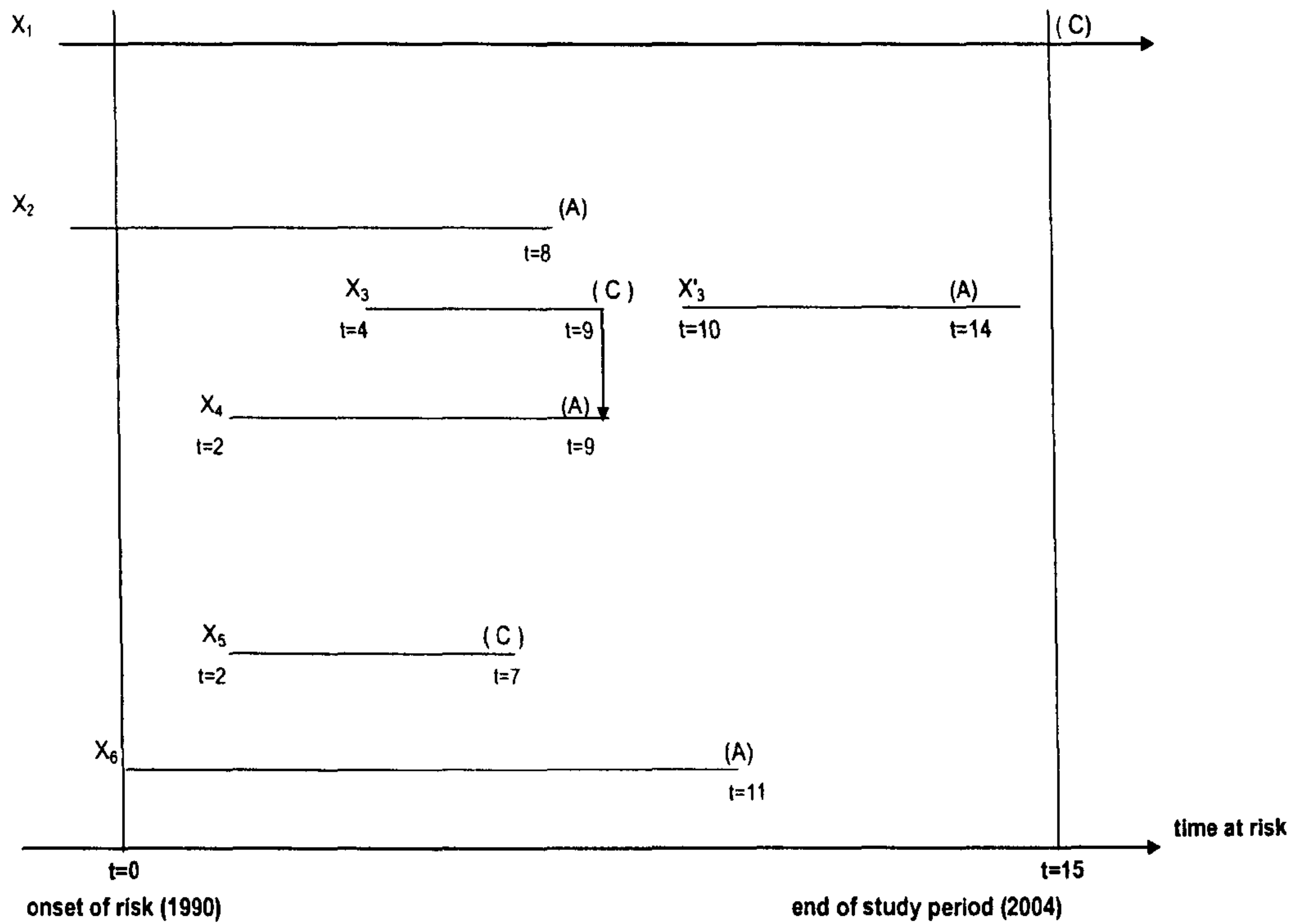
before the onset of risk to some time after the onset of risk. For a while, the firm is not observed, but then the firm comes under observation. We include such firms in our study but we must account for the fact that, had the firm been acquired earlier, we never would have encountered this firm. Although the firm's subsequent survival can be analyzed, we do not want to make too much of the fact that the firm survived up until the point we encountered it (for more details, see Appendix B).

This means that the time origin is not 1990 for each firm, with some firms entering the study later (left truncated survival time data). The survival time (time of acquisition) is measured from each firm's own date of entry in the study. In addition, some firms exit the study before 2004 for reasons other than being acquired (right censored observations). Once an acquisition occurs, the acquired firm can no longer be observed, while the acquirer is considered as a censored observation and exits the study at that time, before reentering it at the next period as a new entity (it must stay in the sample for at least three years before being acquired again). At the end of the observation period (2004), firms that have not been acquired are considered as censored observations. In summary, our sample is characterized as a sample with right censoring and left truncation (delayed entry).

Figure 6.1 depicts all possible life histories of companies over the observation period, 1990-2004. The horizontal axis measures analysis time or time at risk (not calendar time). In other words, this is the time of acquisition or time of censoring for non-acquired companies, t , and is measured from the time origin of each firm (the base year 1990 ($t = 0$) or the entry date ($t = t_o$) for delayed entries).

Figure 6.1 shows six types of company, X_1 to X_6 , classified according to their acquisition activity and entry and exit times during the 1990-2004 period. Company X_1 exists before the beginning of our study (1990) and survives beyond 2004 without being acquired (right censored). X_2 has the same life history as X_1 , but differs in that it is acquired at time $t = 8$. Company X_3 enters the study late, at time $t = 4$, acquires X_4 at time $t = 9$, and exits the study as censored. It re-enters the study as a different firm, X'_3 , at time $t = 10$, and is acquired at time $t = 14$. Company X_4 also enters the study late, at time $t = 2$, and is acquired at time $t = 9$ (by X_3). Company X_5 also enters late at time $t = 2$ and exits the study at time $t = 7$ for a reason other than acquisition. Finally, company X_6 , enters the study at the onset of risk, time $t = 0$, and is acquired at time $t = 11$.

Figure 6.1: Companies' Life Histories over the Sampling Period 1990-2004



Note: (A), (C) refer to acquisition behaviour that is 'acquired' and 'censored', respectively. X_i , where $i=1,2,\dots,6$ refer to different types of companies, with respect to acquisition behaviour, entry and exit times, in the sample. The horizontal axis measures survival time or time at risk of being acquired (the figures in parentheses refer to corresponding calendar time).

It is obvious that the systematic exclusion of companies with incomplete observations (truncated or censored), such as X_1 , X_4 , or X_5 , may introduce a selection bias in the sampling distribution of the model. To account for this, we include such companies in our sample and employ special techniques for estimating the models (see Appendix B). Table 6.3 gives a summary of our sample.

Table 6.3: Summary of the Sample used in Survival Analysis

Description	Number
Acquired firms	234
Firms not involved in any acquisition	546
Total number of firms	780
Total number of observations	4842
Acquisition rate in the sample	0.05

Note: acquisition rate equals number of acquired firms to total number of observations

6.4. Definition and Measurements of Dependent and Explanatory Variables

The dependent variable used in the empirical analysis is the duration time of companies before being acquired (survival time; T). It is measured by the number of years elapsed since the onset of risk (beginning of study), taken to be 1990. For companies who enter the study later (delayed entries), the survival time is counted from the year they enter the study to the year they are acquired. For those companies who are not being acquired by the end of the study or exit the study earlier for reasons other than being acquired, the survival time is right censored.

The explanatory variables used in the duration analysis are time-varying variables hypothesized to affect time of acquisition, and whose relevance is discussed in Chapter 5. The list of explanatory variables included in the model is presented in Table 6.4. The first column presents the theoretical hypotheses that need to be investigated; factors that influence time of acquisition (discussed in Chapter 5). The second column presents the denotation of explanatory variables used in empirical models. The third column describes the measurement of the explanatory variables.

We also include a vector of 11 sector dummies⁶ to control for fixed sector difference in takeover propensities. These sector differences may stem, among

⁶ Although there are 12 sectors, we include only 11 sector dummies, in order to control for multicollinearity problems.

other things, from different sector structure, or different sector-specific regulations.⁷

⁷ In sectors such as media & entertainment, energy and power, telecommunications and financials, mergers are governed by different approval mechanisms or sector specific rules either instead of, or in addition to, the general jurisdiction of the OFT under Enterprise Act.

Table 6.4: Definition and Measurement of Explanatory Variables used in Survival Analysis

Hypotheses	Variable	Description / Measurement
Stock effect	$S_j(t)$: Cumulative number of acquisitions in sector j up to and including time
Order effect	$O_j(t)$: Expected change in the cumulative number of acquisitions in sector j in the interval $[t, t+1]$, measured by $\{S(t+1)-S(t)\}$
Rank effects		
1. Inefficient management hypothesis	<u>Profitability</u> ROE(t) NIA(t) EAR(t)	: Net income divided by total shareholders equity : Net income divided by total assets : Earnings before interest and taxes
2. Growth-resources mismatch hypothesis	<u>Liquidity</u> CR(t) WCTA(t) WCS(t)	: Current assets divided by current liabilities : Net working capital divided by total assets : Net working capital divided by sales
	<u>Leverage</u> TLTA(t) LDMV(t)	: Total liabilities divided by total assets : Long term debt divided by market value of equity
	<u>Growth</u> SGR(t) AGR(t) EPSGR(t)	: 3 years growth in net sales : 3 years growth in total assets : 3 years growth in earnings per share
	<u>Dummy variable</u> GR(t)	: It is assigned a value one for the combinations low growth-high liquidity-low leverage or high growth-low liquidity-high leverage and zero for all other combinations
3. Firm size hypothesis	NS(t) TA(t)	: Net sales : Total assets
4. Dividend Policy	DIV(t)	: Cash dividends common divided by earnings available to common shareholders
5. Investment opportunities	q(t)	: q ratio which is defined as the market value of a firm divided by the book value of total assets
6. Market undervaluation	PE(t) MTBV(t)	: Price-earnings ratio defined as market price per share divided by earnings per common share : Market to book value defined as market value of a firm divided by its book value

Regarding rank effects,⁸ the variables included in the empirical models are specified on the basis of six hypotheses that summarize the relevant literature (discussed in Chapters 3 and 4). Measurements of the variables used in this study are chosen from those in the previous studies of Palepou (1986), Meador et al. (1996) and Dickerson et al (1998, 2002). Specifically, definition and computation of the variables representing the rank effects are as follows (appendix C presents summary statistics of the data used in this study).

1. Inefficient management hypothesis

The inefficient management hypothesis is investigated by including different measurements of profitability in the empirical model. This is done in order to test the sensitivity of the results to different measurements. Table 4 describes these measurements, which are return on equity (ROE), return on assets (ROA), and earnings before interest and taxes (EAR). They are computed and averaged over a period of three years prior to the year from which an observation is drawn. The unit of measurement for ROE and ROA is percentage, while the unit of measurement for EAR is thousands of pounds. A positive relation is expected between profitability and the survival time of a firm.

2. Growth – resources mismatch hypothesis

The growth-resources mismatch hypothesis indicates that growth and resource availability are important variables in determining a firm's acquisition

⁸ Monetary values have been converted to constant values of 2000, by using the GDP deflator (taken by the *Office of National Statistic National Account Data*).

likelihood. Specifically, this hypothesis implies that two types of firm are likely targets: low-growth, resource-rich firms and high-growth, resource-poor firms. In this study, growth, liquidity, and leverage are measured by using different measurements for each in order to test the sensitivity of the results to different measurements.

Specifically, growth of a firm is defined as the annual rate of change in the firm's net sales, total assets, or earnings per share. The annual net sales growth is computed for the three fiscal years prior to the observation year, and the average is used as the net sales growth variable (SGR). (For example, consider a firm from the year 1995 with a December 31 fiscal year. The net sales data from the period January 1, 1992 to December 31, 1994 are used to compute the net sales growth during the three fiscal years 1992, 1993, and 1994, and the average growth rate for these three years is used as the net sales growth variable.) Total assets growth (AGR) and earnings per share growth (EPSGR) are calculated in the same way. The unit of measurement for all these variables is percent per year.

Liquidity is measured by three different ratios: current assets divided by current liabilities (CR), net working capital divided by total assets (WCTA), and net working capital divided by sales (WCS). Leverage is measured by using two ratios: total liabilities divided by total assets (TLTA), and long term debt divided by market value of equity (LDMV). We generate the market value of common shares by multiplying the average share price over each firm's financial year by the average of the opening and closing number of common shares. All these ratios are computed for the three fiscal years prior to observation year, and the average is used as the liquidity and leverage variable, respectively. Liquidity is

expressed as a ratio. The unit of measurement of the leverage variable is percentage. No specific sign is hypothesized for the three variables since a priori it is not known a priori which imbalance is predominant.

In another version of the empirical model, instead of the above three variables⁹ (growth, liquidity, and leverage), the growth-resource dummy variable is included in order to test the mismatch hypothesis. The growth-resources dummy is a 0/1 variable defined on the basis of the three variables, growth, liquidity, and leverage (as defined above). The dummy variable is assigned a value one if the firm has a combination of either low growth-high liquidity-low leverage, or high growth-low liquidity-high leverage. The dummy is set to zero for all the other combinations. Each of the three variables, growth, liquidity, and leverage is defined as 'high' if its value for a firm is larger than the average for all the firms in its sector existing in the DataStream database; otherwise, it is defined as 'low'. A negative relation between the growth-resources dummy and survival time of a firm is expected.

3. Firm size hypothesis

The variable size is defined as the book value of a firm's total assets (TA) or net sales (NS). Two different measurements of firm size are tried in order to investigate the sensitivity of results to these measurements. These variables are measured as of the fiscal year end immediately prior to the observation year. The

⁹ Growth-resources dummy variables are not included in the empirical model together with growth, liquidity, and leverage variables, due to multicollinearity problems.

units in millions. A positive relation between firm size and survival time is expected.

4. Dividend policy hypothesis

Dividend policy hypothesis is investigated, by including the dividend payout ratio in the empirical model. The dividend payout ratio is defined as the book value of cash dividends to common shareholders divided by the book value of earnings available to common shareholders. Both cash dividends and earnings available to common shareholders are measured at the end of the fiscal year preceding the observation year. The variable is expressed as a ratio. A positive relation between dividends payout and survival time of a firm is expected.

5. Investment opportunities

Tobin's q ratio is defined as the firm's market value divided by the replacement cost of a firm's assets. Calculating the market value of the firms raises a number of issues. Share information is available on an end-month basis. We generate the market value of ordinary and preference shares by multiplying the average share price over each firm's financial year by the average of the opening and closing number of ordinary shares. The definition of market value of a firm includes the market value of the firm's debt. However, lack of information on the maturity of debt and on current market prices for debt precludes any straightforward valuation. Instead, we are forced to use the book

value of debt. In addition, calculation of the replacement cost of total assets is complicated because of the lack of information on replacement costs. Instead, we use the book value of total assets as a proxy for replacement cost.¹⁰ q ratio is measured at the end of the fiscal year preceding the observation year. The variable is expressed as a ratio. A positive relation between the q ratio and survival time of firm is expected.

6. Market valuation hypothesis

Two different measurements are used for investigating the market undervaluation hypothesis. The first is the price-earnings ratio (PE), defined as the ratio of a firm's market price per share to its book value of earnings per share. The market price per share is the average share price over each firm's financial year. The price-earnings ratio is computed as of the fiscal year end preceding the observation year. The variable is expressed as a ratio. The second is the market to book value ratio (MTBV), defined as the ratio of the market to book value of the common equity of a firm. Both the market value and the book value are measured at the end of the fiscal year preceding the observation year. The variable is expressed as a ratio. A positive relation between market valuation and survival of a firm is expected.

¹⁰ For a similar approach, see Hasbrouck (1984).

6.5. Nonparametric Analysis of Survival Data

Before estimating any parametric model, it is common practice to investigate duration data using a non-parametric technique, which provides graphic summaries of the survival times of all firms in the sample without making any assumptions regarding the underlying distribution of survival times and how covariates serve to change the survival experience. Because the nonparametric analysis is informative about the pattern of duration dependence, it may suggest appropriate functional forms for parametric analysis and for specification analysis of more complicated models (Kiefer, 1988).

Figure 6.2 presents Kaplan and Meier's estimator, a nonparametric estimate of the empirical survivor function; the probability of survival past time t or equivalently, the probability of failing after t . The horizontal axis in Figure 6.2 denotes the number of years elapsed from the beginning of the study (1990) to the year of acquisition or the year the study ended (2004) for censored observations. In addition, early exit (a firm disappearing before the end of the study) and delayed entry (a firm entering the study after 1990) were taken into consideration when the empirical survivor function was estimated.¹¹ As Figure 6.2 shows, at the end of the sampling period ($t = 15$), the probability of being independent is approximately 60%, or equivalently, the probability of being acquired after $t = 15$, is 40%. It is obvious that our dataset has not reached the median, as the median survival time is calculated as the smallest survival time for which the survivor function is less than, or equal to, 50%.

At time $t = 0$ the survival function takes the value 1, since no firm has been acquired. With the passage of time, survivor estimates decrease because firms

¹¹ For a theoretical discussion, see Appendix B.

are being acquired. The speed of acquisition is slow and persistent until $time = 8$, i.e. in each time interval, a few firms are acquired but the number of acquisition in each interval is fairly stable. Then between time 8-10, the speed of acquisition becomes more rapid, i.e. the number of acquisitions in each interval increases during period 8-10. Towards the end of the study (time 10-15), the speed of acquisition becomes sluggish, i.e the number of acquisitions does not change significantly.

We reach the same conclusions if we, instead, estimate the empirical cumulative hazard function by using the Nelson-Aalen estimator, depicted in Figure 6.3. The horizontal axis in Figure 6.3 denotes the number of years elapsed from the beginning of the study (1990) to the year of acquisition or the year the study ended (2004) for censored observations. In addition, early exit (a firm disappearing before the end of the study) and delayed entry (a firm entering the study after 1990) are taken into consideration when the empirical cumulative hazard is estimated.

The cumulative hazard at the end of the sampling period ($t = 15$) equals 0.50. This means that the probability with which we observe no acquisitions over the interval is $\exp(-0.50) = 0.60$, and thus, the probability of observing an acquisition is $1 - 0.60 = 0.40$.

In contrast to the survival function, at $time=0$, the cumulative hazard function takes the value 0, as no firm had been acquired. As time goes by, a firm's cumulative risk of being acquired increases slowly but persistently. During time 8-10, the cumulative hazard increases more rapidly, meaning that during this

period, more risk is accumulated per year. Finally, after time=10, the cumulative hazard remains constant (there is no increase).

Figure 6.2: Kaplan –Meier Survival Estimate

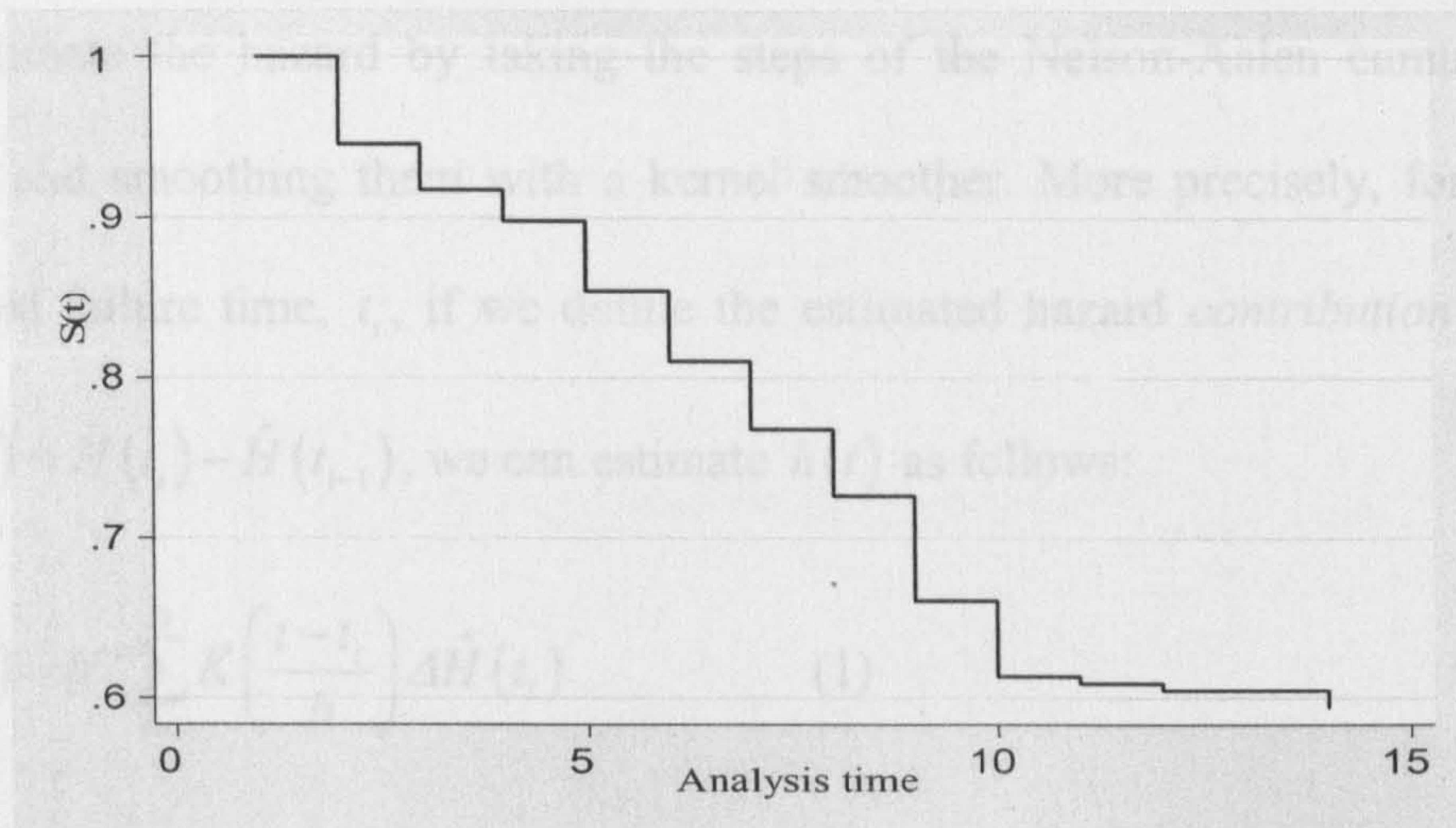
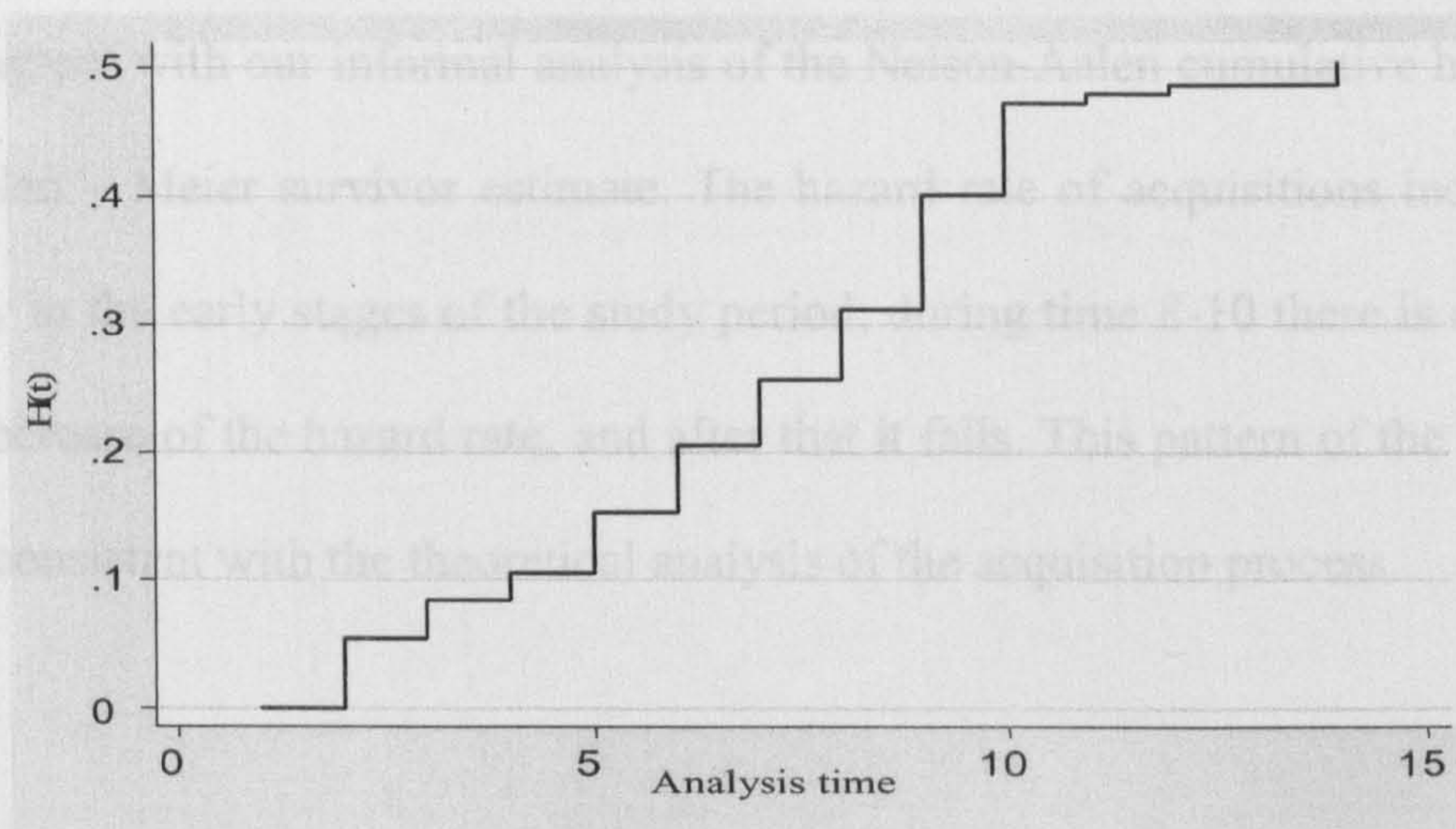


Figure 6.3: Nelson – Aalen Cumulative Hazard Estimate



Note: In both figures, the horizontal axis measures analysis time. The vertical axis in Figure 2 measures the probability of failing after t , $S(t)$, while in Figure 3, it measures the cumulative hazard at time t .

We can use Figure 6.3 to plot an estimate of the hazard function, $h(t)$. We can estimate the hazard by taking the steps of the Nelson-Aalen cumulative hazard and smoothing them with a kernel smoother. More precisely, for each observed failure time, t_i , if we define the estimated hazard *contribution* to be

$\Delta\hat{H}(t_i) = \hat{H}(t_i) - \hat{H}(t_{i-1})$, we can estimate $h(t)$ as follows:

$$\hat{h}(t) = b^{-1} \sum_{i=1}^D K\left(\frac{t-t_i}{b}\right) \Delta\hat{H}(t_i) \quad (1)$$

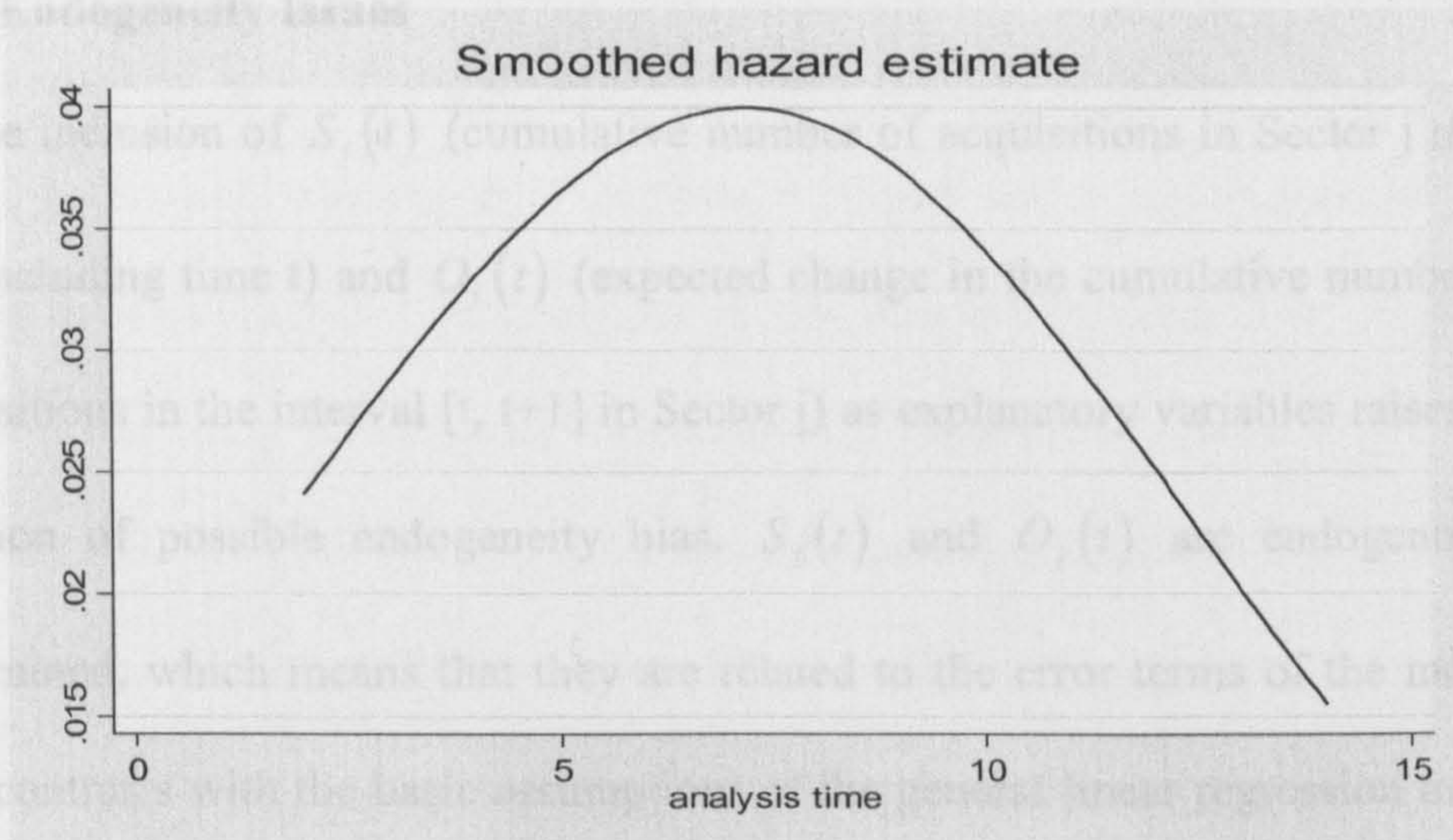
Where $K(\cdot)$ is some symmetric density function, (the kernel) and b is bandwidth. The summation is over the D times at which failures occurs (Klein and Moeschberger, 2003, p.167).

The above procedure produces Figure 6.4 of a smoothed hazard estimate. The graph agrees with our informal analysis of the Nelson-Aalen cumulative hazards or Kaplan – Meier survivor estimate. The hazard rate of acquisitions increases steadily in the early stages of the study period; during time 8-10 there is a more rapid increase of the hazard rate, and after that it falls. This pattern of the hazard rate is consistent with the theoretical analysis of the acquisition process.

6.3. Parametric Analysis of Survival Time Data

In this section, we proceed by estimating parametric models, after dealing with endogeneity issues.

Figure 6.4: Smoothed Hazard Estimate



Note: Horizontal axis measures survival or analysis time, t , while vertical axis measures the hazard rate of being acquired at time t

6.6. Parametric Analysis of Survival Time Data

In this section, we proceed by estimating parametric models, after dealing with endogeneity issues.

6.6.1 Endogeneity Issues

The inclusion of $S_j(t)$ (cumulative number of acquisitions in Sector j up to and including time t) and $O_j(t)$ (expected change in the cumulative number of acquisitions in the interval $[t, t+1]$ in Sector j) as explanatory variables raises the question of possible endogeneity bias. $S_j(t)$ and $O_j(t)$ are endogenously determined, which means that they are related to the error terms of the model. This contrasts with the basic assumptions of the general linear regression model and may lead to inconsistent estimations.

Consistent estimates of the parameters of the model can, nevertheless, be obtained by using a two stages estimation procedure (see, for example, Murphy and Topel, 1985, Greene, 2003, Ch.15), which replaces the endogenous variables with their estimated or predicted values from an auxiliary statistical model. These values are then treated as if they are exogenous for the purposes of estimation and inference in the second-stage model, which is the model of interest.

Regarding stock effects, in the first stage, we estimate an auxiliary statistical model with the endogenous variable as the dependent and the lagged values of the dependent as the exogenous variables:

$$S_{ij}(t) = \alpha_0 + \alpha_1 S_{ij}(t-1) + u_{ij}(t) \quad (2)$$

Where i is a firm belonging to Sector j . It is customary to treat past values of endogenous variables as exogenous (see, for example, Maddala, 2003, p:345). Since past values of endogenous variables are predetermined, they can be regarded as exogenous and independent of the error terms in the model.

Since sector acquisition activity is interrelated (for a discussion, see Chapter 3, Section 3.6.2), we construct a panel dataset in order to estimate an auxiliary model given by Equation 2. The best-developed and most frequently used estimator for a dynamic panel model is the generalized method of moments (GMM), originally developed by Holtz-Eakin, Newey and Rosen (1988) and Arellano and Bond (1991). The basic idea is to take first-differences of Equation 2 to remove unobserved time-invariant firm-specific effects, and then instrument the right-hand-side variable in the first-differenced equation using levels of the series lagged two periods. This avoids the problem raised by the omission of initial stock level and yields a consistent estimator (Arellano and Bond, 1991), the results of which are presented in Table 6.5.

Table 6.5: Auxiliary Statistical Model for Correcting for Endogenous Stock Variable

Coefficient	Variable	Value
α_1	$S_{ij}(t-1)$	0.96 (60.02***)
R-squared	0.15	
Number of observations	180	

Asymptotic standard errors robust to heteroskedasticity are used in the estimation
The t-statistic (figures in parenthesis) , computed to test the null hypothesis that the estimated coefficient is equal to zero
*** indicate significance at 1% level

We substitute the predicted values of $S_{ij}(t)$ from the estimated auxiliary statistical model as presented in Table 6.5, in the main model of interest (given by Equation 3). The expectation term $O_{ij}(t)$ at the second stage is calculated as the first difference of the predicted $S_{ij}(t)$ values.¹²

6.6.2 Estimation of Parametric Models

Given that we have several possible hazard models to choose from, the question is how we can select between them. Theory, as discussed in Chapter 5, gives an indication of the underlying process that generates acquisition times and specifically of the possible shape of the hazard function. That is, the hazard rate first rises with time until a certain level and then falls. In this way, an acquisition wave is generated.

On the other hand, from a purely statistical view, nonparametric analysis (discussed in Section 6.5) provides some information about the pattern of duration dependence which assists with the choice of parametric model. The shape of hazard function presented in Figure 6.4 suggests three different models from the accelerated failure time family of hazard models as being appropriate

¹²However, the standard errors obtained from the second-stage estimation are downward biased (Politis and Romano, 1994). In order to resolve that, we adopt the approach suggested by Politis and Romano, and obtain consistent standard errors by using block resampling techniques, which involve grouping the data randomly in a number of blocks of ten or fewer firms and then re-estimating the model, leaving out each time one of the blocks of observations and then computing the corresponding standard errors as the mean values of these estimates.

for describing our data. These are the generalized gamma model (Model 1), the lognormal model (Model 2), and the loglogistic model (Model 3).¹³ All the above models share a common feature; a hazard function with a flexible shape. They all allow for a hazard rate which first rises with time and then falls monotonically

We start by estimating the above three model specifications. As discussed in Chapter 5, the theoretical model is:

$$h(t) = J[R(t), S(t), O(t)] \quad (3)$$

However, it is not sufficient to say that the timing of acquisition is a function of the above variables and parameterize $\beta X(t)$ just as a summation of the time varying explanatory variables listed in Table 6.4. For instance, the effect of stock may be constant, or it may increase or diminish with the level of stock (as already discussed in Chapter 5). We allow for that in our empirical parameterization, by approximating the effect by including $(stock)^2$ in the model. In similar fashion, we include $(order)^2$ and $(size)^2$ in our model. In addition, the effect of stock and order may increase or diminish with the level of the rank effects, and in such cases, it is common to approximate that by inclusion of cross product terms (for instance, stock x total assets, the interaction of stock and total assets). We also control for fixed sectoral differences in takeover propensity by including 11 dummy variables. The maximum-likelihood estimates of the parameters of the gamma, lognormal, and loglogistic models are shown in Table 6.6.

¹³ For a discussion of these models, see Jenkins (2005)

Table 6.6: Maximum Likelihood Estimates of the Gamma, Lognormal, and
Loglogistic Models

	Dependent Variable	Gamma model (model 1)	Lognormal model (model 2)	Loglogistic model (model 3)
Survival time				
Coefficient	Independent Variables			
β_0	constant	-2.4234 (11.87***)	-2.4370 (12.33***)	-2.3878 (14.89***)
κ	Kappa	-0.2157 (0.39)		
σ	Sigma	0.6266	0.5941	
γ	gamma			0.3183
β_1	S	-0.0609 (4.03***)	-0.0611 (6.13***)	-0.0612 (6.46***)
β_2	O	-0.0292 (3.03***)	-0.0281 (2.97***)	-0.0261 (2.91***)
<u>Rank effects</u>				
β_3	ROE	-0.0172 (0.01)	-0.0100 (0.02)	-0.0037 (0.14)
β_4	DIV	0.3828 (3.6***)	0.3608 (3.79***)	0.3878 (4.24***)
β_5	TA	-0.0113 (3.27***)	-0.0117 (3.35***)	-0.0139 (3.07***)
β_6	q	0.2305 (1.72**)	0.2345 (1.73**)	0.2188 (2.03**)
β_7	PE	-0.1553 (0.99)	-0.1319 (1.03)	-0.0770 (0.71)
β_8	GR	-0.4781 (4.42***)	-0.4939 (4.50***)	-0.5004 (4.37***)
<u>Quadratic terms</u>				
β_9	(S) ²	0.0006 (2.95***)	0.0006 (2.95***)	0.0005 (3.06***)
β_{10}	(O) ²	0.0036 (3.43***)	0.0035 (3.86***)	0.0031 (3.90***)
β_{11}	(TA) ²	0.000131 (2.23**)	0.000132 (2.25**)	0.000152 (2.10**)
<u>Sector dummies</u>				
β_{12}	D ₁	0.3386 (1.16)	0.3392 (1.21)	0.3618 (1.55*)
β_{13}	D ₂	0.2930 (1.00)	0.2907 (1.03)	0.3097 (1.32*)
β_{14}	D ₃	0.7021 (2.20)	0.6834 (2.24)	0.6415 (2.48***)
β_{15}	D ₄	0.3805 (1.28*)	0.3655 (1.28*)	0.3385 (1.38*)
β_{16}	D ₅	0.5500 (1.72**)	0.5648 (1.85**)	0.5715 (2.24**)
β_{17}	D ₆	0.2107 (0.72)	0.2143 (0.72)	0.2395 -1.06
β_{18}	D ₇	0.8806 (2.56***)	0.8407 (2.60***)	0.7872 (2.79***)
β_{19}	D ₈	0.5181 (1.66**)	0.5202 (1.71**)	0.5467 (2.06**)
β_{20}	D ₉	0.5873 (1.94**)	0.5827 (1.99**)	0.5959 (2.4***)
β_{21}	D ₁₀	-0.0327 (0.10)	-0.0305 (0.10)	-0.0055 -0.02
β_{22}	D ₁₁	0.5497 (1.20)	0.4890 (1.16)	0.6262 (1.59*)

(continued on next page)

Table 6.6 (continued) : Maximum Likelihood Estimates of the Gamma, Lognormal,
and Loglogistic Models

	Dependent Variable	Gamma model (model 1)	Lognormal model (model 2)	Loglogistic model (model 3)
	Survival time			
Coefficient	Independent Variables			
<u>Cross-product terms</u>				
β_{23}	S x ROE	-0.0009 (0.16)	-0.0007 (0.13)	-0.0005 (0.11)
β_{24}	S x DIV	0.0048 (0.05)	0.0162 (0.18)	0.0169 (0.22)
β_{25}	S x TA	0.0001 (0.15)	0.0001 (0.19)	0.0001 (0.23)
β_{26}	S x q	0.0435 (1.79**)	0.0429 (1.80**)	0.0373 (1.76**)
β_{27}	S x PE	0.0172 (0.35)	0.0175 (0.36)	0.0197 (0.47)
β_{28}	S x GR	-0.0105 (1.21)	-0.0108 (1.22)	-0.0119 (1.33)
β_{29}	O x ROE	0.0018 (0.10)	0.0018 (0.10)	0.0019 (0.13)
β_{30}	O x DIV	-0.0859 (0.39)	-0.0945 (0.45)	-0.1385 (0.70)
β_{31}	O x TA	-0.0006 (0.96)	-0.0006 (1.01)	-0.0006 (0.99)
β_{32}	O x q	0.0476 (0.77)	0.0475 (0.79)	0.0309 (0.59)
β_{33}	O x PE	0.0341 (0.24)	0.0290 (0.21)	0.0414 (0.35)
β_{34}	O x GR	-0.0080 (0.42)	-0.0070 (0.37)	-0.0082 (0.45)
Pseudo-R-squared		0.23	0.22	0.23
Log - Likelihood		-264.11	-265.86	-264.25
Number of observations		4842	4842	4842
Likelihood-ratio test of $\theta=0$		$X^2_{(1)}=0.01$	$X^2_{(1)}=0.03$	$X^2_{(1)}=0.01$
The t-statistic, computed to test the null hypothesis that the estimated coefficient is equal to zero, is shown in parentheses for each coefficient estimate				
*, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively				

The above findings are statistically satisfactory as indicated by the diagnostic test. The parameter vector remains remarkably stable in moving from one model to the other, indicating that the results are robust to changes in model specification.

The above results are not sensitive to different definitions of variables representing rank effects.¹⁴ We estimated all three models by including liquidity, leverage, and growth as separate variables, in an attempt to investigate the influence of these firm financial characteristics in takeover timing. As their coefficients were not statistically significant in any of the models, we report results with the growth-resources indicator instead of these three variables.

The likelihood ratio statistic is computed to test the following hypotheses:

1. Existence of cross product terms

$$H_0: \beta_{23} = \beta_{24} = \beta_{25} = \beta_{26} = \beta_{27} = \beta_{28} = \beta_{29} = \beta_{30} = \beta_{31} = \beta_{32} = \beta_{33} = \beta_{34} = 0$$

2. Existence of fixed sectoral differences

$$H_0: \beta_{12} = \beta_{13} = \beta_{14} = \beta_{15} = \beta_{16} = \beta_{17} = \beta_{18} = \beta_{19} = \beta_{20} = \beta_{21} = \beta_{22} = 0$$

3. Existence of quadratic terms

$$H_0: \beta_9 = \beta_{10} = \beta_{11} = 0$$

4. Existence of assets

$$H_0: \beta_5 = \beta_{11} = 0$$

5. Existence of stock effects

$$H_0: \beta_1 = \beta_9 = 0$$

6. Existence of order effects

$$H_0: \beta_2 = \beta_{10} = 0$$

¹⁴ Numerous combinations of measurements of rank effects were used, a subset of which is reported in Table 6.6.

Table 6.7 presents the results of the likelihood ratio test for the above hypotheses.

Table 6.7: Summary of Likelihood Ratio Statistic

Hypotheses	Models	Log-likelihood	Calculated X^2	Number of restrictions ^a	Critical values ($\alpha=0.05$)	Null Hypothesis (Ho)
Ho:1	gamma	-272 (-264)	16.14	14	23.68	not rejected
	Lognormal	-272 (-266)	13.25			
	Loglogistic	-273 (-264)	16.97			
Ho:2	gamma	-276 (-264)	23.51	11	19.68	rejected
	Lognormal	-276 (-266)	20.16			
	Loglogistic	-275 (-264)	21.19			
Ho:3	gamma	-283 (-276)	15.08	3	7.81	rejected
	Lognormal	-284 (-276)	15.31			
	Loglogistic	-283 (-275)	15.53			
Ho:4	gamma	-293(-283)	20.35	2	5.99	rejected
	Lognormal	-293(-283)	20.63			
	Loglogistic	-293(-282)	22.79			
Ho:5	gamma	-294 (-283)	23.04	2	5.99	rejected
	Lognormal	-295 (-283)	24.39			
	Loglogistic	-297 (-282)	29.88			
Ho:6	gamma	-293(-283)	21.03	2	5.99	rejected
	Lognormal	-293(-283)	21.56			
	Loglogistic	-294(-282)	23.25			

(a) The number of restrictions equals the number of explanatory variables omitted

Figures in parentheses indicate the log-likelihood for the models with all variables present (unrestricted models)

The test statistic is defined as $-2(L_0 - L_{max})$, where L_0 and L_{max} are the values of the log-likelihood functions for the restricted and unrestricted models, respectively. If the calculated X^2 is less than the critical value of X^2 the null hypothesis is not rejected

The likelihood ratio test fails to reject hypothesis 1, while it rejects the rest of the hypotheses; 2-6. Thus, cross-product terms are statistically insignificant. The results suggest that there is a positive relation between survival time and dividends, and the q ratio. On the other hand, a negative relation exists between survival time and the growth-resources indicator. Size of a firm, stock and order effects have a negative effect on survival time. However, that effect is not constant but increases with the level of size, stock, and order, respectively (see

also Section 6.8). Profitability and market valuation hypotheses do not seem to be supported by the results.¹⁵

¹⁵ We considered that there could be a correlation between the q ratio and MTBV ratio, which may cause the latter to be statistically insignificant. However, when we attempted to estimate the models without the q ratio, the results (regarding the MTBV ratio) did not alter.

6.6.3 Choosing Among Parametric Models

In order to choose one model among the three presented in table 6.6, we first check whether these are nested or non-nested. When models are nested, the likelihood ratio tests can be used to discriminate between them. This can be done in the case of gamma versus lognormal; the gamma model may be collapsed to Weibull (if $k=1$) or to lognormal (if $k=0$) or to exponential (if $k=1, \sigma=1$). When models are not nested, the likelihood ratio test is unsuitable, and we can use the Akaike (1974) information criterion. This is done in the case of gamma (or its nested models) versus loglogistic.

We start with the nested models; gamma and lognormal. Specifically, we test the following hypotheses:

1. $H_0: \kappa=0$, in which case, if H_0 is true, then the model is log-normal.
2. $H_0: \kappa=1$, in which case, if H_0 is true, then the model is Weibull.
3. $H_0: \kappa=1, \sigma=1$, in which case, if H_0 is true then the model is exponential.

Table 6.8 presents the results of the likelihood ratio tests of the above hypotheses

Table 6.8: Likelihood Ratio Test for Testing Nested Models

Hypotheses (H_0)	Likelihood ratio test	Critical values	
		($\alpha=0.05$)	Null Hypothesis (H_0)
$H_0 1: \kappa=0$	0.01	$X^2_{(1)}=3.84$	not rejected
$H_0 2: \kappa=1$	14.82	$X^2_{(1)}=3.84$	rejected
$H_0 3: \kappa=1 \text{ \& } \sigma=1$	6.04	$X^2_{(2)}=5.99$	rejected

The results presented in Table 6.8 preclude the use of Weibull and exponential models for our data. The test results strongly reinforce what we already know about the nature of the hazard for acquisition, namely, that the hazard shape cannot be constant or monotone; rather it is variable.

Having decided between gamma and lognormal, the next step is to compare the lognormal with the loglogistic model. As these two models are non-nested, we use the Akaike information criterion (AIC), which suggests penalizing each model's log likelihood to reflect the number of parameters being estimated and then comparing them. Although the best-fitting model is the one with the largest log likelihood, the preferred model is the one with the lowest value of the AIC. For parametric survival models, the AIC is defined as:

$$AIC = -2 \ln L + 2(\kappa + c) \quad (4)$$

Where κ is the number of model covariates and c the number of model-specific distribution parameters. Table 6.9 gives the log likelihood and Akaike information criterion values from lognormal and loglogistic models.

Table 6.9: Comparison of AIC Values for Lognormal and Loglogistic Models

Distribution	Log Likelihood	κ	c	AIC
Lognormal	-282.63	12	2	593.26
Loglogistic	-281.97	12	2	591.94

Per the AIC criterion, the loglogistic model is selected.

6.6.4 Diagnostics of the Estimated Models

In this section, we present an approach that uses graphical analysis of residuals in order to evaluate the overall fit of our final model.

Since in duration models, residuals are not directly identified, we can estimate residuals by using the accumulated hazard function. Thus,

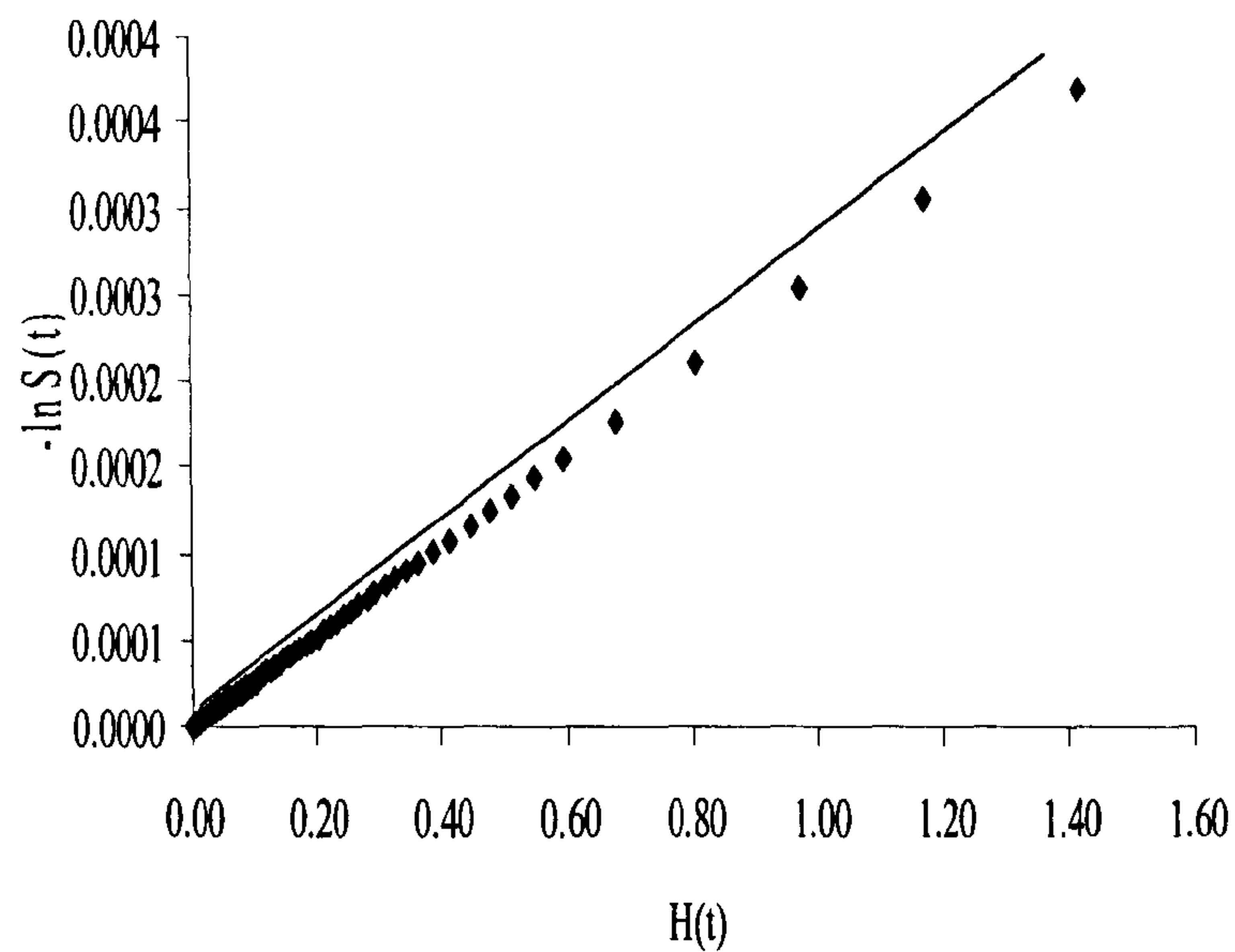
$$H(t) = \int_0^t h(u) du = -\log S(t) \quad (5)$$

If the model fits the data well, i.e. if the specification is correct and important explanatory variables are not omitted, the residuals will behave like observations drawn from a unit exponential distribution. Thus, if a model exhibits a good overall fit, the estimated minus log of the survival function for the integrated hazard evaluated at $H(t, \beta X)$ should equal $H(t, \beta X)$. This implies that for a model that fits the data well, the minus log of survival function for the integrated hazard plotted against the integrated hazard for uncensored observations should lie approximately on a 45° line. A plot that displays a systematic departure from the 45° line indicates that the model needs to be modified either by changing functional form or by including other explanatory variables.

We apply the above test to our final model (Model 3) in order to evaluate its overall fit. Figure 6.5 shows a plot of minus log of the survival function for the integrated hazard against the integrated hazard for firm acquisitions. The plot of the minus log of survival function appears to lie along the 45° line, indicating that there the overall fit of our final model is quite good. Note that some variability around the 45° line is still expected, particularly in the right-hand tail.

This is due to the reduced effective sample caused by prior failures and censoring (see Cleves et al, Chs.11 and 14, 2004).

Figure 6.5: Graphical Analysis of Final model Overall Fit



Note: The horizontal axis measures the integrated hazard, while the vertical axis measures the minus log of the survival function

6.7. Generalizing the Parametric Regression Model

In obtaining results, as presented in Section 6.6, it has been assumed that the correct functional forms have been specified and that the individual firms in the sample, after controlling for observable differences through the inclusion of explanatory variables, are homogenous. However, heterogeneity may arise through functional form misspecification or the presence of unobserved difference, and may then lead to misleading inferences regarding duration dependence and the effects of explanatory variables.

In this section, we consider generalizations of the earlier model to allow for unobserved individual firm effects (unshared frailty models). In unshared frailty models, there is a distinction between the hazard firm's face and the population hazard that arises by averaging over all the survivors. In a heterogeneous population, it turns out that population hazard can fall, while the firm hazards all rise because, over time, the population becomes populated by increasing numbers of robust firms as the more frail members fail. This is known as the frailty effect, and it virtually assures that population hazards decline over time, regardless of the shape of the hazards faced by firms.

The implication of this is that, under the assumption of a heterogeneous population, it could actually be the case that each firm's risk rises with time, even though for the population as a whole, the hazard rate falls.

Under the unshared frailty model, the firm individual hazard function is written as $h(t_i / X_i, v_i) = v_i h(t_i / X_i)$, and the resulting population hazard is written as $h_\theta(t_i / X_i)$. It is shown that as θ tends to zero, the population and individual hazard functions coincide, and that $\lim_{\theta \rightarrow 0} h_\theta(\cdot) = h(\cdot)$

In order to test whether our model is a frailty one, we re-estimate Model 3 and make an assumption about the hazard function each firm faces. The population hazard function is just whatever it turns out to be, given the estimate of θ and the assumed distribution of v_i . Thus, we fit a model with loglogistic individual hazard and gamma and inverse Gaussian distribution frailties. In order to check for unshared frailty, we test the following hypothesis:

Ho: $\theta=0$, in which case, if Ho is true, then the model is without frailty.

The above hypothesis is examined by assuming gamma as well as inverse Gaussian distribution for frailties. Regardless of the choice of frailty distribution, however, from examining the likelihood ratio test for Ho at Table 6.10 we realize that there is not much evidence pointing towards a population that is heterogeneous.

Table 6.10: Likelihood-Ratio Test for Frailty Model

Hypotheses(Ho)	Frailties distribution	Likelihood-ratio test	Critical values	
			($\alpha=0.05$)	Null Hypothesis (Ho)
Ho: $\theta=0$	gamma	0.01	$X^2_{(1)}=3.84$	not rejected
Ho: $\theta=0$	inverse - gaussian	0.01	$X^2_{(1)}=3.84$	not rejected

Clearly, firms are heterogeneous. There is no suggestion that the discussed explanatory variables fully describe the differences. What is really being asked here is whether heterogeneity is so great that it dominates the production of population hazards from individual hazards, or if, instead, for our research questions, that heterogeneity can be ignored. The likelihood ratio test suggests that the population and individual hazard functions coincide.

Indeed, Figures 6.6 and 6.7 present graphs of the individual and population hazards obtained by fitting Model 3. This particular model reproduces the shape of the population hazard which first rises with time and then falls. Individual hazards exhibit the same shape, and so it is not surprising to see that in the reported results above, the likelihood-ratio test for $H_0: \theta=0$ will not be rejected at the 95% level of significance.

Concluding that there are no significant individual specific differences that were not controlled because of unobserved variables is additional evidence that our model fits the data well.

Figure 6.6: Mean Individual Hazard Function

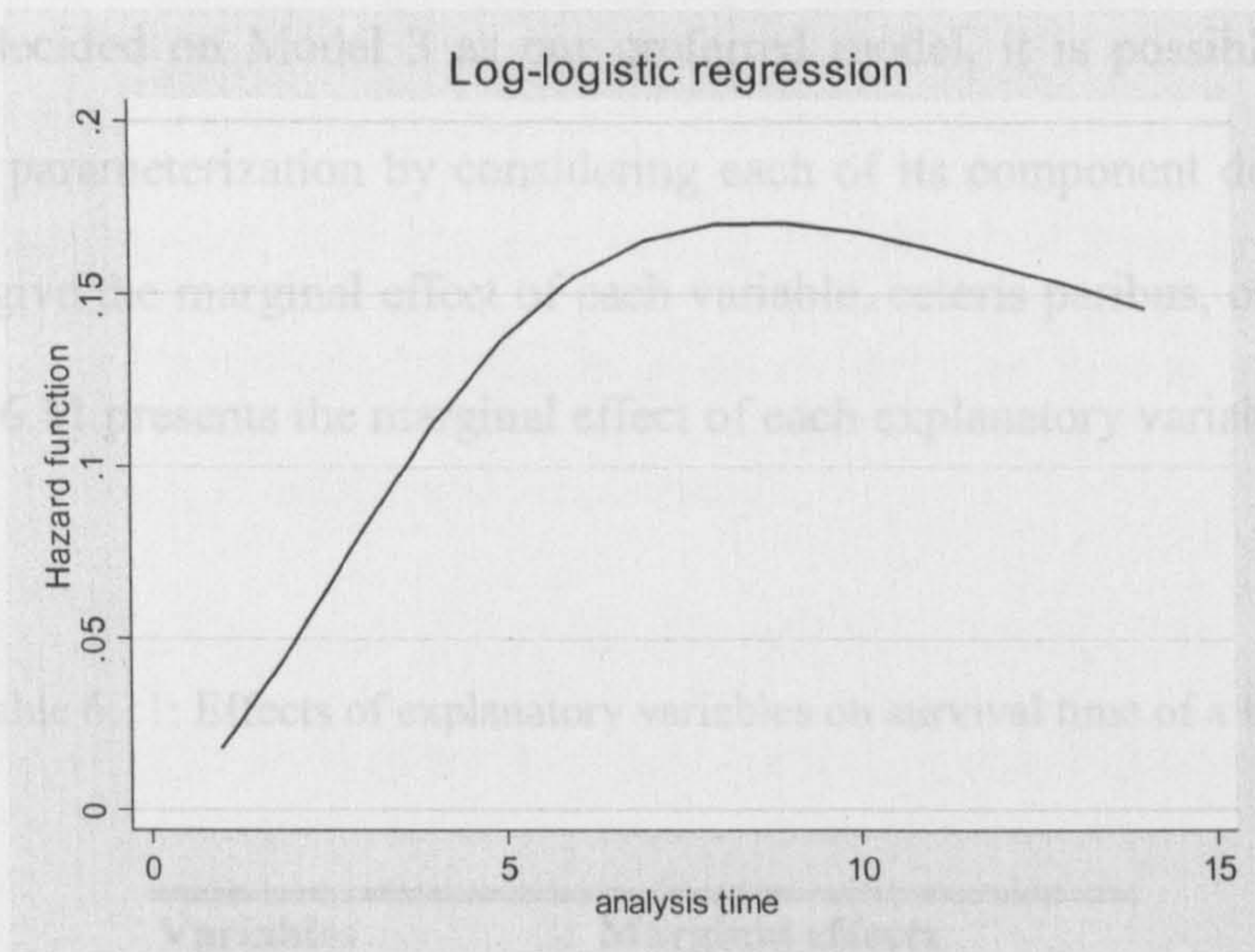
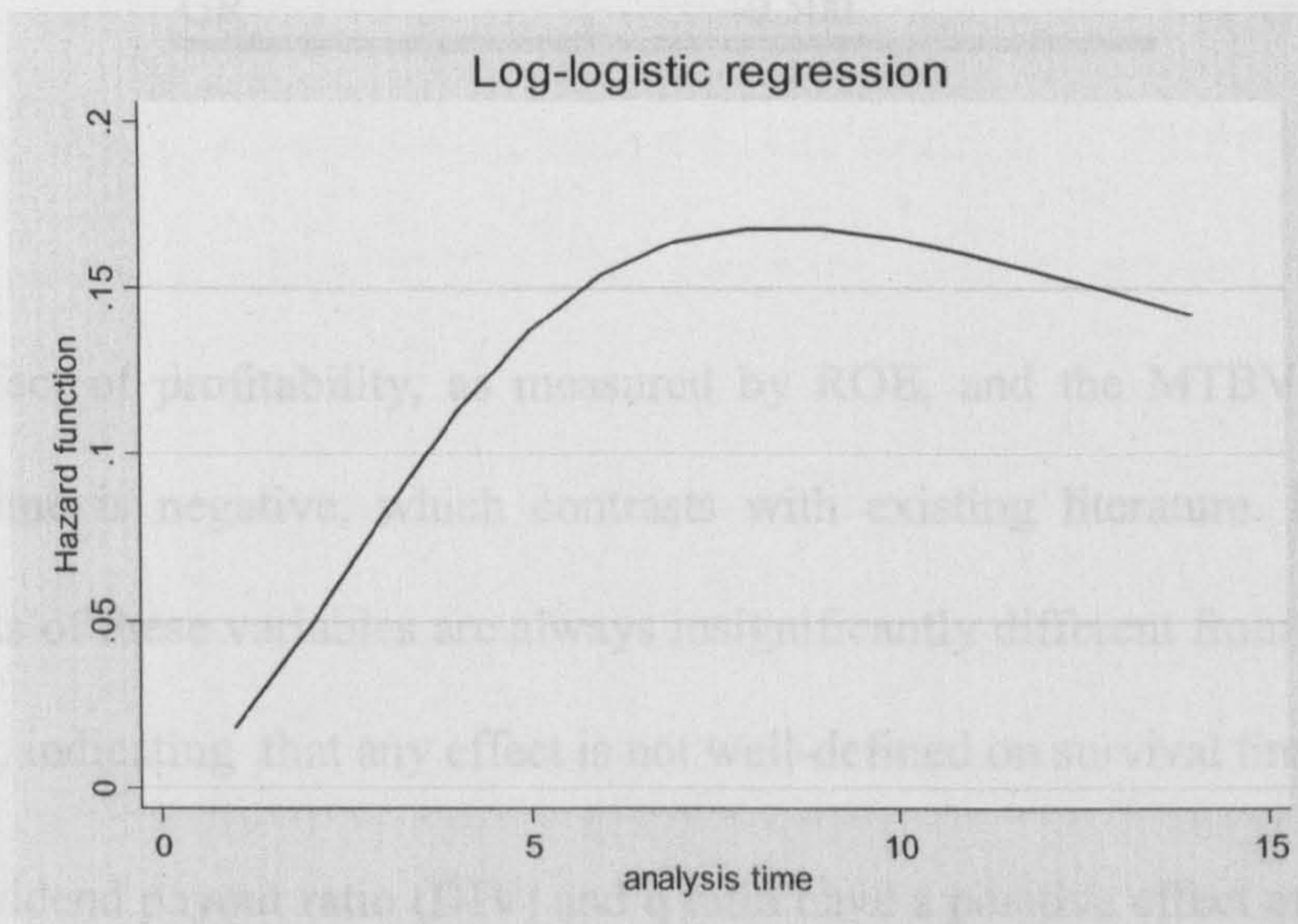


Figure 6.7: Population Hazard Function



6.8. Effects of Explanatory Variables on Survival Time of a Firm

Having decided on Model 3 as our preferred model, it is possible now to interpret its parameterization by considering each of its component derivatives, which will give the marginal effect of each variable, *ceteris paribus*, on survival time. Table 6.11 presents the marginal effect of each explanatory variable.

Table 6.11: Effects of explanatory variables on survival time of a firm

Variables	Marginal effects
S	-0.042
O	-0.011
ROE	-0.004
DIV	0.390
TA	-0.012
q	0.219
MTBV	-0.077
GR	-0.500

The effect of profitability, as measured by ROE, and the MTBV ratio on survival time is negative, which contrasts with existing literature. However, coefficients of these variables are always insignificantly different from zero (see Table 6.6), indicating that any effect is not well-defined on survival time.

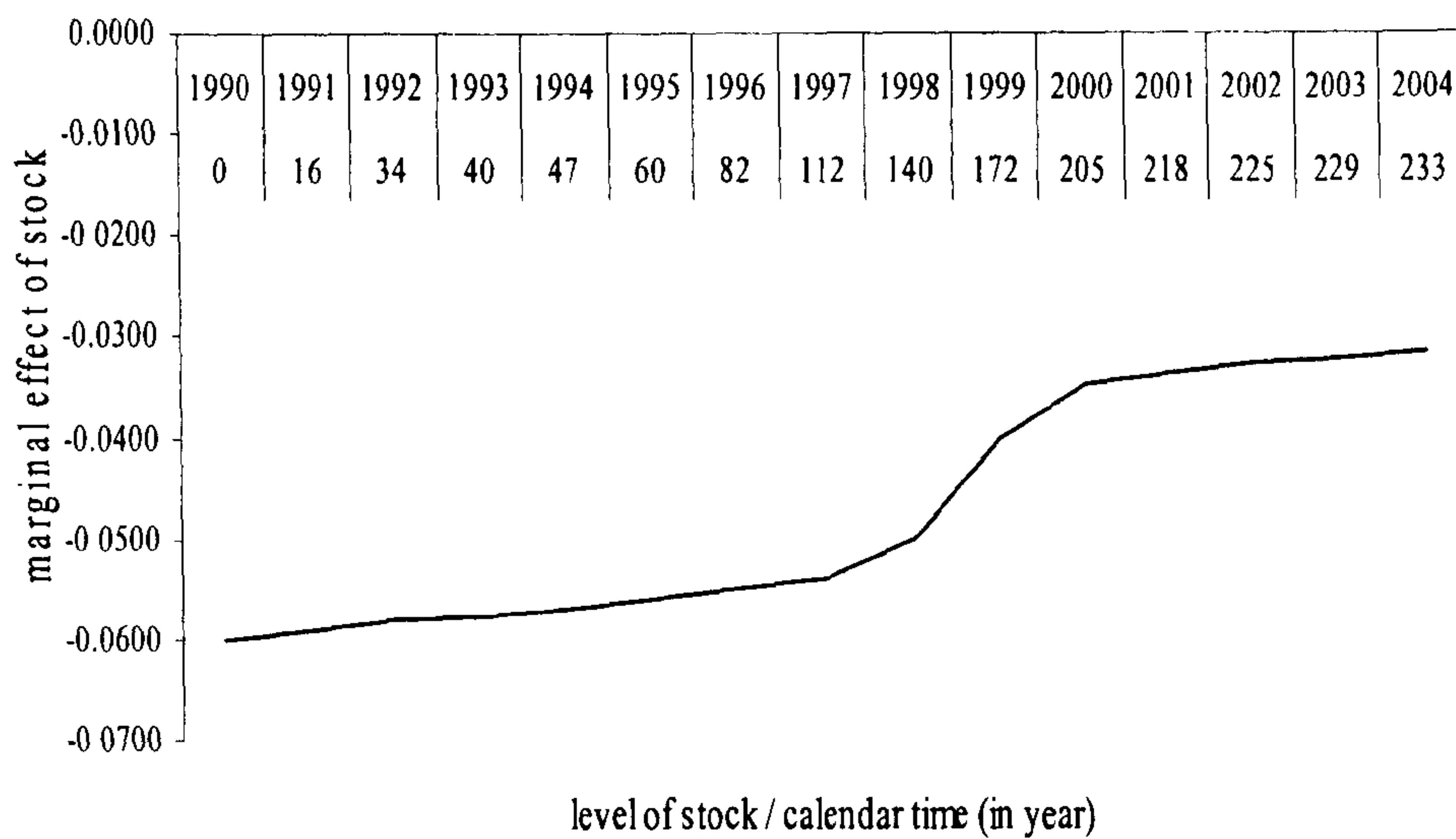
The dividend payout ratio (DIV) and q ratio have a positive effect on survival time. That means that if the dividend payout ratio increases by 1 unit, (log) survival time (time to acquisition) will lengthen by 0.39 years (or 142 days). If the q ratio increases by 1 unit, (log) survival time will also increase by 0.22 years (or 80 days). If a firm moves to the low growth-high liquidity-low leverage

group or high growth-low liquidity-high leverage group, time of acquisition will shorten by 0.50 years (or 183 days). In other words, dividends and q ratio lengthen the time to acquisition and thus, firm acquisition is 'decelerated'. On the other hand, moving to a low growth-high liquidity-low leverage group or high growth-low liquidity-high leverage group shortens the time to acquisition, and thus, in this case, acquisition is 'accelerated'.

Finally, the effect of stock (S), order (O), and total assets (TA) on survival time changes with the level of stock, order, and total assets, respectively. Table 6.11 presents the effect of stock, order, and total assets valued at the average level of these variables. The effect of stock on time to acquisition is negative, meaning that an increase in stock will shorten timing to an acquisition (survival time) in UK economy, *ceteris paribus*, and thus acquisitions are 'accelerated'. Specifically, if stock increases by one acquisition, the survival time of firms will shorten by 0.04 years (or 15 days). In addition, the marginal effect of order on time to acquisition is negative, indicating that an increase in order will shorten timing to an acquisition in the UK economy, *ceteris paribus*, and thus acquisitions are 'accelerated'. If expected acquisitions increase by one, the survival time of firms will shorten by 0.01 (or 4 days). Finally, total assets have a negative effect on survival time; an increase in total assets by £1m will shorten survival time by 0.01 (or 4 days). Figures 6.8, 6.9, and 6.10 present the effect of stock, order, and total assets along different levels of these variables.¹⁶

¹⁶ The level of stock and order refer to aggregate stock and order in our sample.

Figure 6.8: Effect of Stock on Survival Time of a Firm



Note: The horizontal axis measures the level of stock (cumulative number of acquisitions) and calendar time (in years), while the vertical measures the marginal effect of stock on the survival time of a firm

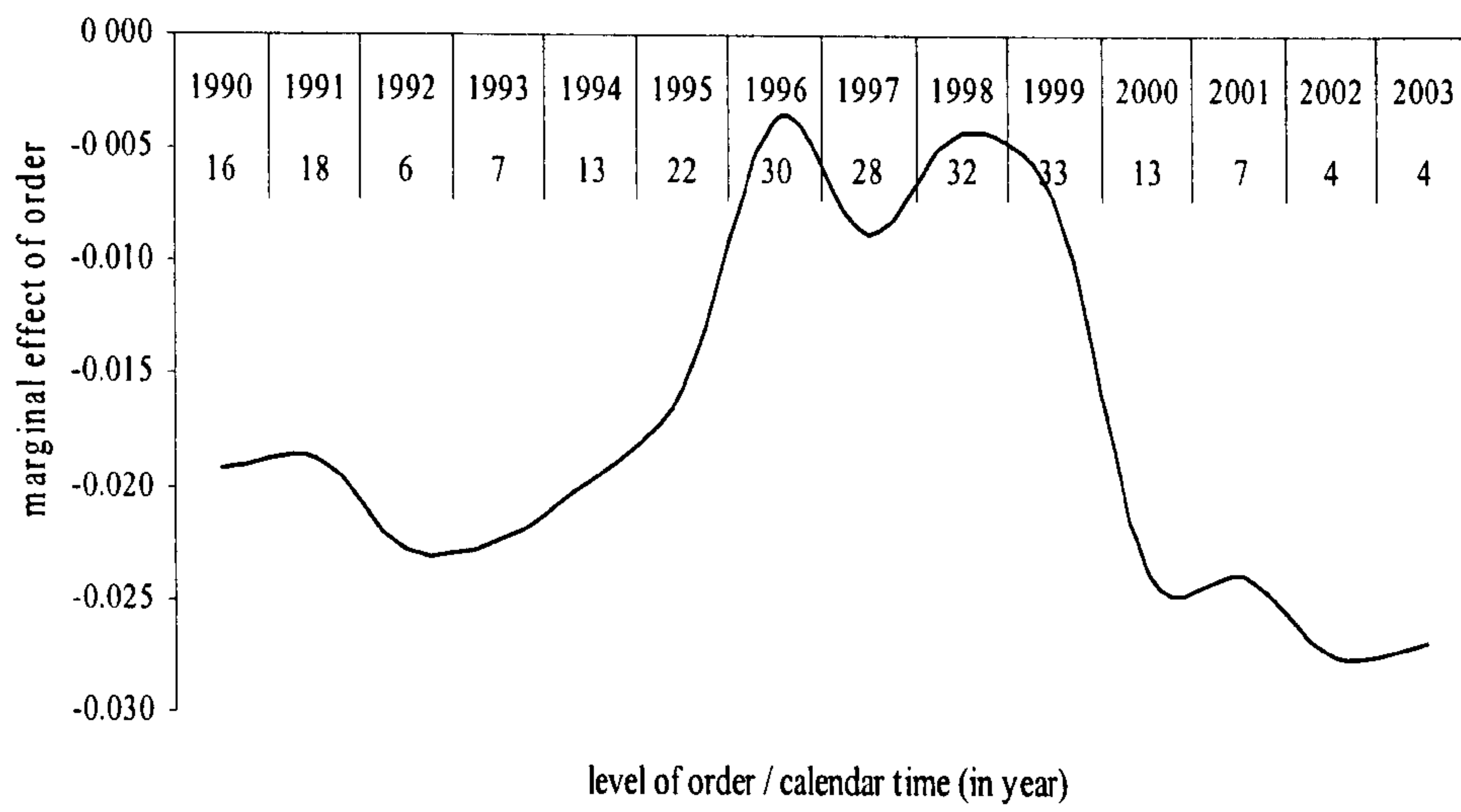
As Figure 6.8 shows, the stock effect is not constant over years. In the early years, when the level of stock is very low, its effect on acquisition timing remains at 0.055 years (or 22 days). During the period 1998-2000, when the level of stock sharply increases, its effect on time to acquisition begins to diminish gradually (in absolute values). For example, in 1998 an additional acquisition shortens time to acquisition by 0.050 years (or 18 days), while in 2000, it shortens acquisition timing by 0.030 (or 11 days). That means that as stock reaches a certain high level, then the effect of an additional acquisition on acquisition timing starts diminishing (in absolute values) which, in turn, means that the rate of acquisitions' 'acceleration' slows down. A possible explanation of the above results is that there is an incentive to acquire firms as the number of

acquisitions increases, but as the economy becomes too concentrated, acquisitions may become privately unprofitable and thus, the acceleration rate decreases.

Figure 6.9 depicts the effect of order on time to acquisition. As Figure 6.9 shows, when order is low (say 7) a marginal expected acquisition results in shortening the time of acquisition by 0.02 years (or 7 days). As the level of order increases, its effect diminishes (in absolute value). Thus, when the number of expected acquisitions is high, say 32, a marginal expected acquisition results in shortening the time of acquisition by 0.005 years (2 days).

The above results suggest that when only a few acquisitions are expected, the survival time of firms is shorter than when the number of expected acquisitions is high. A possible explanation for this is that in the beginning of a potential wave, acquisitions are 'accelerated' in order for firms to reap early mover advantages. If a firm is not acquired early (followers), then it may take longer for an acquisition to occur.

Figure 6.9: Effect of Order on Survival Time of a Firm



Note: The horizontal axis measures the level of order (number of expected acquisitions) and calendar time (in years), while the vertical measures the marginal effect of order on the survival time of a firm

Furthermore, Table 6.12 shows the effect of stock and order over different sectors.¹⁷

Table 6.12: Effects of stock and order per sector

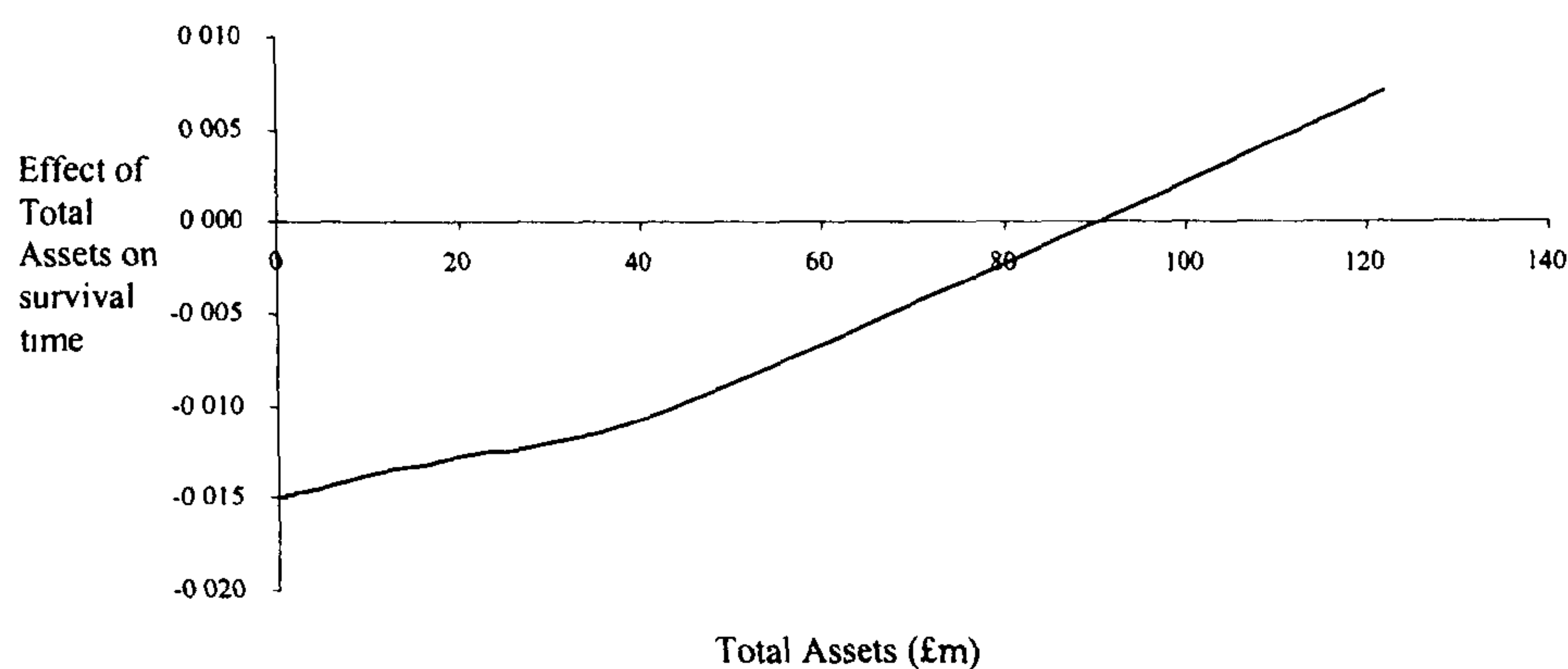
Sectors	1	2	3	4	5	6	7	8	9	10	11	12
Marginal effect of stock	-0.045	-0.048	-0.046	-0.046	-0.046	-0.047	-0.033	-0.031	-0.036	-0.049	-0.058	-0.056
Marginal effect of order	-0.016	-0.021	-0.018	-0.020	-0.017	-0.019	-0.006	-0.006	-0.010	-0.020	-0.029	-0.026

Table 6.12 shows that a marginal acquisition in any sector results in shortening firm survival time. Sstock effect is quite similar among sectors, except for Sectors 7, 8, and 9, where it is higher. On the other hand, there is higher diversity on the effect of order among sectors, its value ranging from -0.006 (sectors 7 and 8) to -0.026 (sector 12). That may be due to the fact that acquisition intensity is not the same among sectors. (As Figure 6.9 shows, the order effect changes considerably as the level of expected acquisitions increases). Sectors 7, 8, and 9 have the highest value of stock and order effects. This is an indication that in these sectors, the intensity of acquisition activity is very high (see also Appendix D for the effect of stock and order by sector and over time).

¹⁷ The marginal effect of stock and order of a sector are calculated at the average level of these variables.

Figure 6.10, measures the effect of firm size on survival time in the vertical axis, and the firm's size in the horizontal one. As the graph shows, at a lower level of total assets, say £30 m, an increase of total assets by £1m results in the shortening of survival time by 0.13 years (or 48 days). At £90m of total assets, the effect becomes positive. After that point, an increase in total assets lengthens firms' survival times. Thus, when total assets are, say, £120m , a £1m increase results in lengthening survival time by 0.005 years (or 2 days). This implies that small firms (but not too small) are more 'attractive' targets than large ones.

Figure 6.10: Effect of Size on Survival Time of a Firm



Note: The horizontal axis measures the firm's size (total assets in £m), while the vertical measures the effect of size on the survival time of firms.

6.9. Herd Effect of Merger Activity

Herd effects are evaluated by estimating Model 3 without any covariates. Table 6.13 gives the maximum likelihood estimates of Model 3 with no covariates.

Table 6.13: Maximum Likelihood Estimate of Loglogistic Model with no Covariates

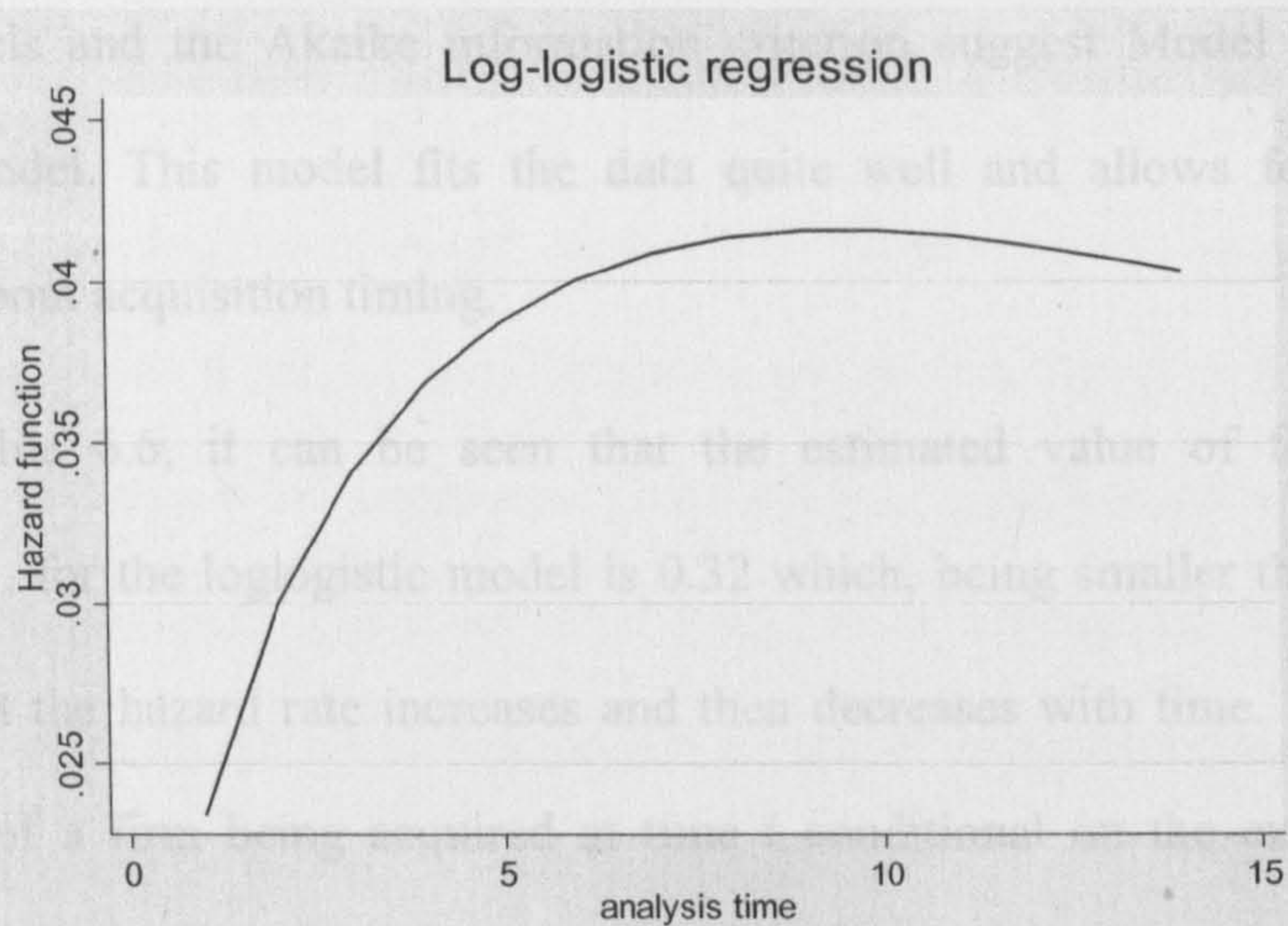
Coefficient	Variable	Loglogistic model (model 3)
β_0	constant	2.9166 (35.51 ^{***})
γ	gamma	0.7167
Log - Likelihood		-341.19
Number of observations		4842

Figure in parenthesis refers to t-ratios
^{***} , indicates significance at 1% level

From Table 6.13, we can see that β_0 is statistically significant, which confirms the existence of herd effects at the aggregate level. Furthermore, the estimated value of the shape parameter, γ , is 0.72 which, being smaller than unity, suggests a positive and then negative duration dependence of acquisition probabilities. Figure 6.11 depicts the shape of hazard function with no covariates. This figure suggests that the probability of a firm being acquired at time t (conditional on not being acquired at time $t-1$) first increases with time and then decreases, the herd effect being a possible explanation for this.

6.10. Discussion of the Results

Figure 6.11: Hazard Function with no Covariates



Herd behaviour of a firm may be based on informational asymmetries. A firm that decides to get involved in an acquisition gives a signal to other firms that acquisition is a profitable strategy. Rivals will observe the choice made by the acquirer. Assuming that it has information that they lack, the rivals will decide to acquire, too. Such behaviour prompts every firm to do what other firms are doing, in an attempt to reap the same advantages. These “defensive” acquisitions will occur until high concentration is reached and mergers either are not allowed by antitrust authorities, or are no longer profitable (firms gain more by being outsiders due to the high selling price of targets in a concentrated industry, or due to reduced competition). Thus, we can conclude that herd behaviour may generate an acquisition wave.

6.10. Discussion of the Results

Table 6.6 presents results for all models estimated. Appropriate tests for nested models and the Akaike information criterion suggest Model 3 as the preferred model. This model fits the data quite well and allows for robust inferences about acquisition timing.

From Table 6.6, it can be seen that the estimated value of the shape parameter, γ , for the loglogistic model is 0.32 which, being smaller than unity, suggests that the hazard rate increases and then decreases with time. Thus, the probability of a firm being acquired at time t conditional on the explanatory variables (and also conditional on not being acquired at time $t-1$) first increases with the passing of time and then decreases. Figure 6.7 presents the shape of a hazard function for acquisitions, and supports the non-parametric results reported in Section 6.5.

Section 6.9 analyses herd effects as depicted in a hazard function for our final model with no covariates. That is, the shape of hazard function depicted in Figure 6.11 is due to acquisition activity per se, rather than to any exogenous factors. It is obvious from the graph that there is interdependence of merger activity over time and the endogenous character of the merger phenomenon. Explanatory variables act like a time scaling factor. The effect of the explanatory variables is to change the time scale by a constant (survival time-invariant) scale factor, and as a result, to 'accelerate' or 'decelerate' acquisition activity. Thus, including explanatory variables in our model broadens or shrinks the curve that depicts the hazard function with no covariates. In comparing Figures 6.7 and 6.11, we can see that hazard functions have similar shapes - shapes that give rise

to the acquisition waves hypothesis where the hazard rate of an acquisition first rises and then falls with time. However, the hazard with no covariates is much lower than that with covariates. In addition, explanatory variables make hazard rates fall more sharply, showing that the herd effect is an important driving force in acquisition waves, while other explanatory variables may amplify these waves. Although herd effects may influence the probability of a firm being acquired, consideration of covariates gives a more complete picture of the acquisition phenomenon. Since our final model is an accelerated failure time model, it is more insightful to discuss the effects of explanatory variables in terms of survival time (time until a firm is being acquired).

Results suggest that stock and order effect influence non-linearly time to acquisition. In particular, the stock effect is negatively related to time to acquisition. A possible explanation for this is that as stock increases, incentives to acquisition increase, which means that the survival time of firms shortens. This result is consistent with theoretical models of acquisitions (see, for example, Perry and Porter, 1985) which state that an acquisition is related to acquisitions occurring in the past because of the strategic interaction between firms in a sector through the product market. Specifically, the new merged firm has an incentive to supply less than did its component firms prior to acquisition and as a result price increase. The profit of the merged firm can exceed those of its constituent firms only if the acquisition results in a price rise sufficient to offset the lower output level. When stock is small, there is a large number of outsiders, so the residual demand facing outsiders considering merger is relatively flat. This means that an output contraction has a small price effect, and the profitability of an acquisition is reduced. As stock increases, the residual

demand is relatively steep, which, in turn, means that a marginal acquisition can more readily increase the price as well as profitability. The implication here is that as stock increases, a merger may take place and as it does so, further acquisitions may occur with an amplified acquisition wave. However, in a very concentrated sector, the gains enjoyed by a firm from an acquisition may be less than those enjoyed by outsiders (see, for example, Kamien and Zang, 1990; 1991). This creates a free rider problem that may dissipate acquisition activity.

Furthermore, order effect is also negatively related to time to acquisition, a finding consistent with theoretical models of pre-emptive acquisitions (see, for example, Fauli-Olier, 2000, Molnar, 2005). A possible explanation for this result is that when a firm anticipates that one of its rivals may be engaged in an acquisition and becomes a low cost producer, or obtains market power, then the first firm may pre-empt this acquisition with a takeover of its own. By pre-empting the rival firm's acquisition, the first firm avoids the loss of profits it would have suffered had its rival been successful. Moreover, when no or only a few acquisitions have occurred, the selling price of a target is low (in relation to periods of intense acquisition activity). This means that a firm acquiring early may have larger gains because it pays less for the target. These early mover advantages may shorten the survival time of firms. Such behaviour, if adopted by many firms, may trigger an acquisition wave. As the occurrence of acquisitions increases, an even higher number of expected acquisitions may lead firms to wait longer before acquiring, as early advantages no longer exist. Firms, at this stage, attempt to delay acquisitions because with intense acquisition activity in the sector, firms may gain more by being outsiders. This is due either to reduced competition or the increased selling price of targets (see, for example, Stigler,

1950; Deneckere and Davidson, 1985; Fauli-Olier, 2000). The Order effect implies that in the beginning of a potential acquisition wave, firms may gain more than those acquisitions occurring at the peak of waves.

Survival time is also influenced non-linearly by firm size. The coefficient on total assets and its square indicate that when the target size is small, an increase in size results in shortened survival time (acquisitions are accelerated). When targets are large, an increase in size results in extension of survival time (acquisitions are decelerated). The turning point is close to £90,000. Thus, small firms (but not too small) are more likely to be acquired than very large firms. This finding contrasts with existing literature which finds a monotonically decreasing relationship between takeover probability and firm size (see Dickerson et al, 1998 for the UK and Palepou, 1986 for the US). On the other hand, Dickerson et al. (2002), using data from the UK during the 1980s, produce findings similar to the present study. Our results may reflect the fact that, during the end of the 1980s, financing constraints were loosened, allowing larger firms (although not the largest) to be taken over (Chatterjee, 1995).

Another variable that is statistically significant with a negative sign is the growth-resources indicator. Growth and resource availability are important variables in determining the timing of an acquisition. These factors do not influence survival time, as their coefficients are not statistically significant. They are combined to construct a single variable which is statistically significant and supports the growth-resources mismatch hypothesis. When a firm belongs to the low growth-high liquidity-low leverage or high growth-low liquidity-high leverage group, its survival time is shortened. This means that two types of firm may be attractive targets: low-growth, resource-rich firms and high-growth,

resource-poor firms, a result that is consistent with the findings of Palepou (1986) for the US.

On the other hand, the impact of dividends on the time until acquisition is positive and significant, indicating that firms giving high dividends have longer survival times; i.e. acquisition is expected to occur later. Such a relationship between dividends and acquisition activity is consistent with existing literature (see, for example, Dickerson et al. 1998) and is open to various interpretations. One line of argument – the ‘free cash flow’ theory (Jensen, 1988) - suggests that managers of a firm who have their own agenda, do not spend retained profits optimally from the shareholders’ perspective (by investing only in projects which have a positive net present value). Thus, if a larger share of the profits is distributed in the form of dividend payments to shareholders (implying that the free cash flow is not used to invest in negative net present value projects), this acts as a signal to the market that the firm’s managers are acting prudently. It is this fact, according to the free cash flow interpretation, that explains why high dividends decelerate acquisition activity. An alternative view suggests that dividends are used in an attempt to reduce the probability of takeover. In this case, high dividends are aimed at inducing shareholders’ loyalty, even though they might be a source of short-termist behaviour. Thus, managers, fearful of takeover, pay out high dividends in order to avoid being taken over.¹⁸

¹⁸ Managers might be averse to takeovers because they are frequently dismissed following takeover. Franks and Mayer (1996) find that, in the case of hostile takeovers, 90% of top management is replaced within two years of the takeover. Partington (1985), in a survey of firms’ dividend policy, finds that shareholder loyalty is frequently given as an important reason for the paying of dividends by firms.

The q ratio has a positive and significant impact on survival time. Low q ratio results in short survival time for a firm, a result consistent with the existing literature (see, for example, Gugler et al. 2005). Several explanations for this relationship of q ratio to acquisition timing may be advanced. The most familiar of these is that firms with low q ratio are more likely to be acquired, thus having short survival time, as these firms provide valuable resources at a cost below that of purchasing assets in new or used capital markets. On the other hand, the q ratio can be regarded as an indicator of investment opportunities of a firm; those with low investment opportunities have shorter survival times, being regarded as inefficient firms and more likely to be acquired.

Empirical evidence suggests that investment depend on retentions (see, for example, Bond and Meghir, 1994). Firms may choose between two possible courses of action. The first involves the payment of low dividends, which, given the trade-off between dividends and investment, allows greater retentions and hence higher investment. The second possibility is for the firm to pay high dividends and consequently, to have lower investment. The coefficients in Table 9 indicate that higher dividends and higher investment both significantly 'decelerate' acquisition activity. In the case of dividends, the marginal effect is 0.39; a unit increase of dividends payout ratio will increase survival time by 0.39 years. This suggests that increasing dividend payments may be an effective strategy to ward off takeover. In contrast, the marginal effect of investment is 0.22; a unit increase of investment opportunities will increase survival time by 0.22 years. Thus, survival time increases more with increasing dividend than with increasing investment. Thus, managers faced with the decision of how to

allocate the marginal 1 pound of earnings, and who wish to avoid takeover, would be better advised to increase dividends rather than investment.¹⁹

The joint significance of the sector dummies reveals that there do appear to be residual significant sectoral differences in the timing of takeovers, although two sectors, Industrials and Retail, experience no significantly different timing from Telecommunications. Coefficients of dummy variables are positive and range from 0.30 to 0.79. Thus, in Financials, for example, timing of acquisitions is longer by 0.64 years, *ceteris paribus*, which means that in that sector, acquisition activity may start almost half a year later in relation to the other sectors. As most of the dummy coefficients are not very high, we can conclude that these results are consistent with a synchronization of sectoral acquisition waves (for a discussion, see Chapter 3).

Finally, profitability and market to book value ratio have statistically insignificant coefficients, indicating that they are not important influences in acquisition timing. Such results contrast with existing literature (see Section 4.3). However, as most existing studies use data from the 1980s or earlier, it would appear that these variables do not play an important role in acquisitions in the 1990s.

¹⁹ These results on dividends and investment give rise to the need for further research. Specifically, an interesting question would be the effect of these variables on survival timing separately for firms that are characterized by having relatively low investment opportunities (low value of q) and those that are not.

6.11. Concluding Remarks

In this chapter, we have empirically examined factors that influence acquisition timing in the UK at the micro-level. The analysis is of particular interest in that our period includes the takeover boom of the late 1990s.

Our sample consists of the same proportion of acquired firms as in the population in the UK during the sampling period. In addition, the sample is objective in the sense that it does not include only firms for which the probability of takeover is likely to be particularly influenced by variables investigated in this study. Thus, our sampling methodology avoids several methodological flaws present in previous acquisition literature, and leads to unbiased and correct inferences.

We use secondary data collected from two main datasets. *Thomson ONE Banker* is used to gather information about acquisitions in the UK during 1990-2004, and *DataStream* is used to obtain firms' accounting data. We use accounting data in order to investigate factors that influence the timing of acquisitions. We are aware that this itself has problems. In particular, it is well-known that firms can use creative accounting techniques, which may imply that their published accounts may not be a true and fair reflection of the firms' financial position (Griffiths, 1986). However, the use of accounting data does have the advantage of allowing us to test directly the hypothesis in which we are interested.

The results indicate that there is evidence that firm-specific characteristics are an important influence of takeover timing. The payment of high dividends is used by managers to induce shareholders' loyalty and thus, to delay any potential

takeover. On the other hand, high investment opportunities may also delay a takeover, as this is a signal to the market that the firm's managers are acting prudently. However, given the trade-off between dividends and investment, empirical evidence in this study suggests that managers who wish to avoid takeover would be better advised to increase dividends, rather than investment.

The size of a firm has a negative relation to survival time. However, in contrast to the existing literature, this relation is non-linear, indicating that when firms are small, increased size is associated with shortened survival time, while at larger firms, an increase in size results in lengthened survival time. This means that small (but not too small) firms are regarded as attractive targets. Furthermore, low growth, resource-rich firms or high-growth, resource-poor firms are considered attractive targets.

On the other hand, takeover activity per se plays an important role in the survival time of a firm. Specifically, stock, order, and herd effects have all been found to exert significant influence on takeover timing. These results support empirical evidence on theoretical models that analyze takeover in a static industrial organization framework, pre-emptive takeovers, and sequence of takeovers (see Chapter 4). On the other hand, by incorporating all these effects into a dynamic framework, evidence that takeover waves may be shaped by takeover activity per se is provided. Stock, order, and herd effects (together with the rank effects) fuel the dynamics within a wave. This is consistent with results provided in the empirical analysis in Chapter 3, which shows that merger activity is an endogenous process. It is influenced by takeover activity occurring in previous (stock effect), current (herd effect) and also expected (order) takeovers. However, empirical analysis implies that these effects are not equally important

over different stages of a takeover wave. In the early stages of a potential wave, the order effect is vital, while towards the peak, the stock effect seems to prevail. Herd effects describe the endogenous character of a takeover wave. Finally, rank effects are significant determinants of a takeover during the duration of an entire wave.

The empirical analysis presented in this chapter suggests that although macro factors may create a hospitable environment for merger activity (see Chapter 3), the micro forces may reinforce it and generate dynamics which shape a merger wave.

PART 4: THE OVERVIEW

CHAPTER 7: DISCUSSION AND CONCLUDING REMARKS

7.1 Summary of the Findings

Existing research into the determinants of merger timing has lacked an encompassing analytical framework within which the numerous proposed hypotheses of merger determination put forward can be assessed. The plethora of studies at the micro-level have largely concerned themselves with single motive models of merger, rarely considering the interdependence of merger determinants and decisions over time. A common aspect of studies at this level of analysis is their apparent inability to explain in themselves the recorded episodic nature of merger activity and thus, a lack of strong statistical results from their empirical evaluation. At the macro-level, the apparently stronger results of some studies have been insufficient to form the basis of a widely accepted theory of merger waves. Although the predications are closer to the observed procyclical and episodic behaviour of the process, the findings of the macro-literature have been limited, in most cases, to confirmation of what is evident by casual observation.

We argue that a better understanding of the nature of merger and its timing can be provided by an analytical framework that combines the micro- and macro-levels of analysis. In this study, we presented such a framework and used it in analyzing merger waves in the UK. At the macro-level, we first employed

univariate spectral techniques to investigate the dynamic behaviour of merger at the aggregate and sector levels. Results suggest that aggregate merger in the UK exhibits a regular cycle of 6 years, most of the variation in merger series being due to that cycle. However, a smaller cycle of 2.5 years also exists, but is considered less regular. At the sectoral level, most sectors have a cycle of 5 years. Only Consumer Staples and Telecommunications do not exhibit a regular cycle. There is, also, a synchronization of merger cycles for most of the sectors. These results suggest that there may be a bandwagon effect to merger activity that influences most sectors in the UK economy. Having identified merger cycles at the aggregate level, we employed multivariate spectral techniques to empirically investigate the synchronization of these cycles with business or capital market cycles. Results from multivariate spectral analysis suggest that the relation of aggregate merger cycles to business cycles or to fluctuations of interest rate and stock prices differs over cycles with different duration. There is clear evidence of a strong coherence between an aggregate merger cycle of 6 years and the business cycle. These two cycles synchronize, although the amplitude of the former is much higher than that of the latter. A less strong coherence exists along the same cycle between aggregate mergers and interest rates, with the former leading the latter by approximately 2 years.

The above results indicate that as the economy expands, it would seem that business becomes more optimistic and confident about the future, and when excess capacity is exhausted, mergers may be undertaken with borrowed finance, triggering the interest rate cycle. On the other hand, there is no strong coherence between the aggregate merger cycle of 6 years and that of stock prices. A stronger relation between these two exists in smaller cycles of about 2.5 years.

However, along this cycle, the coherence of aggregate mergers with interest rates and the business cycle is very small. This indicates that the observed relation between high stock market valuations and merger activity may have been misattributed to expectations about future economic conditions. The relation is actually driven by behavioural misvaluation factors in the short-run. This relation becomes weaker in the long-run, when stock prices return to efficiency. Finally, results suggest that a large portion of fluctuations in aggregate mergers cannot be explained by the business cycle, interest rates, or stock prices alone. Thus, we may conclude that these factors are necessary, but not sufficient to trigger a merger wave.

Complementary to the macro-analysis is the analysis at the firm level. At this level of analysis, we constructed a decision-theoretic model of merger timing. This model encompasses different merger motives, as suggested by existing literature, simultaneously within a dynamic framework which endogenizes the merger process. Our model exploits the dynamics of merger process by assuming that a target accepts an offer at time t (and thus, merger occurs) if it does not expect to gain more by waiting one more period before merging. Potential targets should have different preferred takeover dates; in other words, at any given date, only some of the potential targets will wish to actually be acquired. We argue that four micro-forces may influence the timing of mergers. Firstly, the propensity of firms to merge increases as the number of merged firms increases (stock effect of mergers). Secondly, if a firm expects that one of its rivals will gain from merging, then it is rational for the first firm to pre-empt this merger with a takeover of its own (order effect of mergers). Thirdly, a merger may trigger another merger as firms attempt to mitigate the action of rivals and match

the gains, if any, of the first merger partners (herd effects of mergers). Finally, firm-specific characteristics play an important role in a merger decision and its timing (rank effects of mergers).

We test the above model by using merger data from the UK during the period from 1990 to 2004. The empirical approach taken is survival analysis. Results indicate that firm-specific characteristics play an important role in merger timing. Specifically, low growth, resource-rich or high growth, resource-poor firms or firms that pay low dividends, have low investment opportunities, or are small (but not too small) are considered “attractive” targets and are more likely to be acquired. On the other hand, the results also suggest that merger activity per se, such as stock, order, and herd effects, may influence the timing of mergers.

7.2 Contribution to Knowledge

This study provides an alternative framework for investigating merger waves. We argue that both micro- and macro-levels of analysis are necessary for a better understanding of merger nature and timing. The contributions of this study can be summarized as follows.

Firstly, the study has examined the existence of UK merger waves by using frequency domain techniques. The UK experience has received little attention in the empirical literature on merger waves. Hypotheses about mergers and structural change have tended to be derived from the US experience and then applied to UK data. We are filling this gap by using spectral analysis and filtering techniques to empirically examine for merger waves. Spectral analysis is an alternative approach better suited to describing and analyzing quasi-cyclical fluctuations at different frequencies. In this way, in contrast to existing studies, we uncover waves of different duration, regularities, and explanatory power. In the multivariate case, we examine the synchronization between mergers cycles of different duration and regularities with business cycles and capital market fluctuations. Furthermore, filtering techniques overcome the important but controversial issue of detrending. This minimizes the risk of introducing a spurious cyclical structure of the merger series, which is something that many studies suffer from (see Chapter 3).

Secondly, the thesis constructs a decision-theoretic model of merger timing. The merger decision is analyzed from the target perspective, which provides an alternative (and innovative) approach to analyzing the merger process. Past studies in mergers have tended to follow a pre-selected point of view - either an industrial organization or finance perspective - in isolation and have not

combined approaches. This model encompasses both perspectives within a dynamic framework and uses their findings to explain merger waves. It provides an effective way of analyzing merger timing without a pre-selected perspective. In this way, existing research has been extended to provide explanations on merger timing (see Chapter 5).

Thirdly, the theoretical model is estimated by means of merger data from the UK from 1990 to 2004. The empirical approach taken in this study is survival analysis. There are at least two advantages in using survival analysis over the alternative static models found in most existing studies. First, there is the issue of unobserved firm heterogeneity. Survival analysis can be used to either mitigate the effect of unobserved firm heterogeneity or to incorporate explicitly the unobserved heterogeneity directly into the functional specification. The second advantage is that survival analysis allows for time varying explanatory variables. Firms are allowed to develop, to be dynamic entities, not just random characteristics at any point in time. This framework explicitly allows for dependency over time, in that it estimates the conditional probability of merger; that is, the probability of merger by t , given that it has not occurred by time $t-1$. It is ideally suited to empirically examine merger timing, since it allows us to investigate whether, given that a firm has survived up to a certain point in time, changes in firm-specific characteristics or changes in merger activity per se will lead to a change in the timing of merger. Such analysis, to the best of our knowledge, provides the first supporting empirical evidence of theoretical models of pre-emptive and sequential mergers. It also provides strong statistical evidence that micro-theories of mergers can be used effectively in explaining the dynamics within merger waves (see Chapter 6).

7.3 Concluding Remarks and Further Research

This study proposed a two-staged framework to illuminate the dynamics of merger wave activity and to help explain the persistence of this phenomenon. The first stage refers to the macroeconomic environment that sets the context for the development of a merger wave. In building the dynamics of the first stage of merger activity, we explored the key macro- and financial factors and forces stimulating a wave and leading to initial merger activity. These factors are indicative of the influence that the macro-environment exerts on merger activity. Macro-environmental forces not only create receptive conditions for the development of an initial merger activity, but they also interact with competitive factors within industrial sectors in essence that may influence competitive motives for mergers.

Thus, in addition to key macro-factors, a range of micro-forces is necessary for merger activity to intensify at an increasing rate to shape a wave. These micro-dynamics feed into and fuel merger diffusion, and further reinforce merger activity. In building the dynamics within a merger wave, we explored key micro-forces such as firm financial characteristics, and merger activity per se.

Based on the empirical results of this study (at both micro- and macro-levels of analysis), we offer the following account of merger waves. Although merger waves repeat themselves, they are far from being periodic. A fairly regular long cycle, as well as a less regular, less powerful cycle of mergers exist. Even though no two merger waves are identical, they usually have some important features in common. Their coherence with macro- and financial factors varies in strength over cycles of different duration and regularity. Long waves coincide with the business cycle of an economy. Periods of expansion of economic activity may

pave the way for initial merger activity and remove barriers for merger diffusion. A loosening of financial conditions may also help the development of the initial merger activity. However, such cycles do not seem to cohere with stock price fluctuations.

The existence of merger cycles of different duration, regularity and power may explain why empirical studies give mixed results regarding the relation between aggregate mergers and economic fundamentals. Previous studies have applied time domain techniques, which do not distinguish between cyclical fluctuations of different duration and regularity, a fact which may be enlightening when such relations are examined. Further research may investigate the driving forces of these different merger cycles in an attempt to provide a complete picture of the merger phenomenon. In addition, studies investigating and comparing merger activity among different countries or industries may further distinguish between cycles of different duration and regularity. That is because fluctuations of significant importance in the merger series may not make an important contribution to the contemporaneous covariance between merger series of different countries or industries simply because they are in a different phase of the implied cycle.

On the other hand, firms decide whether to engage in merger activity based on the gains of merger. When several potential acquirers may achieve these gains, they compete for the opportunity to acquire a target. An acquirer that moves fast and buys a target first may gain more than followers because it pays less for its target by exploiting the competition among target firms. Moreover, the reservation price of a target may be low when no mergers have taken place. On the other hand, the winning firm who acquires the target could become a lower

cost producer and increase its product market share if the costs saving are large enough. If the merged firm increases its market share, rivals are worse off. Early mover advantages, as described above, may be a strong motive for merger and may reinforce the initial merger activity.

Furthermore, the propensity of firms to merge increases as the number of merged firms already formed increases. A merger is related to mergers that have occurred in the past because of the strategic interaction between firms in a sector through the product market. That motive for merger may amplify a merger wave.

In addition, mergers may trigger more mergers as firms attempt to mimic the action of rivals and match the gains of the first merger partners. Once the bandwagon is rolling, firms choose to merge not because it is likely that it will be profitable and efficient, but because a number of other firms are already doing it. Such behaviour may shape a merger wave.

Finally, firms' financial characteristics, the rank effect, are important determinants of merger activity. Since these characteristics may change over time as firms develop, they generate different merger timing.

The findings at the micro-level provide strong empirical evidence of the endogenous character of mergers. The fact that mergers may be influenced by the past, present and future merger activity is related to theoretic models of endogenous mergers (see, for example, Gorton et al., 2005; Toxvaerd, 2004; Fridolfsson et al., 2005), and adds to the new, so called, endogenous merger theory framework. The endogenous character of merger activity may, for example, explain the merger paradox of why mergers that reduce profits may be rational. If the target will otherwise be taken over by competitors, profits may be

reduced even more. The stock market realizes the dilemma and rewards the merging firms.

A combination of the above micro-level events is the driving force within a wave and keeps the bandwagon rolling at full speed. The importance of these micro-forces may differ at different stages of a merger wave. Thus, order effects are more important at the early stage of a wave. As the merger diffusion accelerates, stock effect outweighs order effect. Rank effects maintain the same amount of significance along a wave. Finally, herd effects describe the endogenous character of a merger wave. The above implies that merger motives may be different along different stages of a wave. As a result, the performance of merger may change as the wave develops. This is related to recent studies (see, for example, Bhagat et al. 2004; Harford, 2003; Moeller et al.; 2003) on merger performance which demonstrate that the total gains of mergers occurring in periods outside the merger waves are always significantly lower than the gains earned during merger waves. Furthermore, they reveal that the highest combined merger gains are realized at the beginning of merger waves. As a consequence, the dynamics within a wave provide new evidence that may be utilized in explaining the gains to acquirer and acquired firms, and the way in which these may change along different stages of a wave.

Overall, the above analysis that utilizes macro- and micro-driving forces provides a satisfactory explanation of merger waves. Macro-factors may pave the way for the development of initial merger activity, while micro-forces fuel merger diffusion and build the dynamics within a wave. The presented framework stresses the importance of both levels of analysis and provides motivation for further research to fully integrate macro- and micro-factors within

a single model. In addition to the macro-factors examined in this study, further research could investigate the influence of technological change, regulation change, and globalization, among others, on merger activity. Doing so may lead to a more complete theory of merger activity and its timing.

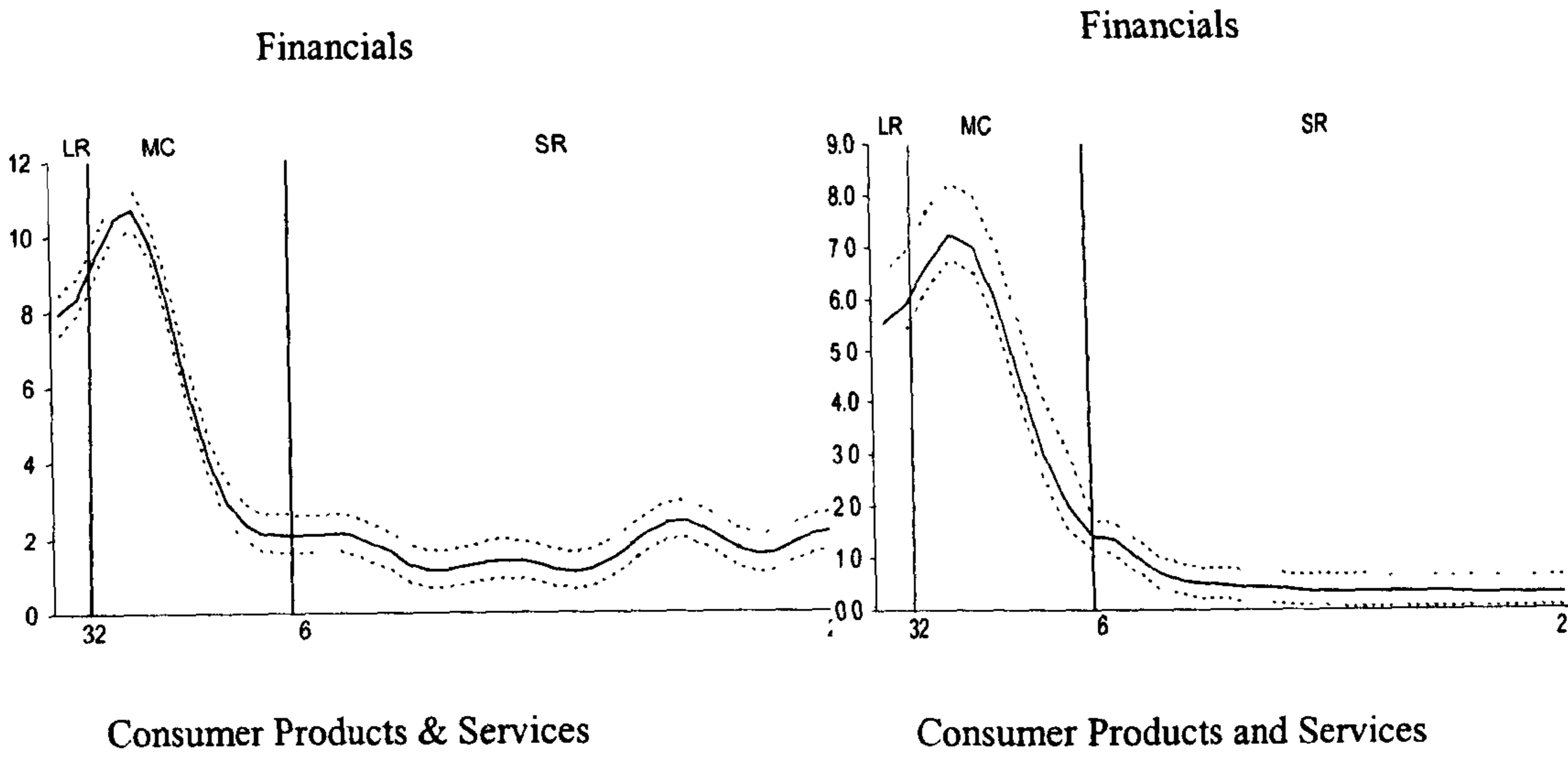
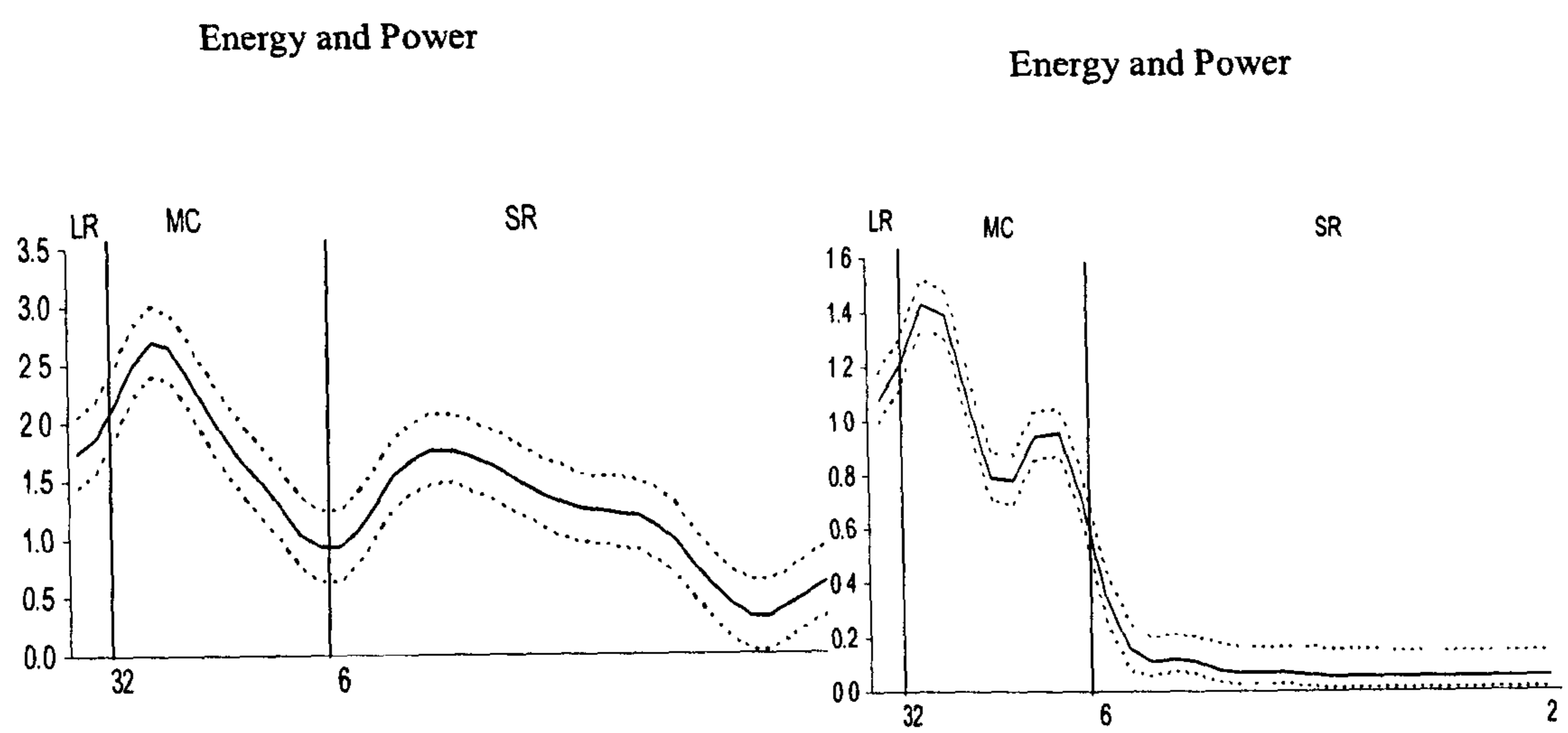
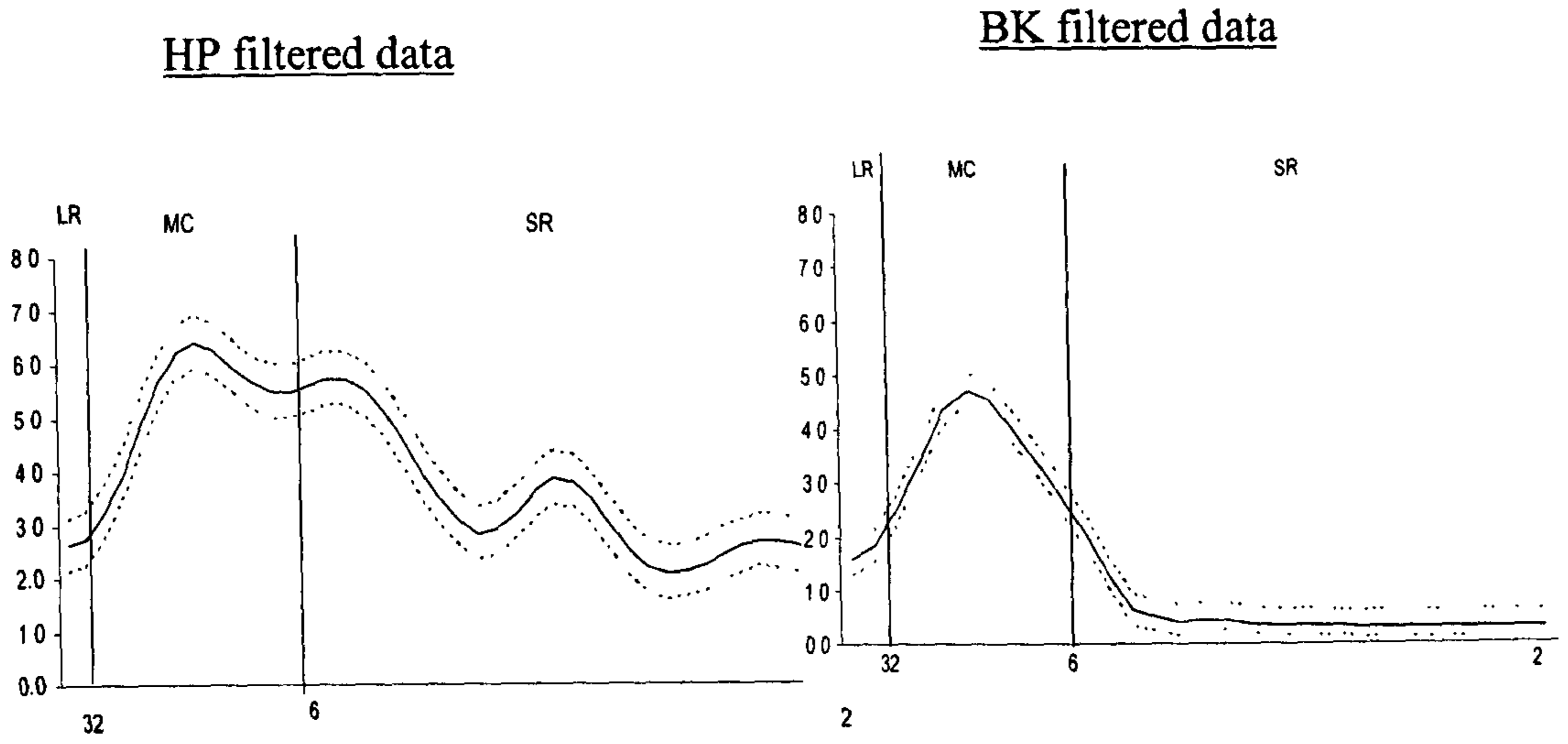
APPENDIXES

APPENDIX A

UNIVARIATE SPECTRUM OF SECTOR MERGERS

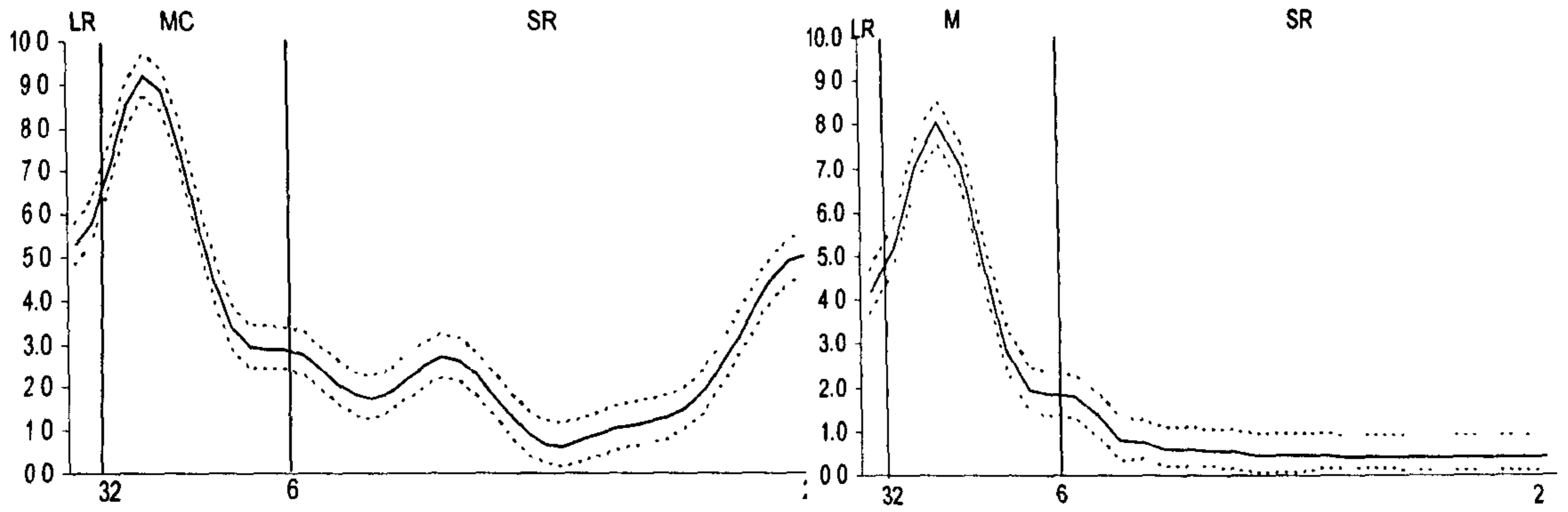
In this section the univariate estimated spectrum of sector mergers using HP and BK filtered data are presented.

The horizontal axis measures the cycle length in quarters while the vertical one the power of spectrum of mergers series (variance of merger series). The dashed line gives the 95% confidence interval. The area in the plot is divided into three segments: the long run periodicity band (LR) which corresponds to cycles of 32 quarters or longer, the merger cycles band (MC) which corresponds to cycles of 6-32 quarters, and the short run (SR) periodicity band which corresponds to cycles of 2-6



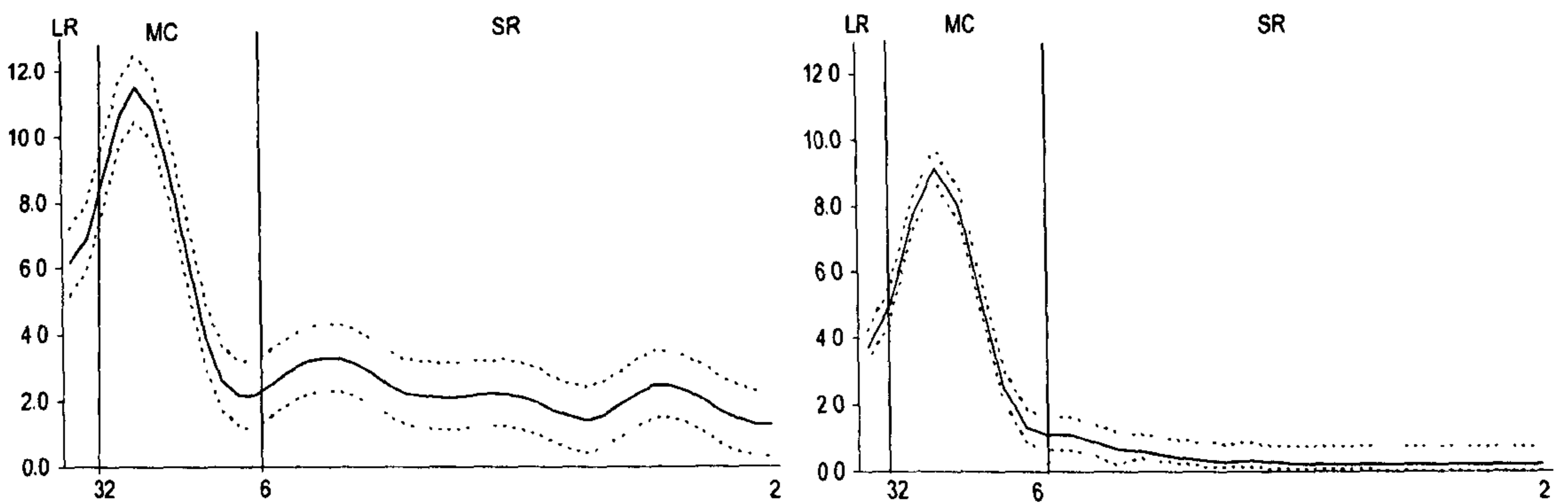
HP filtered data

BK filtered data



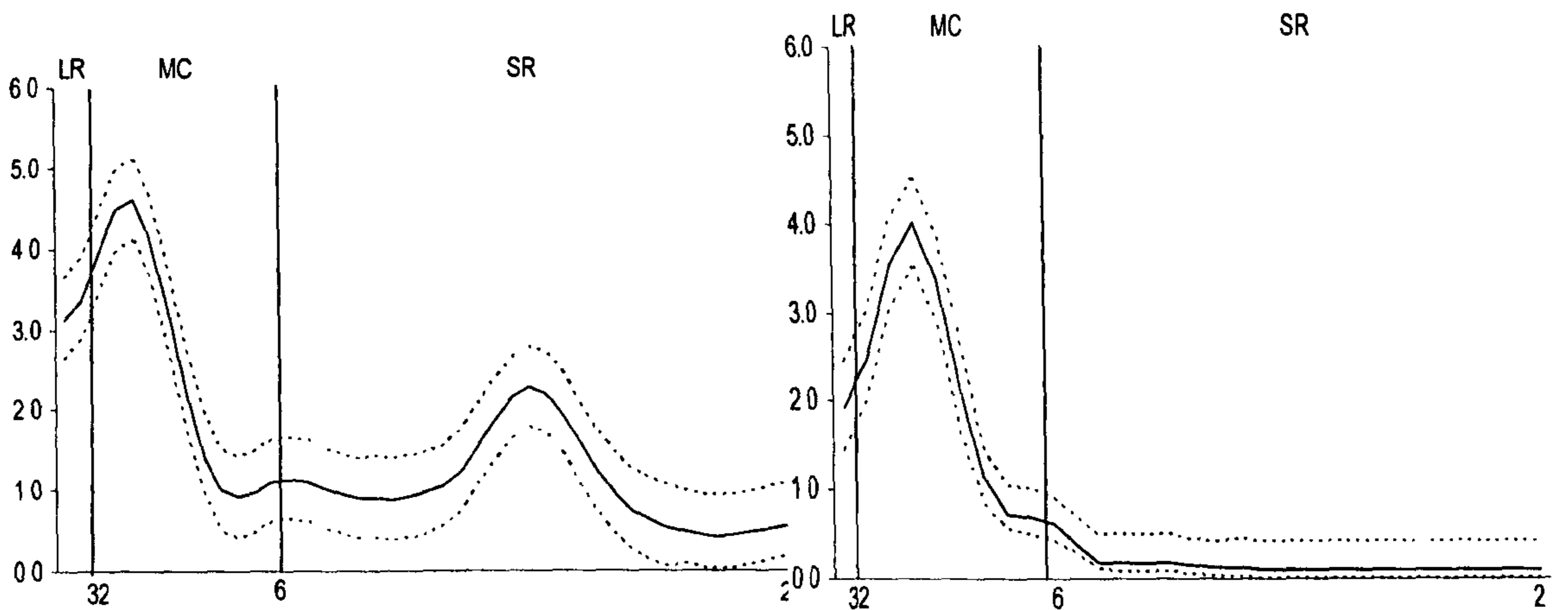
Healthcare

Healthcare



Industrials

Industrials

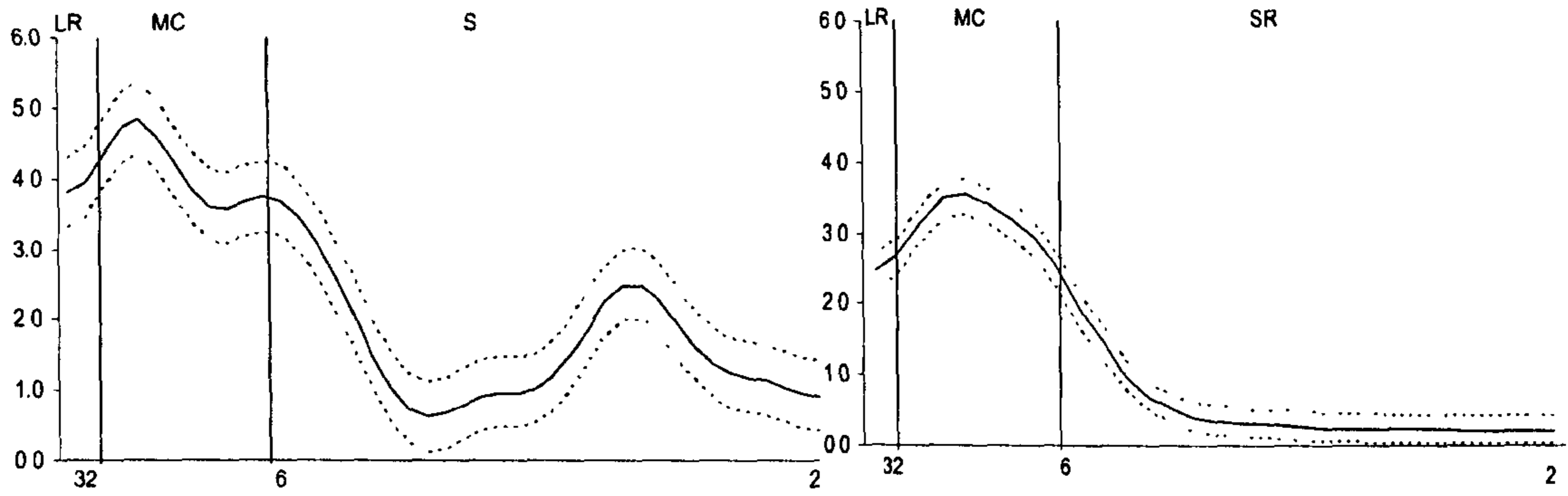


Materials

Materials

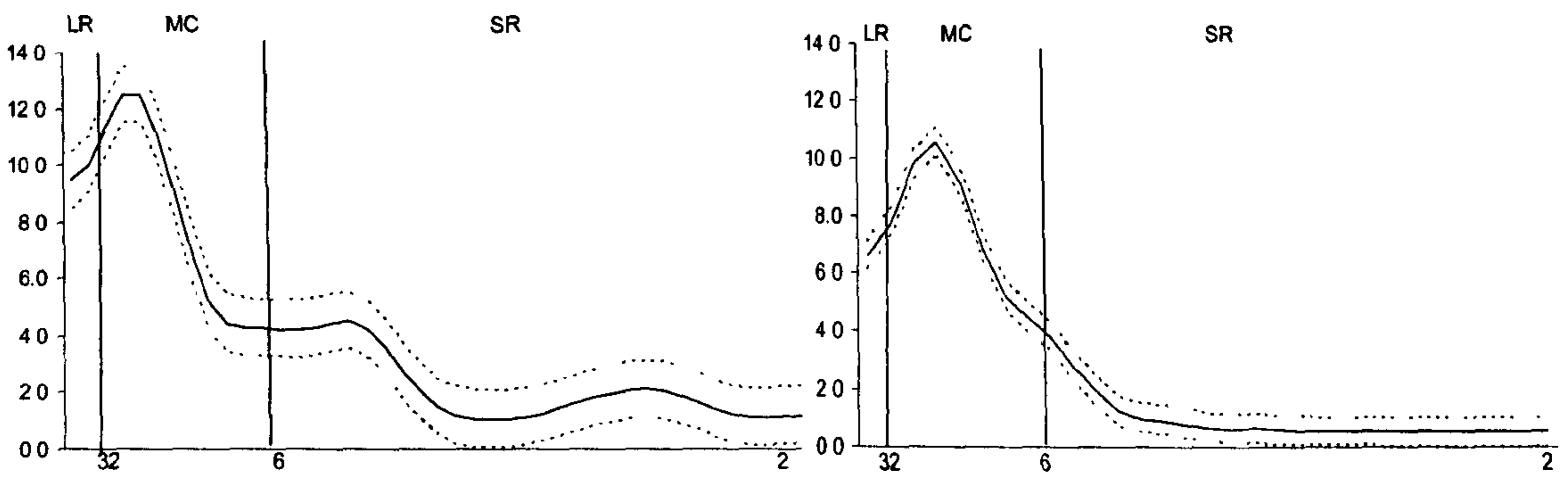
HP filtered data

BK filtered data



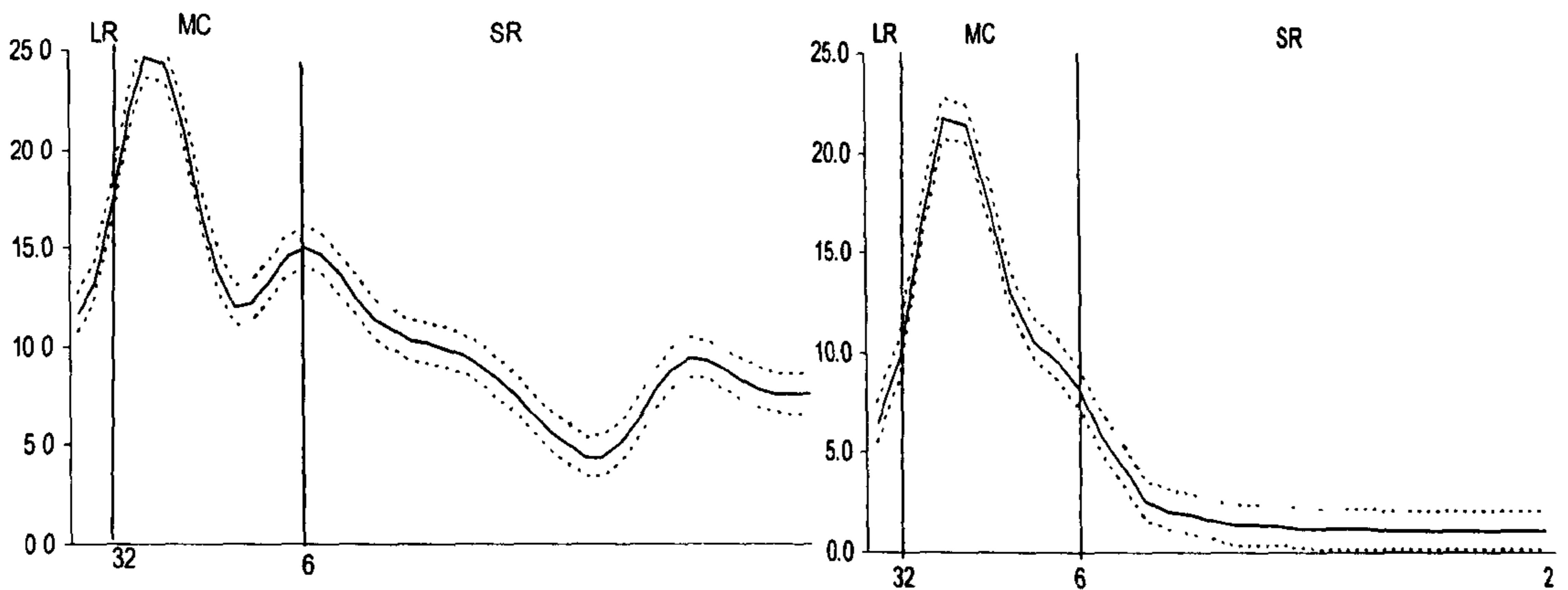
Media and Entertainment

Media and Entertainment



Real Estate

Real Estate

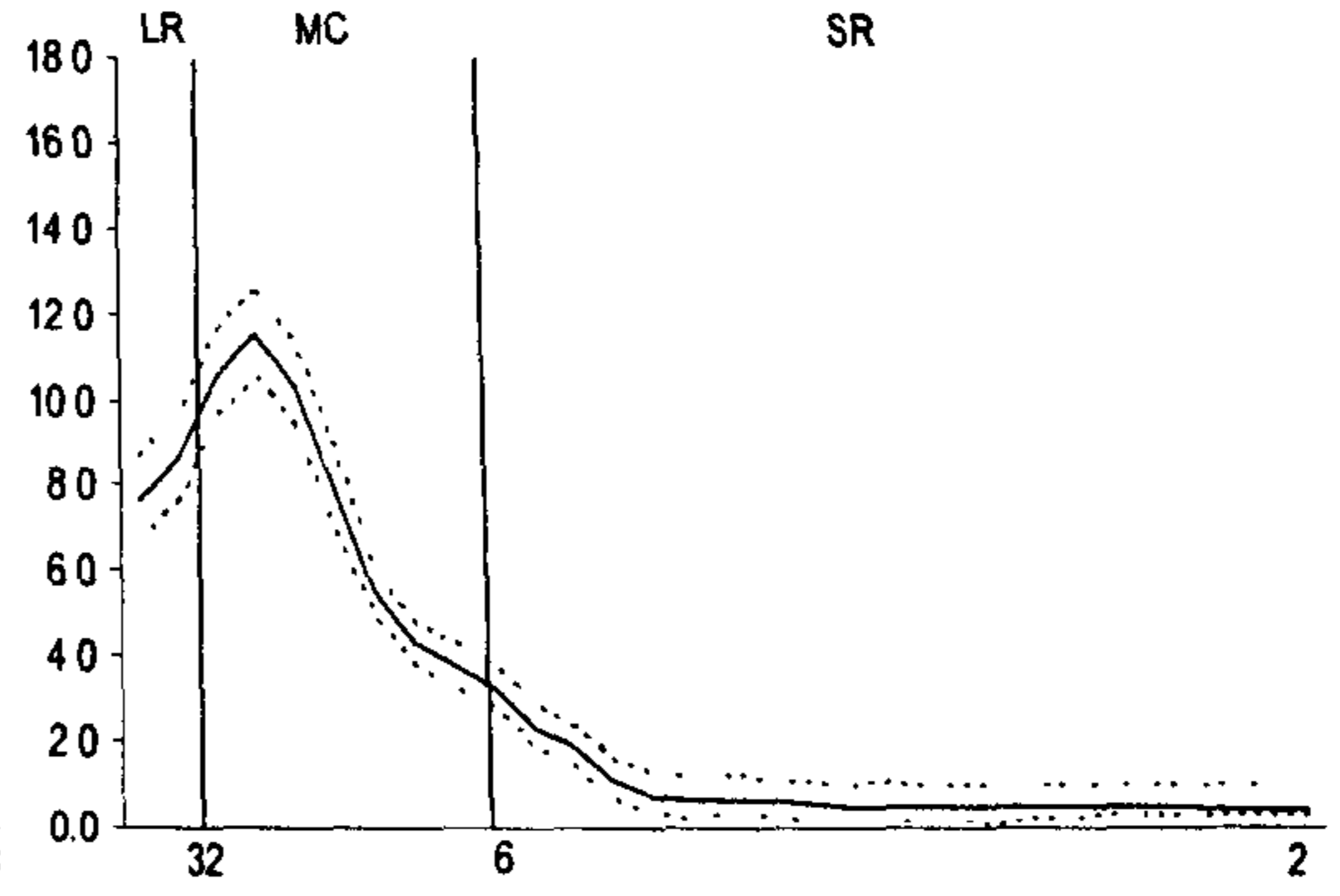
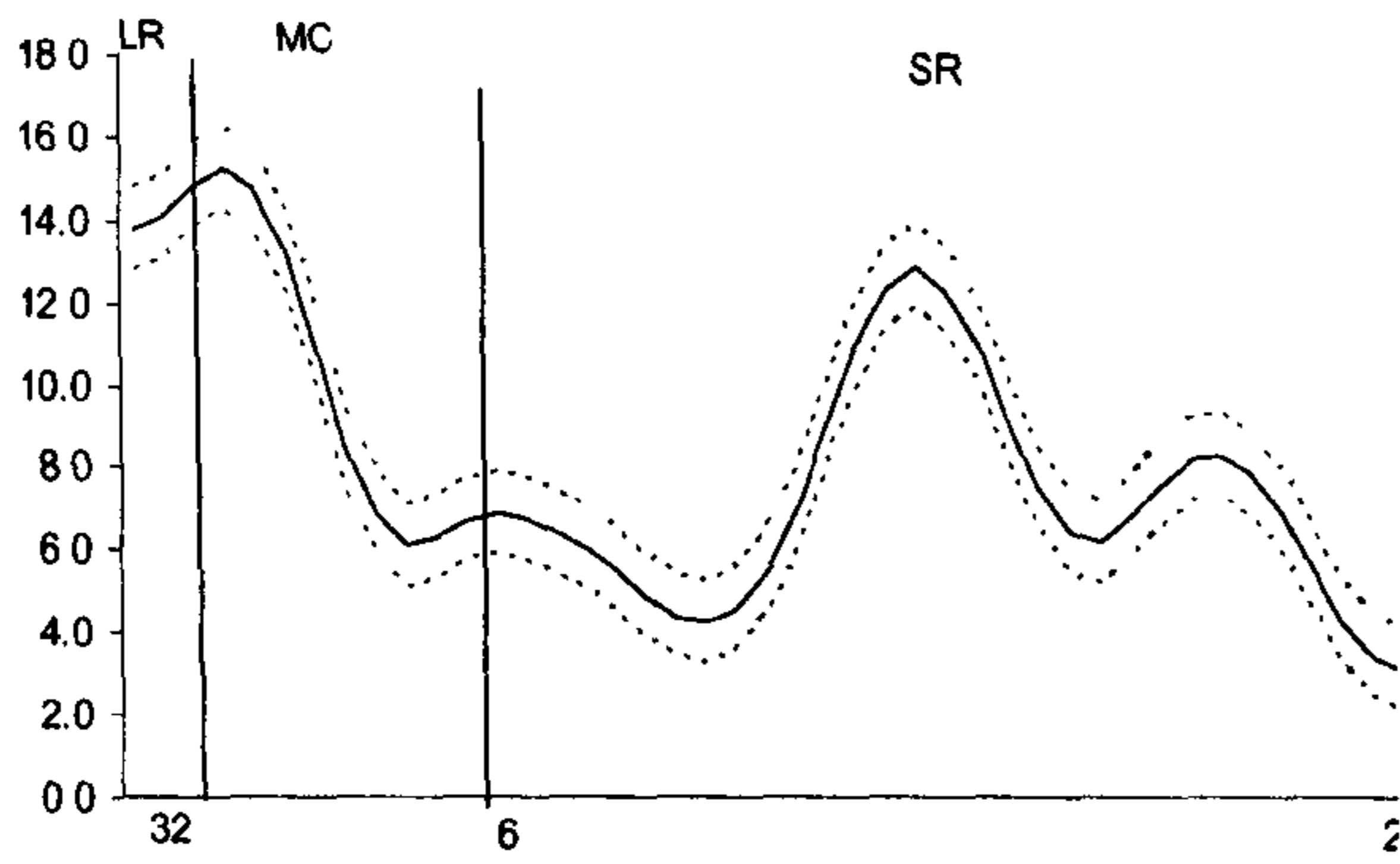


Retail

Retail

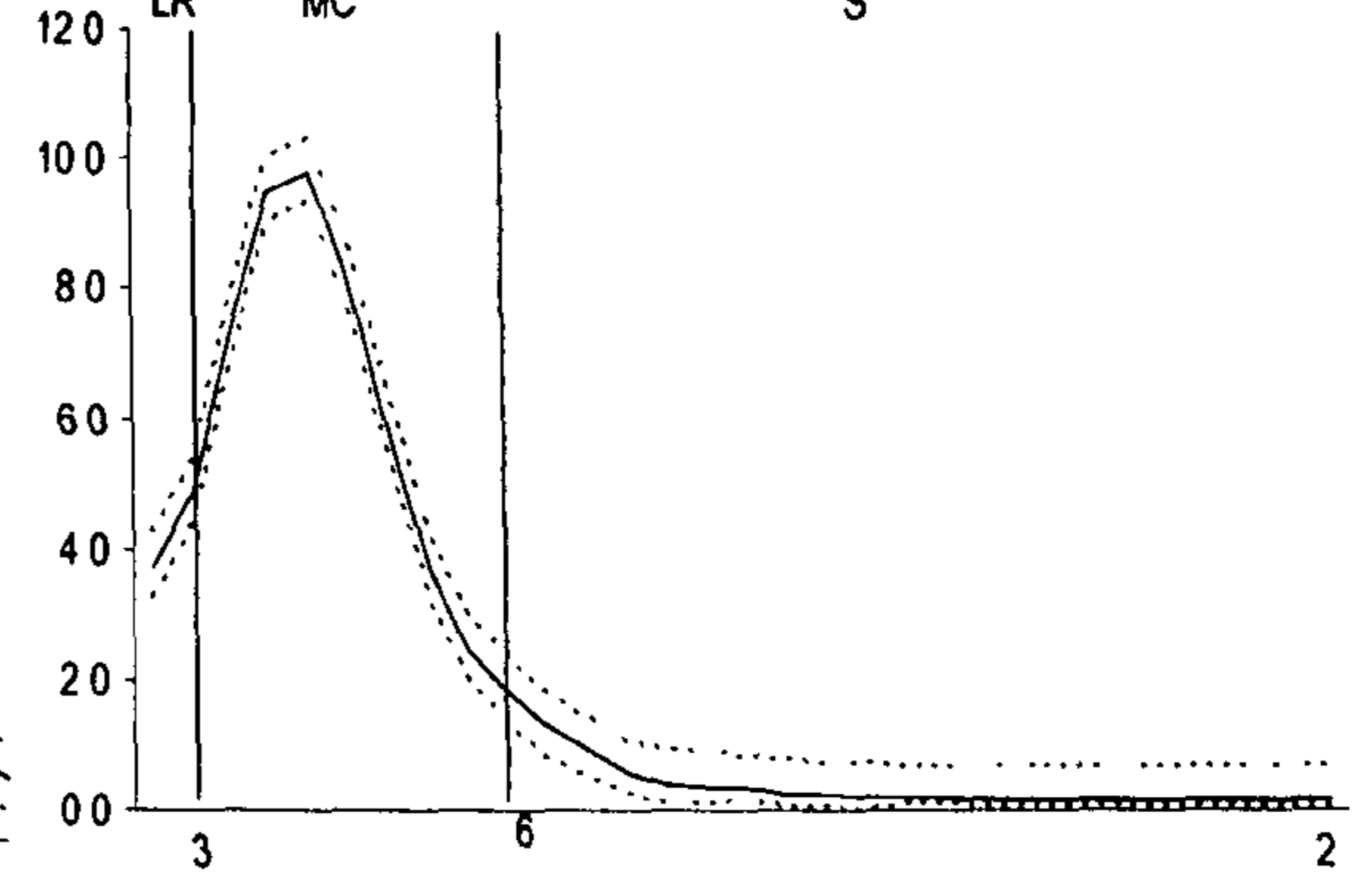
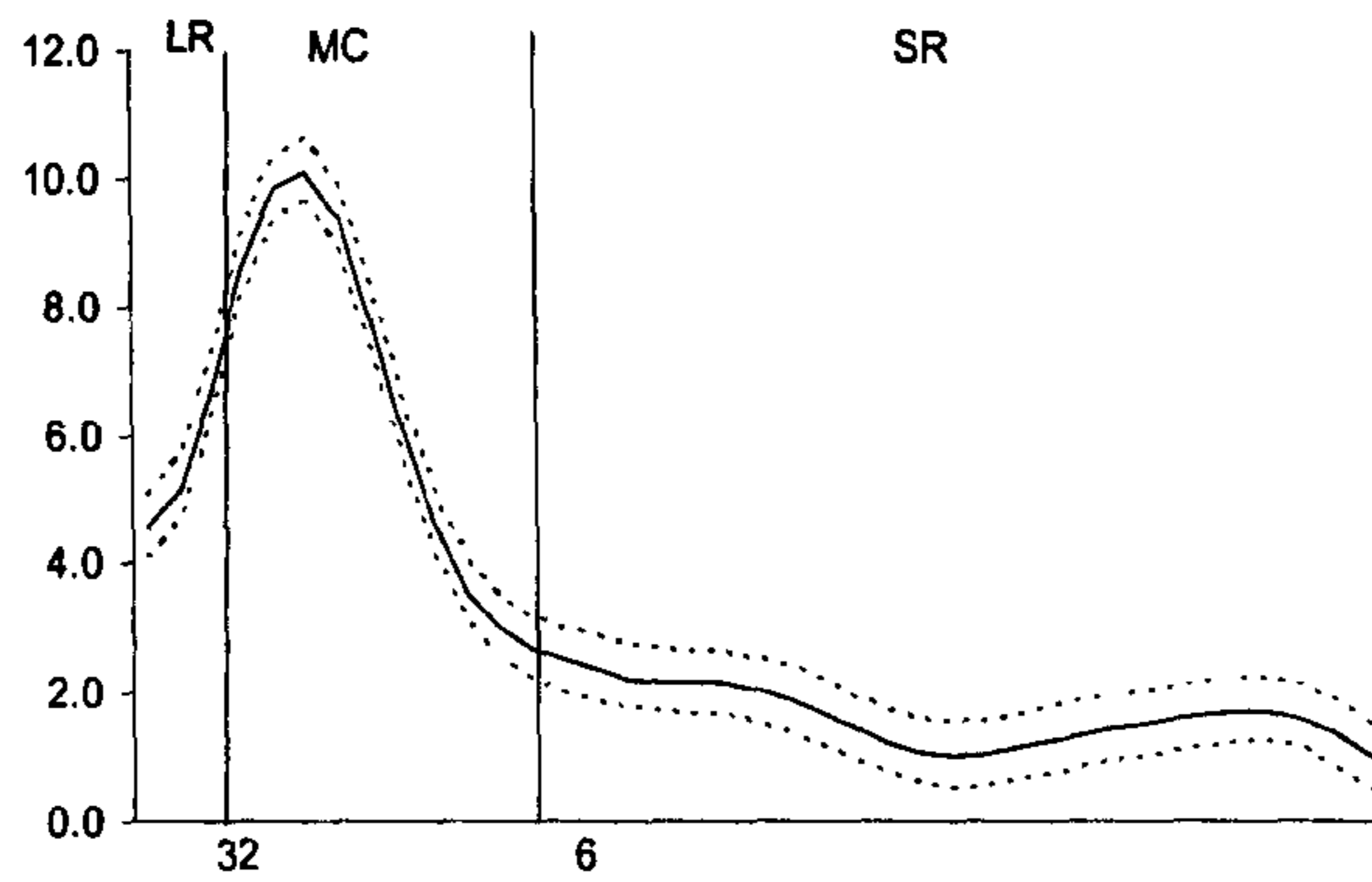
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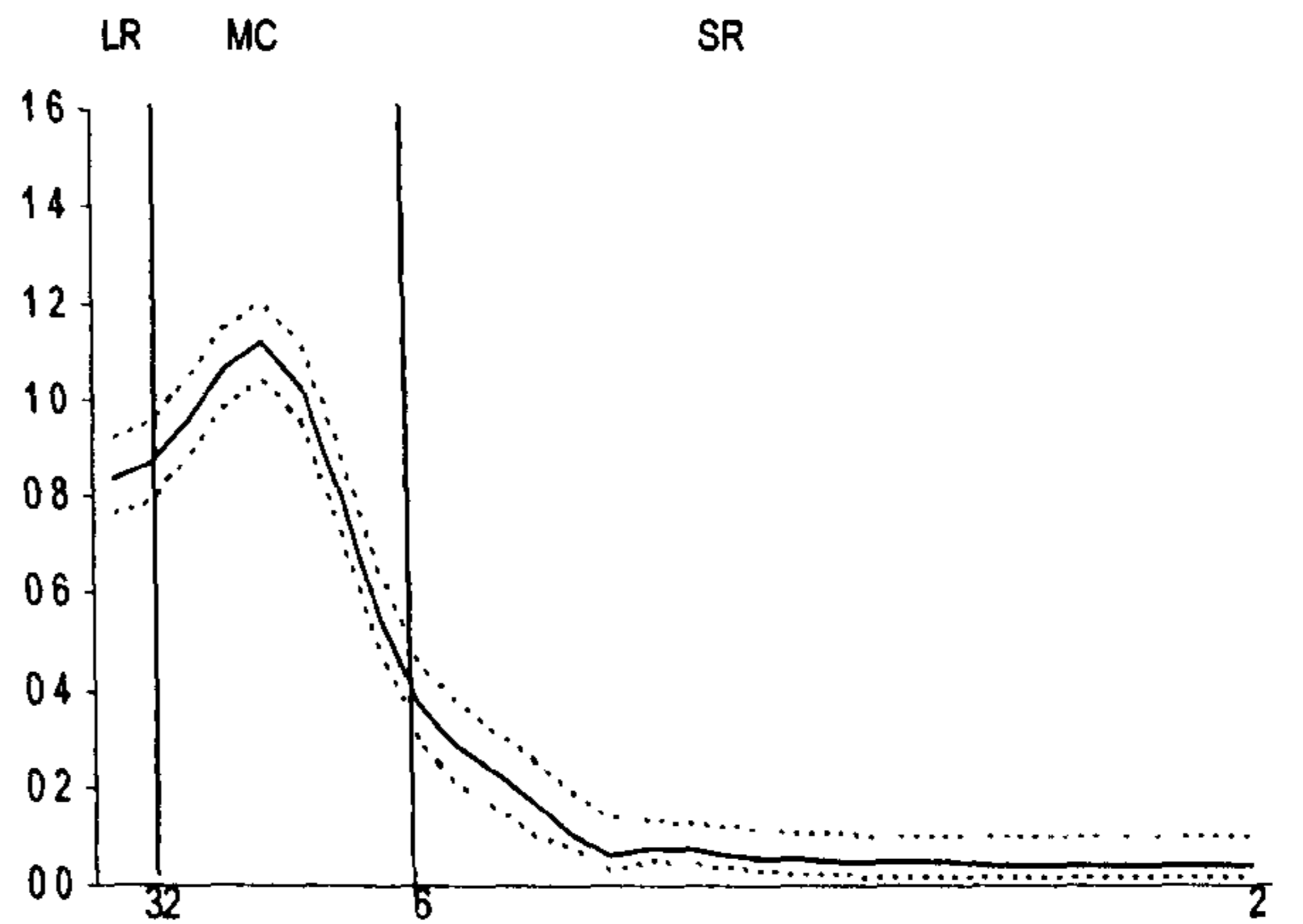
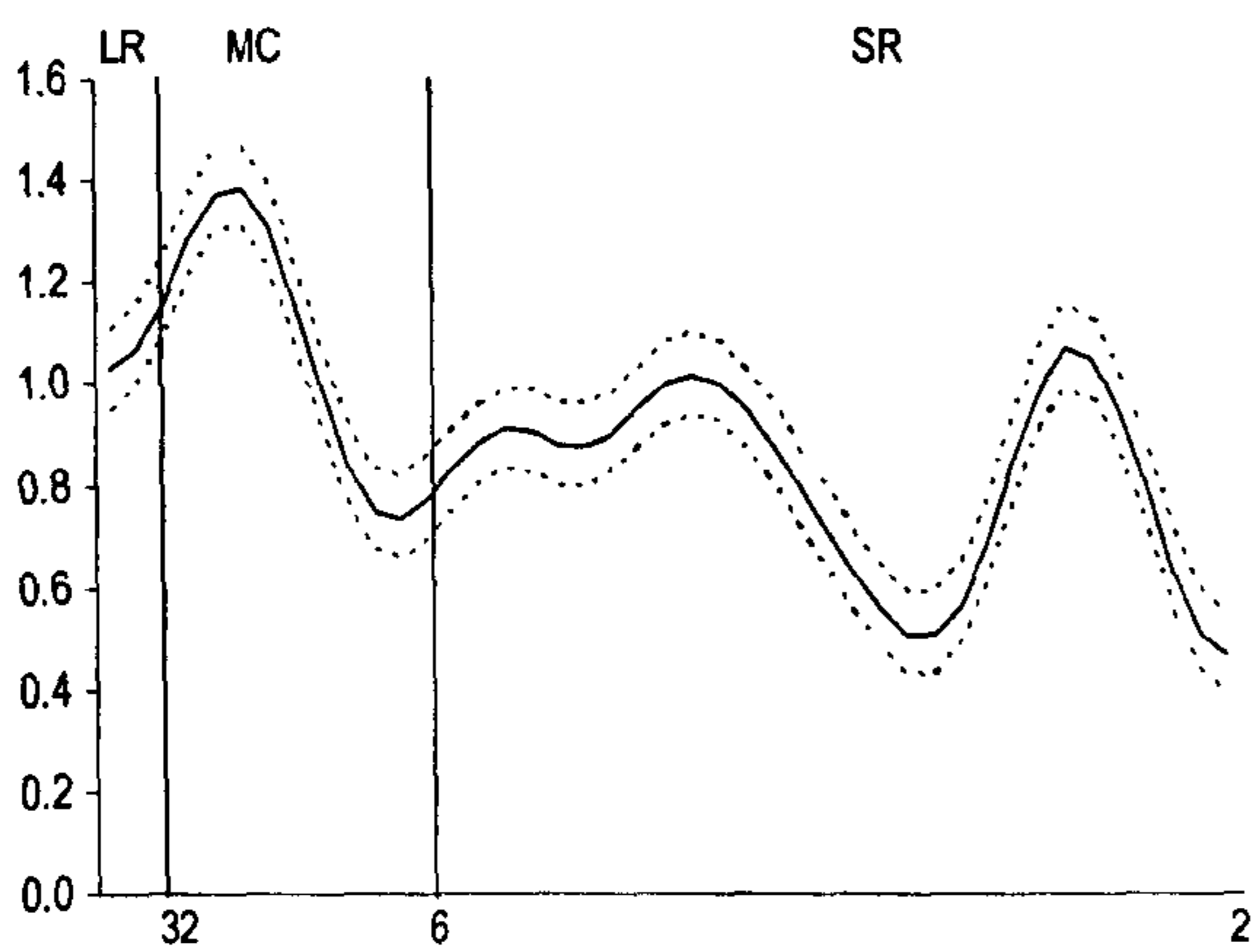
Consumer Staples

Consumer Staples



High Technology

High Technology



Telecommunications

Telecommunications

APPENDIX B

THE SCOPE OF SURVIVAL ANALYSIS

B1. Introduction

The empirical approach taken in this study is based upon survival analysis. Survival analysis is concerned with analyzing the time to the occurrence of an event.

In survival analysis we make some simplifying assumptions. Firstly, the chances of making a transition from the current state do not depend on transition history prior to entry to the current state (there is *no state dependence*). Secondly, entry into the state being modeled is exogenous- there are no *'initial conditions' problems*. Otherwise the models of survival times in the current state would also have to take account of the differential chances of being found in the current state in the first place. Finally, the model parameters describing the transition process are fixed, or can be parameterized using explanatory variables-the process is *stationary*.

B2 Survival time data

This section describes features of survival time data. It provides a definition of failure times and describes two important aspects of survival time data: censoring and truncation.

B2.1 The definition of failure times

We are following firms over time, and that data collection effort is typically called a study (it is the period during which the firm is under observation). During the study period, firms are enrolled and data are collected. Data collection stops on a firm because the firm is acquired (fails), the study ends, or the firm leaves the study for other reason (for example no available data). The event can only occur once, and once it does occur, the firm can no longer be observed.

To determine failure time precisely, there are three requirements: a time origin must be unambiguously defined, a scale for measuring the passage of time must be agreed and finally the meaning of failure must be entirely clear.

The time origin should be precisely defined for each firm. It is also desirable that, firms to any known differences on explanatory variables, all firms should be as comparable as possible at their time origin. The time origin need not be and usually is not at the same calendar time for each firm. Each firm's failure time is usually measured from its own date of entry in the study. The time origin need not always be at the point at which a firm enters the study, but if it is not, special methods for analysis are needed (see, truncation in Section B2.3).

The 'scale' for measuring time is clock time (real time), although other possibilities may arise¹. One reason for the choice of a timescale is that two firms treated identically should, other thing being equal, be in a similar state after the lapse of equal 'times'.

Finally, the meaning of the point event of failure must be defined precisely. In this study, failure means the first instance at which a firm is being acquired. The

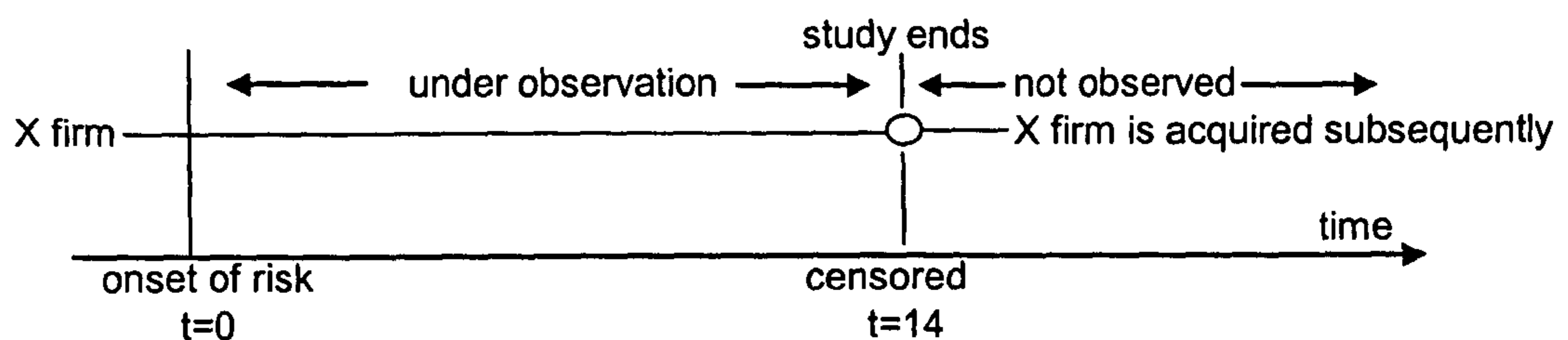
¹ Indeed, in many industrial reliability applications, time is most appropriately measured by cumulative usage, in some sense. Or failures may consist of flaws in textile yarn, when failure 'time' would be the length measured up to the first flaw.

analysis is concentrated on time until a firm is being acquired (failure time). In this study, the unit of time is a year.

B2.2 Censoring of survival time data

A special source of difficulty in the analysis of survival data is the possibility that some firms may not be observed for the full time until they are acquired. For example, as figure 1 depicts, a firm that is observed, failure free (no acquisition), for 14 years and then withdrawn from study has a failure time which must exceed 14 years. Such incomplete observation of the failure time is called right censoring.

Figure B1: Right censoring of survival time data



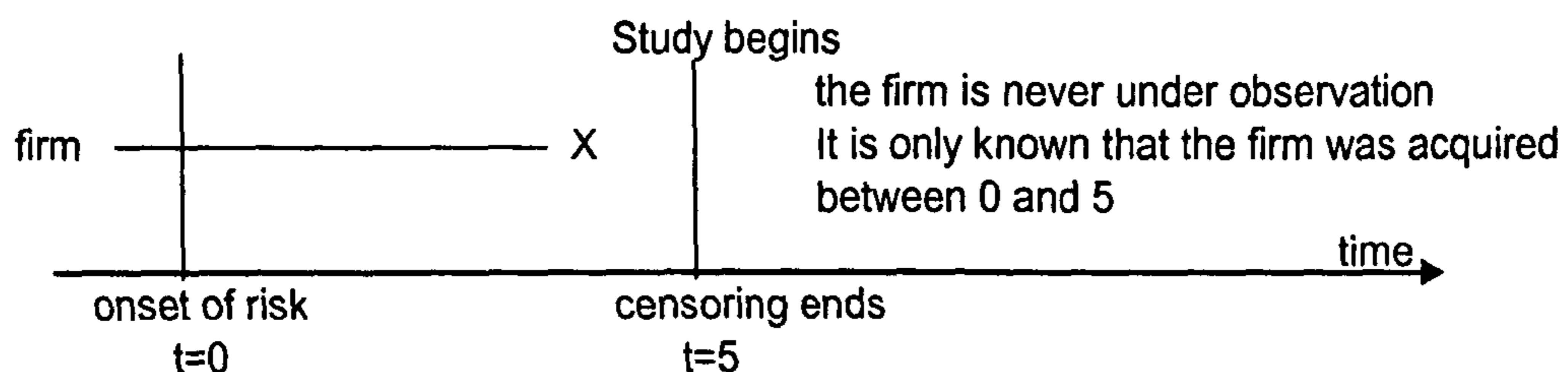
Thus, in this type of censoring, the firm participates in the study for a time and, thereafter, is no longer observed (see e.g. Klein and Moeschberger, 1997). In this study, this can occur because we run a study for a pre-specified length of time, and by the end of that time acquisition has not yet occurred for some firms

or because a firm disappears for unknown reasons. Like failure, censoring is a point event and the period of observation for censored firms must be recorded.

We suppose that, in the absence of censoring, the i^{th} firm in a sample of n firms has failure time T_i , a random variable. We suppose also that there is a period of observation c_i such that observation on that firm ceases at c_i if failure has not occurred by then. Then the observations consist of $N_i = \min(T_i, c_i)$, together with the indicator variable $V_i = 1$ if $T_i \leq c_i$ (uncensored), $V_i = 0$ if $T_i > c_i$ (censored).

On the other hand, left censoring means that the event (acquisition) occurred at some time before the firm enters the study but it is not known when (see e.g. Klein and Moeschberger, 1997). As figure B2 presents a firm may have been acquired well before we have started observing it.

Figure B2: Left censoring of survival time data



When most researchers say censoring, they mean right censoring. The analytic tools we use assume that, if censoring occurs, it occurs randomly and is unrelated to the reason for failure.

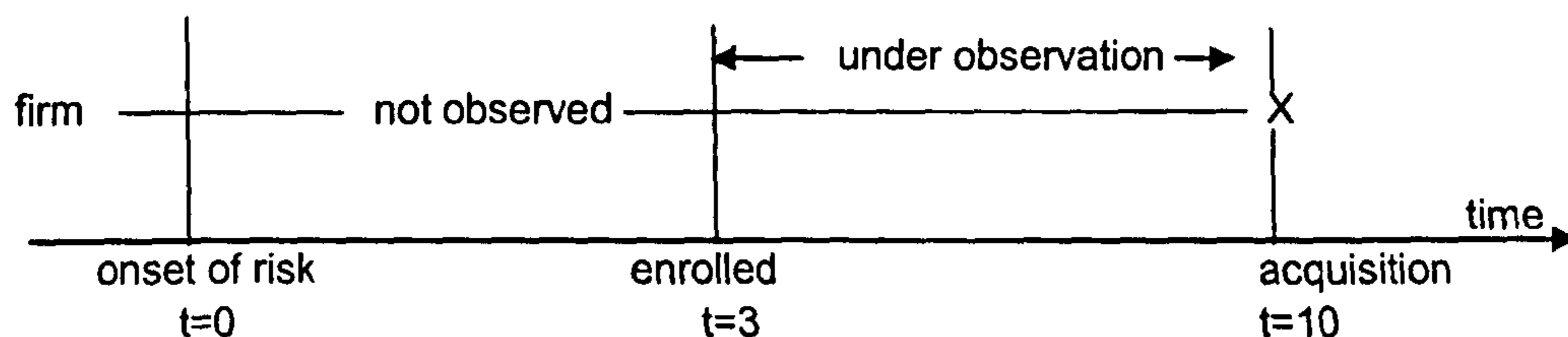
B2.3 Truncation of survival time data

Truncation is often confused with censoring because it also gives rise to incomplete observations over time. Truncation, in most statistical applications, refers to complete ignorance about the event of interest and about the covariates over a portion of the distribution. In survival-data applications, truncation is defined as a period over which the firm is not observed but is, *a posteriori*, known not to have failed. The statistical difficulty that truncation causes is that, had the firm failed (acquired), it would never have been observed. We may distinguish two types of truncation: left (delayed entry) and right truncation.

In left truncation, as figure B3 shows, there is a period of ignorance extending from on or before the onset of risk to some time after the onset of risk. For a while, the firm is not observed, but then the firm comes under observation. Left truncation usually arises because we encounter a firm that came at risk some time ago.

Can we include this firm in our study? The answer is yes, but we must account for the fact that, had the firm been acquired earlier, we never would have encountered this firm. The firm's subsequent survival can be analyzed, but we do not want to make too much out of the fact that firm survived up until the point we encountered it.

Figure B3: Left truncation of survival time data



Right truncation is indistinguishable from right censoring, which is previously discussed (see e.g. Cleves et al, 2004). There is a point beyond which the firm is not observed, and since time may extend all the way to infinity, failure is certain to occur eventually.

B3. The hazard rate and survivor function

For survival analysis, we need methods that directly account for the sequential nature of the data, and are able to handle censoring and incorporate time-varying covariates. The solution is to model survival times indirectly, via the so - called ‘hazard rate’, which is a concept related to chances of making a transition out of the current state at each instant (or time period) conditional on survival up to that point.

Specifically, let the dependent variable of interest be the duration of a process, or the time to exit from a state (firm staying independent, in our case). Let this continuous random variable be denoted T with an associated probability density function $f(t) = Pr(T = t)$. It is implicit in this formulation that firms enter the state at time $T = 0$. It need not be the case that T represents calendar time. Given that we are going to look at durations across sample of firms each of whom may start their existence in the state in question at different dates, T is effectively set to zero for each firm at the time they enter the state. The duration distribution function $F(t)$ represents the probability of exit from the state by time t , where

$$F(t) = Pr(T < t) = \int_{s=0}^t f(s) ds \quad (1)$$

Which implies that

$$f(t) = \frac{dF(t)}{dt} \quad (2)$$

We are commonly interested in T 's survivor function $S(t)$ or its hazard function $h(t)$. The survivor function is nothing more than the reverse cumulative distribution function of T :

$$S(t) = 1 - F(t) = Pr(T \geq t) \quad (3)$$

The survivor function reports the probability of surviving beyond time t . Said differently, it is the probability that there is no failure event (no acquisition) prior to t . The function is equal to one at $t = 0$ (at the start of the spell) and decreases towards zero as t goes to infinity. The survivor function is a monotone, nonincreasing function of time. Thus:

$$0 \leq S(t) \leq 1, \quad S(0) = 1, \quad \lim_{t \rightarrow \infty} S(t) = 0 \quad (4)$$

$$\frac{\partial S}{\partial t} < 0, \quad \frac{\partial^2 S}{\partial t^2} < 0 \quad (5)$$

The basic building block in duration modeling is the exit rate or hazard function at some time t , commonly denoted $h(t)$, which represents the

instantaneous exit rate from the state at time t . In discrete terms, the probability that an individual who has occupied the state (a firm is independent) until time t leaves the state (firm is acquired) in a short interval of length dt after t is

$$Pr(t \leq T \leq t + dt / T \geq t) \quad (6)$$

An average probability of exit per unit of time within the short interval dt is

$$\frac{Pr(t \leq T \leq t + dt / T \geq t)}{dt} \quad (7)$$

As we shorten the length of the interval over which this average probability is defined, we converge to the hazard rate $h(t)$. That is,

$$h(t) = \lim_{dt \rightarrow 0} \frac{Pr(t \leq T \leq t + dt / T \geq t)}{dt} = \frac{f(t)}{S(t)} \quad (8)$$

The probability density function $f(t)$ summarizes the concentration of spell lengths (exit times) at each instant of time along the time axis. The hazard function summarizes the same concentration at each point of time, but conditions the expression on survival in the state up to that instant, and so can be thought of as summarizing the instantaneous *transition intensity*.

The hazard rate (or function) can vary from zero (meaning no risk at all) to infinity (meaning the certainty of failure at that instant). Over time, the hazard rate can increase, decrease, remain constant, or even take on more serpentine shapes. There is a one-to-one relationship between the probability of survival past a certain time and the amount of risk that has been accumulated up to that time. The hazard rate measures the rate at which risk is accumulated.

Given one of the four functions² that describe the probability distribution of failure times, the other three are completely determined. In particular, one may derive from a hazard function the probability density function, the cumulative distribution function, and the survivor function. In order to show these relationships, it is first convenient to define another function, the cumulative hazard function:

$$H(t) = \int_0^t h(u) du \quad (9)$$

And thus

$$H(t) = \int_0^t \frac{f(u)}{S(u)} du = - \int_0^t \frac{1}{S(u)} \left\{ \frac{d}{du} S(u) \right\} du = - \ln \{ S(t) \} \quad (10)$$

The cumulative hazard function measures the total amount of risk that has been accumulated up to time t . From equation 10, we can see the relationship between accumulated risk and the probability of survival. We can write:

$$S(t) = \exp \{ -H(t) \} \quad (11)$$

$$F(t) = 1 - \exp \{ -H(t) \} \quad (12)$$

$$f(t) = h(t) \exp \{ -H(t) \} \quad (13)$$

When data are left truncated we do not observe firms from the onset of risk. That is, rather than observing firms from $t = 0$ until failure, we observe them from $t = t_0$ until failure with $t_0 > 0$. When the failure is an absorbing event (e.g.

² All forms, $S(t), h(t), F(t), f(t)$, describe exactly the same probability distribution for T

a firm being acquired), after which observation is pointless, we will instead want to deal with the conditional variants of $S(\cdot), h(\cdot), F(\cdot), f(\cdot), H(\cdot)$. The important features here is that those who failed (being acquired) during period 0 to t_o will never be observed in our datasets. The conditional forms of the above functions are:

$$h(t/T > t_o) = h(t) \quad (14)$$

$$H(t/T > t_o) = H(t) - H(t_o) \quad (15)$$

$$F(t/T > t_o) = \frac{F(t) - F(t_o)}{S(t_o)} \quad (16)$$

$$f(t/T > t_o) = \frac{f(t)}{S(t_o)} \quad (17)$$

$$S(t/T > t_o) = \frac{S(t)}{S(t_o)} \quad (18)$$

Note that $h(t)$ is unaffected by the conditioning; it is an instantaneous rate and so is not a function of the past.

B4. Accelerated failure time (AFT) models

In this study we make use of models belonging to the accelerated failure time (AFT) family of survival time models. The AFT models assume a linear relationship between the log of (latent) survival time t and characteristics X :

$$\ln(t) = \beta X + z \quad (19)$$

Where β is a vector of parameters, and z is an error term.

This expression can be re-written as

$$Y = \mu + \sigma u \text{ or } \frac{Y - \mu}{\sigma} = u \quad (20)$$

Where $Y \equiv \ln(t)$, $\mu \equiv \beta X$, and $u = \frac{z}{\sigma}$ is an error term with density function $f(u)$, and σ is a scale factor which is related to the shape parameters for the hazard function. Distributional assumptions about u determine which sort of regression model describes the random variable t . Table 1 presents different AFT models as implied by different error term distributions.

Table B1: Different error term distributions imply different AFT models

Distribution of error term	Distribution of t
Extreme Value (1 parameter)	Exponential
Extreme Value (2 parameter)	Weibull
Logistic	Log-logistic
Normal	Lognormal
Log Gamma (3 parameter Gamma)	Generalized Gamma

From equation 19 and letting $\psi \equiv \exp(-\beta X) = \exp(-\mu)$, it follows that:

$$\ln(t\psi) = z \quad (21)$$

The term ψ , which is constant by assumption, acts like a time scaling factor.

Thus,

- If $\psi > 1$: it is as if the clock ticks faster. The time scale for a firm with characteristics X is $t\psi$, whereas the time scale for a firm with characteristics $X = 0$ is t . Failure is 'accelerated' or survival time shortened.
- If $\psi < 1$: it is as if the clock ticks slower. Failure is 'decelerated' or survival time lengthened

This time scaling property is also present in the survivor function. The survivor function of AFT models is given by:

$$S(t, X) = S_o[t \exp(-\mu)] = S_o[t\psi] \quad (22)$$

Where $\psi \equiv \exp(-\mu)$.

It follows that $\psi > 1$ is equivalent to having $\mu < 0$ and $\psi < 1$ is equivalent to having $\mu > 0$. In sum, the effect of the covariates is to change the time scale by a constant (survival time-invariant) scale factor $\psi \equiv \exp(-\mu)$. The AFT regression coefficient relates proportionate changes in survival time to a unit change in a given regressor, with all other characteristics held fixed.

Also, the relationship between the hazard rate for a firm with characteristics X and the hazard rate for the case when $X = 0$, i.e. the 'baseline' hazard $h_o(\cdot)$, is given for AFT models by:

$$h(t, X) = \psi h_o(t\psi) \quad (23)$$

A relatively straightforward generalization of the AFT hazard to allow for time-varying covariates is to suppose that:

$$h(t, X_t) = \psi_t h_o(t\psi_t) \quad (24)$$

B5. Estimation of the survivor and hazard functions

In this section we consider estimators of the survivor and hazard functions- the empirical counterparts of the concepts that we considered in the previous sections. These estimators are distinguished into two³ forms nonparametric and parametric all depending on what we are willing to assume about the form of the survivor function and about how the survival experience is affected by covariates.

B5.1 Nonparametric analysis

Nonparametric estimators, make no assumptions about neither the distribution of the failure (acquisition) times nor how covariates serve to change or shift the survival experience. With survival data, the key insight into removing the distributional assumption is that, because events (acquisitions) occur at given times, these events may be ordered and the analysis may be performed using ordering of the survival times exclusively. Because the nonparametric analysis is informative about the pattern of duration dependence, it may assist with the choice of parametric model. Nonparametric analysis follows the philosophy of letting the data speak for itself.

We can use nonparametric methods such as Kaplan and Meier (1958) or the method of Nelson (1972) and Aalen (1978) to estimate the probability of survival

³ There is also semiparametric estimators but are not considered in this study (see section B5.2 for a justification)

past a certain point in time. These methods take into account censoring and other characteristics of survival data⁴.

The estimator of Kaplan and Meier is a nonparametric estimate of the survivor function $S(t)$, the probability of survival past time t (or equivalently, the probability of failing after t). For a dataset with observed failure times, t_1, \dots, t_k , where k is the number of distinct failure times observed in the data, the Kaplan-Meier estimate at any time t is given by

$$\hat{S}(t) = \prod_{i/t_i \leq t} \left(\frac{n_i - d_i}{n_i} \right) \quad (25)$$

Where n_i is the number of firms at risk at time t_i and d_i is the number of failures at time t_i . The product is over all observed failure times less than or equal to t .

The Kaplan-Meier estimate operates only on observed failure times and not at censoring times. When censoring occurs at some time other than an observed failure time, the effect is simply that the censored firms are dropped from the ‘the number at risk’ total without processing the firm as having failed. However, when some firms are censored at the same time that others fail we assume that failure occurred before censoring (see Cleves et al, 2004). On the other hand, left truncation causes no problems with the Kaplan-Meier calculation. In n_i is the number of firms at risk (eligible to fail), and this number simply needs to take into account that firms are not at risk of failing until they come under observation. When they enter, we increase n_i to reflect this fact.

⁴ There exists a vast literature on performing nonparametric regression using methods such as lowess or local polynomial regression; however, such methods do not adequately deal with censoring and other issues unique to survival data.

On the other hand, Nelson-Aalan estimator provides a nonparametric method for obtaining the empirical cumulative hazard function. That estimator is given by

$$\hat{H}(t) = \sum_{i/t_i \leq t} \frac{d_i}{n_i} \quad (26)$$

Where n_i is the number at time t_i , d_i is the number of failures at time t_i , and the sum is over all distinct failure times less than or equal to t .

Theoretically, the survival and cumulative hazard functions are related by equation 10. We can by using this relation to convert one estimate to the other. It has been shown that, in small samples, the Kaplan-Meier estimator is superior when estimating the survivor function, and the Nelson-Aalen estimator is superior when estimating the cumulative hazard function. For the survivor function and the cumulative hazard function, both the Kaplan-Meier estimator and the Nelson-Aalan estimator are consistent estimates of each, and the statistics are asymptotically equivalent (see Klein and Moeschberger, 2003). That is, in very large samples, it does not matter how one estimates the survivor function, whether by Kaplan-Meier or by transforming the Nelson-Aalen.

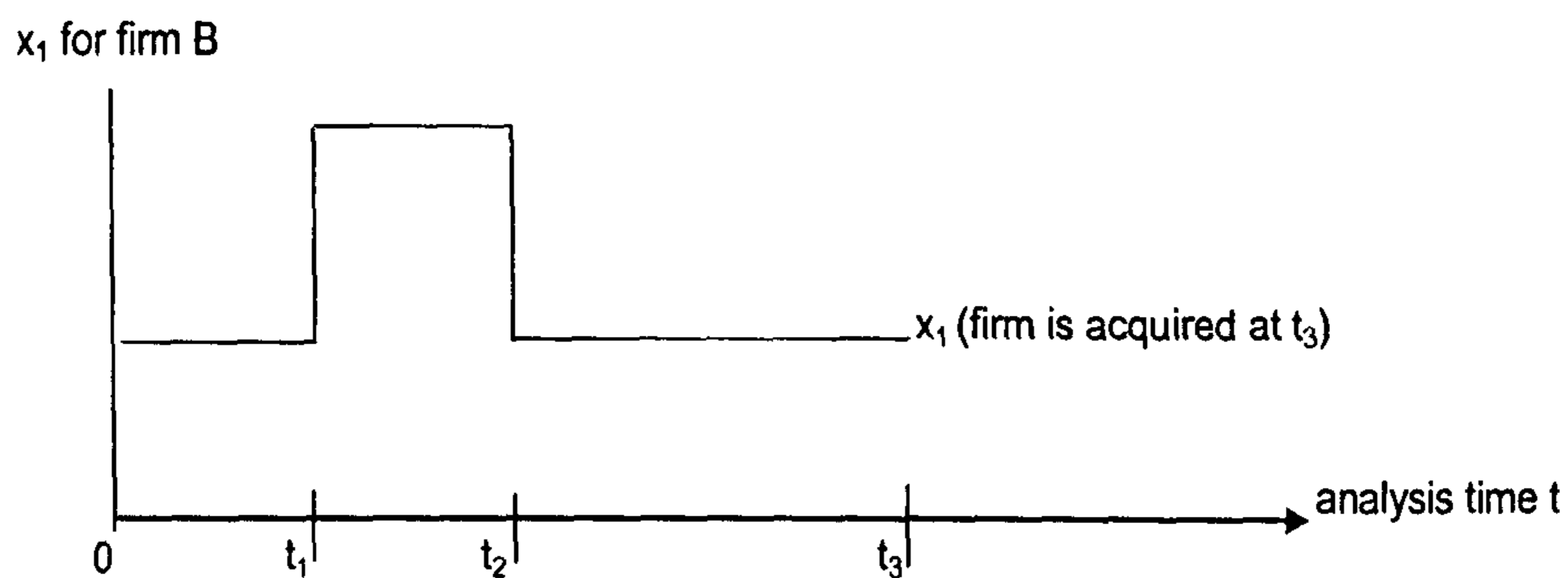
B5.2 Parametric analysis

Nonparametric and semiparametric methods compare firms at the times when acquisitions happen to occur. Parametric methods, on the other hand, do not base their results on such comparisons. Rather, for each record in the data spanning $(t_0, t_1]$, parametric estimation schemes use probabilities that depict what occurs over the whole interval, given what is known about the firm during this time. For

example, consider a survivor model where failure depends on a covariate x_1 .

Hypothesize that one of the firms in the dataset has the following x_1 profile:

Figure B4: Example of a firm's survival profile



In semiparametric analysis (for example, cox regression), if no other firm is acquired between t_1 and t_2 , it simply does not matter that x_1 blipped up for this firm because no comparisons will be made in that interval using the temporarily higher value of x_1 . In other words, in this case, we would obtain the same results in semi-parametric models if the blip in the time profile for this subject did not exist; i.e., if x_1 remained at its initial value throughout. The blip in x_1 , however, would be of importance in a parametric model, regardless of whether other failures occurred in the interval because the parametric model would exploit all the information.

Semi-parametric models are not making an error by ignoring the blip- it is merely being inefficient. Suppose that higher values of x_1 increase failure rates. Conditional on having survived beyond time t_2 , the fact that the blip occurred becomes irrelevant in terms of subsequent survival. The information in the blip is

that it indeed occurred and the firm managed to survive it, which means that this firm provides evidence that higher values of x_1 really do not lead a firm to fail. Semi-parametric models would ignore that unless other failures occurred in the interval, in which case some amount of the information contained in the interval would be exploited in improving the estimate of the effect of x_1 . Parametric methods would not ignore that information.

The likelihood functions of the parametric models-regardless of the particular one under consideration- all follow the same general form:

$$L(\beta_x, \Theta) = \prod_{i=1}^n \left[\frac{f(t_i / X_i \beta_x, \Theta)}{S(t_{0i} / X_i \beta_x, \Theta)} \right]^{c_i} \left[\frac{S(t_i / X_i \beta_x, \Theta)}{S(t_{0i} / X_i \beta_x, \Theta)} \right]^{1-c_i} \quad (27)$$

Where $f(\cdot)$ is the density function of the assumed distribution, $S(\cdot)$ is the corresponding survivor function, and (t_{0i}, t_i, c_i, X_i) is the information on the i^{th} firm. The parameters β_x and Θ are estimated from the data: β_x are the coefficients on X , and Θ are ancillary parameters, if any, required by the assumed distribution.

The triple (t_{0i}, t_i, c_i) summarizes the survival experience for the firm: the firm is observed and known not to fail during the period $t_{0i} < t < t_i$, and then at $t = t_i$, the firm either fails ($c_i = 1$) or is censored ($c_i = 0$). Thus, the powers $(1 - c_i)$ and c_i in 27 serve to select either $S(\cdot)$ or $f(\cdot)$ as the numerator of the ratio. If censored, $S(\cdot)$ is chosen, and that is the probability that the firm survives from 0 to t_i without failure. If $c_i = 1$, if the firm fails, $f(\cdot)$ is chosen, and that is the ‘probability’ of failure at time t_i . Either way, the numerator is divided by $S(t_{0i} / X_i \beta_x, \Theta)$, which is the probability of surviving up to time t_{0i} , and thus

whichever is the numerator is converted to a conditional probability or probability density for the time span under consideration.

Equation 27 may be equivalently written as

$$L(\beta_x, \Theta) = \prod_{i=1}^n \left[h(t_i / X_i \beta_x, \Theta) \right]^{c_i} \left[\frac{S(t_i / X_i \beta_x, \Theta)}{S(t_{0i} / X_i \beta_x, \Theta)} \right] \quad (28)$$

The first part $h(t_i / X_i \beta_x, \Theta)^{c_i}$, becomes $h(t_i / X_i \beta_x, \Theta)$ if the span ends in failure (which is the corresponding risk of that event at time t_i), or 1 if the span ends in censoring. The second part is the probability of survival from t_{0i} until t_i .

Furthermore, equation 28 can be written as:

$$L(\beta_x, \Theta) = \prod_{i=1}^n \left[h(t_i / X_i \beta_x, \Theta) \right]^{c_i} \left[w_i S(t_i / X_i \beta_x, \Theta) \right] \quad (29)$$

Or

$$\log L(\beta_x, \Theta) = \sum_{i=1}^n \left\{ c_i \log h(t_i / X_i \beta_x, \Theta) + \log \left[w_i S(t_i / X_i \beta_x, \Theta) \right] \right\} \quad (30)$$

Where $w_i \equiv 1 / S(t_{0i} / X_i \beta_x, \Theta)$. Think of the w_i as being like weighting variable: one weights the delayed entry observations by a type of inverse-probability weight to account for the left truncation. The later in time that t_{0i} is (the closer to t_i), the larger the weight. If there is no left truncation ($t_{0i} = 0$), then $S(t_{0i} / X_i \beta_x, \Theta) = 1 = w_i$

All parametric likelihoods are of the above form, and the only difference among the models is how $S(\cdot)$ (and therefore $f(\cdot)$ and $h(\cdot)$) is chosen.

Note that the terms of the likelihood function are stated in terms of firms. In simple survival data, there is one-to-one correspondence between observations and firms. But in more complex cases, a firm may have multiple observations. In that case, parametric models are generalized to allow time-varying covariates.

In specific estimation of continuous time parametric regression models incorporating time-varying covariates requires *episode splitting*. We have to *split* the survival time (*episode*) for each firm into subperiods within which each time-varying covariate is constant; i.e. we have to create multiple records for each firm, with one record per subperiod. What is the logic behind this?

Consider a firm i with two different values for a covariate:

$$x_1 \text{ if } t < u$$

$$x_2 \text{ if } t \geq u$$

The log likelihood contribution for a firm i in the data structure that we have is:

$$\log L_i(\beta_x, \Theta) = c_i \log h(t_i / X_i \beta_x, \Theta) + \log [w_i S(t_i / X_i \beta_x, \Theta)] \quad (31)$$

But

$$\begin{aligned} \log [w_i S(t_i / X_i \beta_x, \Theta)] &= \log \left[S(u / X_i \beta_x, \Theta) \frac{w_i S(t_i / X_i \beta_x, \Theta)}{S(u / X_i \beta_x, \Theta)} \right] = \\ &= \log [S(u / X_i \beta_x, \Theta) w_i] + \log \left[\frac{S(t_i / X_i \beta_x, \Theta)}{S(u / X_i \beta_x, \Theta)} \right] \end{aligned} \quad (32)$$

Thus the log of the probability of survival until t_i equals the log of probability of survival to time u (weight w_i incorporates left truncation as above) plus the log of probability of survival to t_i , conditional on entry at u .

So what we do is to create one new record with $c_i = 0, t = u$ (a right censored episode), plus one new record summarizing an episode with 'delayed entry' at time u and censoring indicator c_i has the value as in the original data. In the first episode and record, the time-varying covariate takes on the value x_1 and in the second record the time-varying covariate takes on the value x_2 . Table B2 presents a summary of the old and new data structures.

Table B2: Example of episode splitting

Record#	Censoring indicator	Survival time	Entry time	Time varying covariates value
<u>Single data record for i</u>				
1	$c_i=0$ or 1	t_i	t_{0i}	-
<u>Multiple data records for i (after episode splitting)</u>				
1	$c_i=0$	u	t_{0i}	x_1
2	$c_i=0$ or 1	t_i	u	x_2

B6. Unobserved heterogeneity ('frailty')

In the multivariate models considered so far, all differences between firms were assumed to be captured using observed explanatory variables (the X vector). In this section, we consider generalizations of the earlier models to allow for unobserved individual effects. Variables captured these unobserved individual effects might be relevant because of omitted variables (unobserved in the available data, or intrinsically unobservable) and of measurement errors in observed survival times or regressors (see Lancaster, 1990, chapter 4).

If these effects are important but 'ignored' in modeling the literature suggests several findings:

- The 'no-frailty' model will over-estimate the degree of negative duration dependence in the hazard (i.e. under-estimate the degree of positive duration dependence). In other words, the hazard rate from 'no-frailty' model increases less fast, or falls faster, than does the 'true' hazard. Controlling for observable differences, firms with unobserved characteristics associated with higher exit rates leave the state more quickly than others. Hence 'survivors' at longer t increasingly comprise those with low unobservable individual effects which, in turn, implies a lower hazard, and the estimate of hazard is an underestimate of 'true' one (see, Gutierrez, 2002)
- The proportionate response of the hazard rate to a change in a regressor k declines with time
- One gets an under-estimate of the true proportionate response of the hazard to a change in a regressor k from the no-frailty-model

In order to present the unobserved heterogeneity concept in continuous time case we consider the model (assuming that there are no time-varying covariates):

$$h(t, X / \nu) = \nu h(t, X) \quad (33)$$

Where $h(t, X)$ is the hazard rate depending on observable characteristics X , and ν is an unobservable individual effect that scales the no-frailty component.

Random variable ν is assumed to have the following properties:

- $\nu > 0$
- $E(\nu) = 1$, unit mean
- Finite variance $\sigma^2 > 0$
- Distributed independently of t and X

It is shown that the relationship between the frailty survivor function and the no-frailty survivor function is:

$$S(t, X / \nu) = [S(t, X)]^\nu \quad (34)$$

Thus the individual effect ν scales no-frailty component survivor function. Firms with above-average values of ν leave relatively fast (their hazard rate is higher, other things being equal, and their survival times are smaller), and the opposite occurs for firms with below-average values of ν .

How does one estimate frailty models, given that the individual effect is unobserved? Clearly we cannot estimate values of ν themselves since, by construction, they are unobserved. In other words, there are as many individual effects as firms in the data set, and there are not enough degrees of freedom left to fit these parameters. However if we suppose the distribution of ν has a shape

whose functional form is summarized in terms of only a few key parameters, then we can estimate those parameters with the data available.

We first specify a distribution for the random variable ν , where this distribution has a particular parametric functional form (e.g. summarizing the variance of ν). Then we work with some survivor function $S_\nu(t, X) = S(t, X / \beta, \sigma^2)$ and not $S(t, X / \beta, \nu)$.

Then

$$S_\nu(t, X) = \int_0^\infty [S(t, X)]^\nu g(\nu) d\nu \quad (35)$$

Where $g(\nu)$ is the probability density function for ν ('mixing' distribution).

The most commonly used specification for the mixing distribution is the Gamma distribution, with unit mean and variance σ^2 . An alternative mixing distribution to the Gamma is the *Inverse Gaussian* distribution. But this is less commonly used (see Lancaster, 1990)

APPENDIX C

DESCRIPTIVE STATISTICS OF DATA USED IN
SURVIVAL ANALYSIS

Variable	Mean	Std. Dev.	Min	Max
Duration	7.80	3.90	1	15
Stock	18	15	0	58
Order	3	6	-10	20
<u>Profitability</u>				
ROE(t)	0.20	0.90	-33.04	18.81
NIA(t)	0.04	0.18	-5.81	0.62
EAR(t)	1185	6341	-50545	158826
<u>Liquidity</u>				
CR	0.15	0.21	0.04	1.29
WCTA	1.70	8.13	0.01	4.90
WCS	1.59	12.12	0.08	4.62
<u>Leverage</u>				
TLTA	0.19	0.16	0.08	4.18
LDMV	0.12	0.15	0.04	3.89
<u>Growth</u>				
SGR	0.48	8.35	-1	18.90
AGR	-0.27	11.57	-4	28.50
EPSGR	-0.84	29.48	-17	23
<u>Size</u>				
NS	1987	2632	0.45	20089
TA	11316	53087	3.38	631783
DIV	0.04	0.04	0.03	0.91
q ratio	0.19	0.16	0.01	4.18
PE	0.29	1.23	0.06	60.07
MTBV	2.51	7.06	0.22	13.80

APPENDIX D

EFFECTS OF STOCK AND ORDER BY SECTOR AND OVER TIME

Figure D1 and D2 present effect of stock and order by sector and over time, respectively.

Figure D1: Effect of Stock by Sector over Time

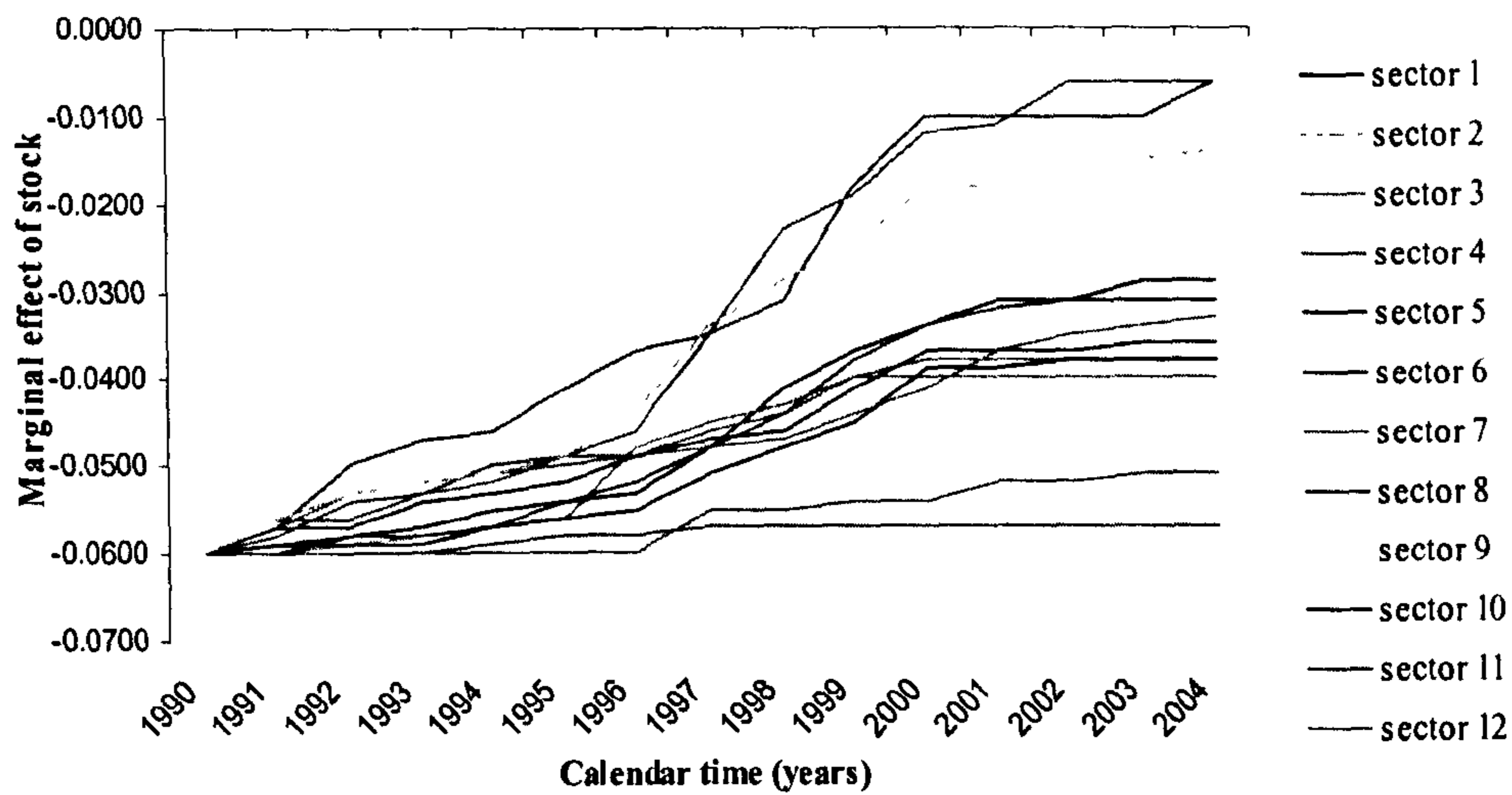
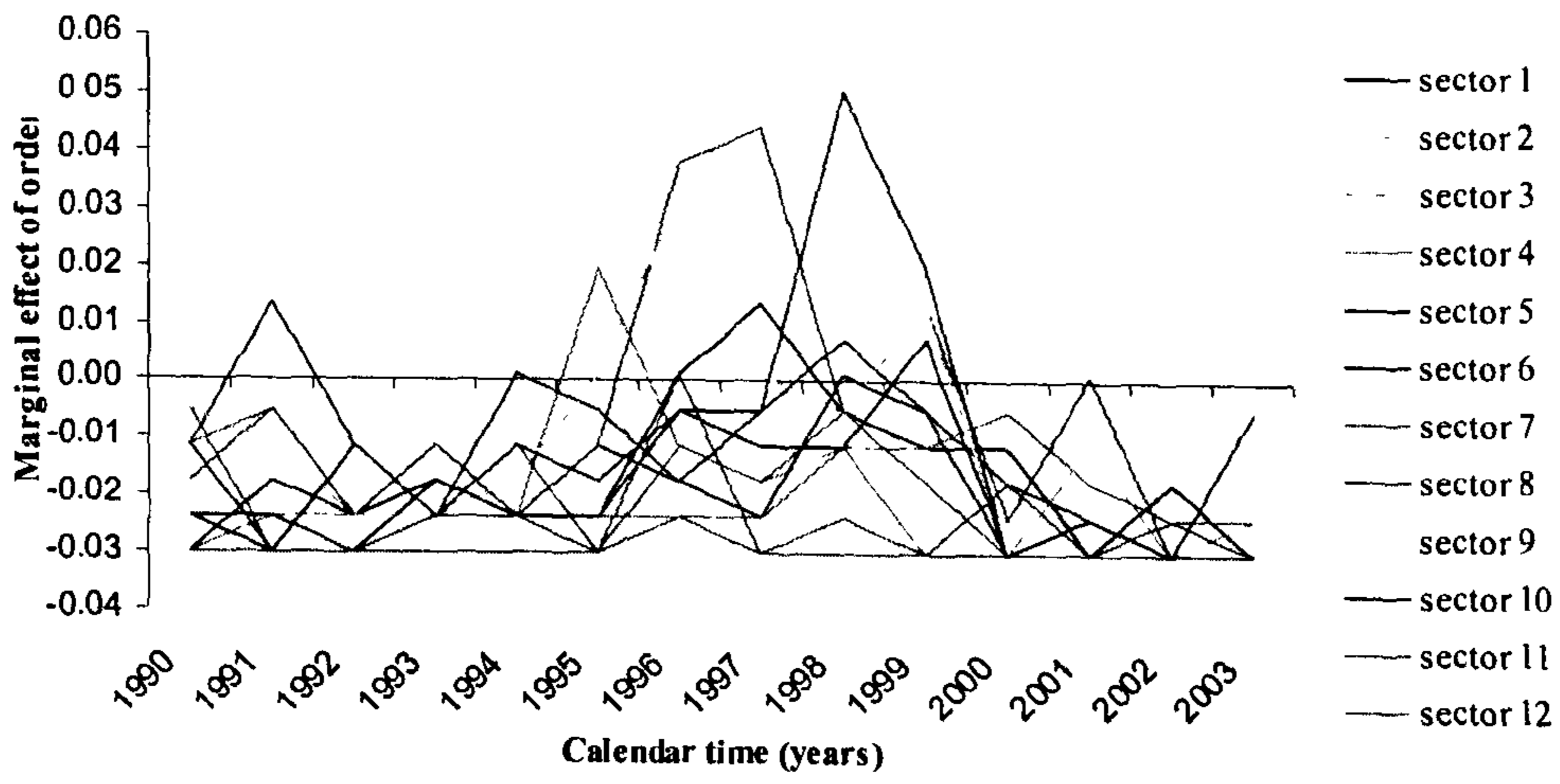


Figure D2: Effect of Order by Sector over time



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