Michiel van Leuvensteijn graduated from the VU University Amsterdam in 1991. Before joining CPB Netherlands Bureau for Economic Policy Analysis in 2000 as Senior Economist, he was affiliated with the Ministry of Social Affairs and Employment in the Netherlands. In 2006, he was engaged in research on the nature of competition in EU insurance and banking markets as Expert at the European Central Bank.

This thesis is devoted to the topic of measuring competition in financial markets. This topic is relevant because the soundness and stability of the financial system is in various ways influenced by the degree of competition. The recent financial crisis has once again pointed out the importance of a healthy financial system for economic development. Therefore, the issue of competition in the financial sector warrants close attention. The structure of the thesis is as follows. The first part of the study emphasizes the importance of financial markets for the real economy, such as for instance the labour market and the housing market. The second part focuses on the degree of competition in financial services in general, and in the banking sector in particular. Here, a new measure of competition, the so-called Boone indicator, has been introduced and applied to both loan markets in the euro area and the market for life insurance. The US had the most competitive loan market, whereas Germany and Spain were among the most competitive EU markets in the period 1994 - 2004. The Netherlands occupied a more intermediate position whereas competition declined significantly over time in Italy. The French and UK loan markets were generally less competitive. In Japan, competition was found to increase over the years. Furthermore, competition in the financial markets reduced interest rates and enhanced the pass through of changes in policy rates. Finally, based on the Boone indicator, the results indicate that competition in the Dutch life-insurance sector is weak.

Measuring Competition in Financial Markets

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Measuring Competition in Financial Markets

Het meten van concurrentie in financiële markten
(met een samenvatting in het Nederlands)

Proefschrift

ter verkrijging van de graad van doctor aan de Universiteit Utrecht op gezag van de rector magnificus, prof.dr. J.C. Stoof, ingevolge het besluit van het college voor promoties in het openbaar te verdedigen op vrijdag 20 november 2009
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Aan mijn lieve ouders, mijn pappa en mamma

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1 Introduction

1.1 Background and motivation

This thesis presents several empirical studies concerning the measurement of competition in different financial markets. The most important reason to focus this thesis on the financial market is the great importance that this sector has for the whole economy. The financial market provides the necessary capital to companies to produce goods and services and it gives consumers the opportunity to smooth expenditures over the life cycle. In the euro area, banks are the main suppliers of external funds and play a more important role, in this sense, than capital markets do. For consumers, the mortgage markets are the most important financial market in terms of size. Homes are the largest assets of consumers. For small- and medium-sized companies, bank loans are their main external source of finance. Life insurance companies produce insurance against old age, and improve the possibilities to save over the life cycle.

Measuring the level of competition in financial markets is important, as strong competition may result in a more efficient production process of financial products, thereby increasing welfare. At the same time, fierce competition could result in more risk-taking behaviour by financial institutions, which in turn could threaten the stability of the financial system. There is some evidence of the existence of this link between competition and financial stability.[1] However, competition could also result in more stability, as the ill-functioning institutions with large operational risks are either compelled to adjust, forced to leave the market or are taken over. Although it is unclear which of these effects is dominant, the quest for a good method to measure competition is an important enterprise.

Finally, the functioning of financial markets is important also from a monetary policy perspective. The European Central Bank has defined an objective of price stability. It sets its policy rate to achieve this aim. The effectiveness of monetary policy instruments in reaching the ECB's objective relies on the degree to which policy rate changes are passed on to bank lending rates. This depends, among other things, on the level of competition in the market.

[1] See Martinez-Miera and Repullo (2008) for an overview of the literature.

The considerations mentioned above led me to focus the thesis on the functioning of a number of these financial markets. The aim of this thesis is to measure competitiveness in the following markets: loan markets in general, mortgage markets more specifically, as well as markets for life insurance.

1.2 Place in the literature

How the level of competition can best be measured is open to debate, and a great many measures of competition exist. The most commonly used measures are the Lerner Index and the Hirschman-Herfindahl Index (HHI). These, however, have some major theoretical deficiencies, as Boone (2008) rightly points out.

A broad literature explores the measurement of competition in the financial sector using concepts as market power and efficiency. A well-known approach to measuring market power, which was suggested by Bresnahan (1982) and Lau (1982), has recently been used by Bikker (2003) and Uchida and Tsutsui (2005). They analyse bank behaviour on an aggregate level and estimate the average conjectural variation of banks. A high conjectural variation implies that a bank is highly aware of its interdependence with other firms in terms of output and prices.

Panzar and Rosse (1987) propose an approach based on the so-called H-statistic, which is the sum of the elasticities of the reduced-form revenues with respect to the input prices. This H-statistic ranges from $-\infty$ to 1. An H-value equal to or smaller than zero indicates monopoly or perfect collusion, whereas a value between zero and one provides evidence of a range of oligopolistic or monopolistic types of competition. A value of one points to perfect competition.

A third indicator for market power is the Hirschman-Herfindahl Index (HHI), which measures the degree of market concentration. This indicator is often used in the context of the 'Structure Conduct Performance' (SCP) model (see e.g. Berger et al. 2004; Bos 2002), which assumes that market structure affects banks' behaviour, which in turn determines their performance.[2] The idea is that banks with larger market shares may have more market power and use it. Moreover, the smaller number of banks makes collusion more likely. To test the SCP hypothesis, performance (profit) is explained by market structure as measured by the HHI. Many articles test the SCP model jointly with an alternative explanation of performance, namely the efficiency hypothesis, which attributes differences in performance (or profit) to differences in efficiency (e.g. Goldberg and Rai 1996; Smirlock 1985).

Market power may also be related to profit, in the sense that extremely high profits may be indicative of a lack of competition. A traditional measure of profitability is the price-cost margin (PCM), which is typically measured by the output price minus the marginal costs, divided by the output price. The PCM is frequently used in the

[2] Bikker and Bos (2005), pp. 22-23.

empirical industrial organization literature as an empirical approximation of the theoretical Lerner Index.[3]

Finally, a whole strand of literature has focused on X-efficiency, which reflects managerial ability to drive down production costs, controlling for output volumes and input price levels. The X-efficiency of firm i is defined as the difference in costs between that firm and the best-practice firms of similar size and input prices (Leibenstein 1966). Heavy competition is expected to force banks to drive down their X-inefficiency, so that the latter is often used as an indirect measure of competition.

This thesis uses many of the above concepts to analyse competition in financial markets. I pay specific attention to a relatively new indicator of competitiveness: the Boone indicator. The Boone indicator has a better theoretical foundation than the PCM or the HHI. For instance, in case an inefficient firm is taken over by an efficient firm, the HHI would point to less competition, while the Boone indicator would reflect the strengthening of the relationship between efficiency and performance and rightly point to more competition. Also, competitive pressure may have compelled firms to become more efficient and to have at the same time higher mark-ups (skimming off the surplus created due to more efficient production techniques). The PCM would point to less competition, whereas in reality competition has been enhanced. The Boone indicator in that case would also point to more competition, as the relationship between reward and efficiency has been strengthened. This thesis introduces the Boone indicator in the literature on banking and life insurance.

1.3 Thesis outline

The outline of this thesis is as follows. Chapters 2 to 4 focus on the Dutch mortgage market and introduce the relevance of competition for this market. Chapter 4 provides a prelude on the topic of competition by addressing two aspects of competition for the Dutch mortgage market: namely, transparency and pricing power. Chapters 5 to 8 continue in this line. Here the attention is directed to the level of competition in the financial sector at large, particularly looking at banks and life insurance companies. Chapter 5 introduces a new measure of competition, the Boone indicator. In Chapters 6 and 7, I measure the level of competition for the loan market with a slightly adjusted version of this measure of competition and extend the scope of the analysis to the euro area. Furthermore, here I analyse the impact of bank competition on the interest rate channel of monetary policy by the European Central Bank. Finally, Chapter 8 looks at

[3] The Lerner Index derives from the monopolist's profit maximisation condition as price minus marginal cost, divided by price. The monopolist maximises profits when the Lerner Index is equal to the inverse price elasticity of market demand. Under perfect competition, the Lerner Index is zero (market demand is infinitely elastic); in monopoly, it approaches one for positive non-zero marginal cost. The Lerner Index can be derived for intermediary cases as well. For a discussion, see Church and Ware (2000).

the level of competition in Dutch life insurance companies. The following paragraphs in this subsection expand on the outline of each chapter.

Chapter 2 investigates the relevance of homeownership, and thus also the mortgage market, for the labour market. To become a homeowner, a household typically has to borrow from banks or other financial intermediaries. In various macro-studies, homeownership is found to hamper job mobility and to increase unemployment. This chapter tests one of the Oswald hypotheses: homeownership limits job mobility due to high transaction costs in the housing market. Consequently, it increases the probability to become unemployed. After all, homeowners are less willing to accept jobs outside their own region due to high moving costs, and therefore would have a higher probability to become unemployed than renters would. For the Netherlands, I find, however, that homeowners do not change their jobs less often than renters, and they have also a smaller probability to become unemployed than renters. This first result may be explained by the high population density in the Netherlands, the strong increases in house prices (that may have compensated moving costs) and by the strong regulation of the social renting sector (which may have resulted in high moving costs for tenants as well). This latter result is explained by the higher job commitment of homeowners versus renters. So for this aspect, homeownership seems to be beneficial for individual homeowners.

Chapter 3 shows how banks value the probability that households move. Here, I investigate empirically to what degree the level of the lending rate for endowment mortgages can be attributed to differences in prepayment risks of households. Prepayment risk is the risk that a household will prepay its mortgage prior to maturity. I claim that for this type of mortgage, prepayment is mostly the result of mobility in the housing market. I am able to investigate the relevance of income shocks and wealth shocks for the moving behaviour of households on the housing market, according to banks. I find that changes in income are the main driver behind residential mobility, according to banks. The income-to-value ratio is far more important than the loan-to-value ratio. The liquidity position of a household has more influence on the decision to move residence than its solvency does. Thus, fluctuations in the value of the residence have a smaller impact on moving behaviour than changes in income do.

Chapter 4 is dedicated to the subject of the transparency of the Dutch mortgage market. An empirical study of pricing in the Dutch mortgage market is presented. Transparency is measured by the degree of price dispersion between the best offer and worst rip-off in terms of interest rate. Price dispersion may hint at the presence of imperfect competition, caused by search costs of borrowers or by agency costs of lenders. In general, this points to a lack of transparency, which impedes competition on the mortgage market. On the Dutch mortgage market, supply partly comes from intermediaries (middlemen) and partly is supplied over the counter by banks. We observe substantial differences in price dispersion between the mortgages of banks, on the one hand, and the mortgages of insurers and pension funds (so-called non-banks), on the other. This result implies that the mortgage market is less transparent in the

segment dominated by non-banks compared to that of banks. A test whether non-banks have more pricing power than banks provides mixed results. We therefore have only limited evidence that less transparency in markets results in more pricing power for lenders.

Chapter 5 provides an empirical underpinning for a new way to measure competition: the Boone indicator. The indicator, which was introduced by Boone (2008), is based on the relationship between performance and efficiency. Whether the indicator is able to correctly measure competition in practice is as yet an unanswered question. To demonstrate that the Boone indicator is able to identify regimes of competition, I use data collected by Genesove and Mullin (1998) for the American sugar industry for the period 1890-1914. From my analysis it follows that the Boone indicator is able to identify different regimes of competition and that its results are similar to the elasticity-adjusted Lerner Index.

After providing the Boone indicator with an empirical underpinning in Chapter 5, I continue in Chapter 6 with an application of this indicator to the European loan market. In contrast to many well-known measures of competition (such as the Panzar-Rosse method) that consider only entire banking markets, this indicator has the advantage of being able to measure bank market segments, such as the loan market. My evidence suggests that the US had the most competitive loan market, whereas Germany and Spain were among the most competitive EU markets. The Netherlands occupied a more intermediate position, whereas in Italy competition declined significantly over time. The French and UK loan markets were generally less competitive. In Japan, competition was found to increase over the years.

Chapter 7 takes the analysis of Chapter 6 a step further, and looks at how competition, measured by the Boone indicator, affects the monetary policy transmission mechanism in the euro area. My findings show that stronger competition causes both lower bank interest rates and a stronger pass-through of changes in market interest rates. I observe also that bank interest rates in more competitive markets respond more strongly and (for short-term loans to enterprises) more rapidly to changes in market interest rates than in non-competitive markets. These findings have important monetary policy implications, as they suggest that measures to enhance competition in the European banking sector will tend to render the monetary policy transmission mechanism more effective.

Chapter 8 turns the attention to life insurance companies. Here, I apply the Boone indicator to the Dutch life insurance industry, because due to a lack of data on prices, competition could not be measured directly by any of the other concepts of competition. Based on the outcomes of the Boone indicator, I find that competition in this sector is weak. This is confirmed by other indirect indicators of competition, such as scale economies, profit margins and X-inefficiencies.

1.4 General conclusions

The first three chapters of this thesis allow us to draw the lesson that capital market imperfections in the mortgage market could hamper the beneficial effects of homeownership: namely, the more permanent relationship that it entails between homeowners and their job. Furthermore, I conclude that negative income shocks hamper residential mobility, at least according to the expectations of banks. This is in line with another Oswald hypothesis: that homeowners are less likely than renters to move to accept a job outside their own region after becoming unemployed: Homeowners are not likely to move after a negative shock in income. At the same time, negative shocks in the value of the residence seem to have little relevance for decisions to move or not.

Chapter 4 focuses on the transparency of the Dutch mortgage market in particular. It follows from the analysis that banks have more pricing power than non-banks, and thus that the level of competition in this market could be enhanced. Banks dominate this market in terms of market share, and they are price leaders. The non-transparency of the intermediaries segment of the Dutch mortgage market seems to be relevant, but in light of the issue of pricing power it is less important. In other words, this non-transparency does not translate into more pricing power for non-banks compared with that of banks.

Competition is the main issue in the remaining part of this study. The degree of competition in financial services, in general, and in the banking sector, in particular, is of the utmost importance, taking into account the crucial role of the financial system for economic development. Moreover, the banking system in the euro area is the main provider of financing, followed often at considerable distance by financial markets. A more competitive banking market drives down bank loan rates, as is shown in Chapter 7, adding to the welfare of households and enterprises. In this sense, the degree of competition in the banking sector can have an impact on the overall macroeconomic performance and social welfare of a country. The empirical results of Chapter 6 indicate that important differences exist between the degree of competition in the loan markets of a selected group of countries including the main global industrial powers and the countries with the most important national banking markets in the euro area. This result is important not only for economic policymakers (who strive to optimize the results of their policies) but also for banks in their role as providers of financing and for non-financial corporations seeking funds to finance their operations. It suggests that various countries (including France and the UK) may potentially gain from improving competitive conditions in their loan markets. The results over time indicate that indeed competitive conditions can improve. Consider, for example, the results for Japan, where loan market competition in more recent years reached levels comparable with some of the most competitive markets as recorded in the study.

The importance of banking competition for economic policymakers is rather straightforward, particularly for central banks and supervisory authorities implementing monetary and prudential policy. First, owing to its position at the centre of the financial

system, the banking sector plays a pivotal role in the transmission of monetary policy impulses. In a more competitive market for bank services, changes in the central bank's main policy rate will supposedly be passed through more strongly and quickly to bank interest rates. The results of Chapter 7 indicate that competitive conditions in banking markets are indeed significant for the transmission process of monetary policy in the euro area. Thus, competition policy in Europe may be important not only in order to bring about lower-cost provision of higher-quality banking services for European households and businesses, but also for enhancing the effectiveness of monetary policy such as implemented by the European Central Bank. Second, the soundness and stability of the banking sector may in various ways be influenced by the degree of competition. Since maintaining the health and stability of the banking system is of crucial importance for economic developments (as has been demonstrated once more by the financial crisis that shook the foundations of the global financial system in 2008), the issue of bank competition warrants close attention.

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2 The effect of homeownership on labour mobility in the Netherlands

With co-author: Pierre Koning

2.1 Introduction

The European labour market is often characterized by its low mobility, both within and between countries. Since the introduction of EMU, this problem has become more prominent, as the mobility of labour is one of the few short-term adjustment mechanisms still left. One reason for the low labour mobility in Europe is that there are cultural and linguistic barriers. This, however, does not explain the differences in interregional mobility within a country, or changes in labour mobility through time. One of the explanations for this may be that homeownership diminishes labour mobility and increases unemployment. The idea is that homeowners will not move to other regions when faced with an economic downturn, as they are more attached to their home. Also, they may be faced with decreases in housing prices. Thus, the probability of unemployment would be higher for homeowners.

Although the idea that homeownership has a positive effect on unemployment is based on micro-economic assumptions, most studies addressing the effect of homeownership on labour mobility and unemployment use macro- or meso-economic data. With aggregated data for the US, Green and Henderschott (2001) show that homeownership indeed constrains labour mobility, and thus increases unemployment for middle-aged cohorts, due to high transaction and moving costs involved. Using data of the OECD countries, Nickell (1998) finds similar results. However, these studies do not reveal the underlying behaviour of individuals. For example, it may well be that the lower job mobility of homeowners stems from higher job commitment, also reducing the risk of unemployment. This obviously cannot be measured in meso- or macro-studies.

Instead of using macro- or meso-economic data, we use longitudinal data of individual employees. This helps us to correct for spurious relationships and to identify

effects of homeownership on labour mobility, and vice versa. Movements on both the housing market and the labour market are used to estimate the impact of homeownership on job mobility as well as on the probability of becoming unemployed. We use longitudinal data that are collected by the Dutch tax department (Income Panel Research data (IPR); for 1989-1998). The IPR follows about 75,000 individuals over time. These individuals may change between jobs, between unemployment and employment, between homes and between regions. In modelling these transitions, several variables in the IPR may be useful: age, income, the number of children, gender, homeownership, job tenure, and housing duration.

Our analysis contributes to the literature on labour and housing-market mobility in a number of aspects. First, the IPR provides us with a rather unique panel allowing us to link individual labour and housing-market histories of a large sample of employees. The IPR data are comparable with the British Household Panel Survey, which also combines both types of information (see e.g. Boeheim and Taylor 2000). Second, and in contrast to many other empirical studies on job mobility, we also explicitly model the probability of homeownership, so as to correct for endogeneity bias. To minimize the biasing impact of distributional assumptions, this is done in a nonparametric fashion. Third, we analyze the impact of homeownership not only on job-to-job mobility, but also (and simultaneously) on the risk of becoming unemployed or a non-participant. This means we estimate a job-duration model with multiple ('competing') risks.

The chapter proceeds as follows. Section 2.2 describes the literature on the relationship between the housing market and labour mobility. Section 2.3 presents the empirical model, whereas the data are described in Section 2.4. Sections 2.5 and 2.6 present the estimation results and conclusions.

2.2 Theory and review

Two strands of literature describe the relation between the housing market and the labour market, depending on the macro- or micro-economic focus. Contributions in the first strand mostly try to explain labour migration. Here, the starting point is the Harris-Todaro model. Harris and Todaro (1970) develop a neoclassical model in which (international) migration is caused by geographic differences in the supply and demand for labour. The expected wage in regions with a limited supply of labour will be relatively high, which is the product of the complement of the unemployment rate and the wage if employed. Higher expected wages will attract a large inflow of labour from low-wage regions. This inflow of labour is mirrored by an outflow of capital.

Green and Henderschott (2001) add to this the role of homeownership to explain high unemployment and low labour migration. Homeownership influences labour migration in a number of ways. First, in regions with an economic downturn homeowners are faced with a drop in house prices, making homes highly illiquid assets. Moving to another region to find a job may therefore be costly for homeowners.

Second, high interest rates in times of recession may also result in a lock-in to below-market mortgages, with similar consequences for labour mobility. Third, high transaction costs may cause a decrease in labour mobility.

Various macro studies address empirically the relationship between homeownership and unemployment. For example, Nickell (1998) analyzes the relationship between homeownership and unemployment, using a panel of 20 OECD countries, from 1989 to 1994. With these data, Nickell shows that unemployment is (seemingly) positively correlated with homeownership, with an elasticity of 0.13. This means that a rise of homeownership of 10%-points results in an increase in unemployment of 1.3%-points. Green and Henderschott (2001) estimate an elasticity of 0.18, using aggregated data for the different states of the United States for the period 1970-1990. This estimate is close to the estimate of Oswald (2008, Chapter 2), with an elasticity equal to 0.2. He analyzes the relationship between homeownership and unemployment, using panel time-series data of 19 OECD countries, from 1960 to 1990. This relationship is found not only between countries, but also between the regions of France, Italy, Sweden, Switzerland, the US and the UK.

For the Netherlands, Hassink and Kurvers (1999) show that regions with high homeownership rates do not have high unemployment rates when tested on a meso economic level. They estimate the relationship between the unemployment rate and homeownership for 348 regions for the period 1990 to 1998, and find homeownership to have a negative impact on unemployment. This suggests a simultaneity problem: workers in regions with high economic growth and low unemployment will have higher incomes, and therefore be more likely to buy a house. Apparently, this is what is picked up in the estimation of the model.

Next to this, the relationship between labour mobility and the housing market is also studied on in a micro-economic context. Van Ommeren (1996) develops a theoretical search model in which the acceptance of a job offer depends not only on the direct gain in wage utility, but also on the once-only costs associated with moving residence and on search costs. These on-the-job search costs are modest for most professions, compared to the once-only costs associated with moving residence. The once-only costs associated with moving to another residence depend strongly on housing status (see e.g. Van den Berg 1992).

Recently, various empirical studies have addressed the relationship between the housing market and labour mobility, making using of individual longitudinal data. Using the British Household Panel Survey, Henley (1998) finds for the UK that unemployed persons are less likely than employed workers to move. Using the same data, Boeheim and Taylor (2000) arrive to a similar result. Using Probit models with pooled data for the UK, they find that regions with high unemployment show less home mobility. Also, they find that homeowners change their jobs less often than renters do. For the Netherlands, Van Ommeren et al. (2000) estimate a search model for job movers with (retrospective) panel data from the beginning of the nineties. They find that homeowners are less likely to move to another home than tenants are. Also, they

find no evidence that job and residential moves are mutually related. Van der Vlist (2001) concludes that homeowners are less likely to move to another home and to change jobs.

To sum up, the two strands of literature portray different, but not necessarily contradictory, pictures. Macro studies, using variation between countries or regions over time, suggest that high homeownership rates may lead to higher unemployment, particularly in periods of economic downturn. Micro studies, using (longitudinal) data of individuals or households, find homeownership to be associated with lower residential mobility and lower job-to-job mobility. This suggests that homeowners have more job commitment, and thus also may have a lower risk of unemployment. However, little is known on the exact causality of these effects. The question remains to what extent homeownership is driven by job commitment, and to what extent the reverse holds.

2.3 The Empirical Model

Our empirical model consists of two parts: the job-duration model and the housing model. In the job-duration model, we explain the individual labour market histories of a flow sample of employees. We use this information to identify the way in which various explanatory variables, including the housing state, affect labour mobility. Also, since individuals are followed over time, we control for unobserved heterogeneity. Within the context of duration models, this means that we assume a (nonparametric) distribution of random effects. The same principle holds for the housing model. Here, we explain a sequence of housing states, measured on a yearly basis. These data allow us to estimate a Random Effects Logit model.

Initially, the job-duration model and the housing model are treated separately, and without the inclusion of random effects. As a result, the estimated impact of the housing state on job mobility may be biased. Next, we estimate a simultaneous model in which the job duration model and the housing model are linked by the possible correlation of their random effects.

2.3.1 The job-duration model

This chapter uses hazard-rate models or— stated differently— duration models to examine the impact of homeownership on job spells. The hazard rate is defined as the rate at which an event takes place over a short period of time, given that this event has not occurred so far. The hazard rate, θ, measures the probability of leaving a job in a specific (small) time interval [T,T+dt], given that one occupies this job up to T:

$$\theta(t) = \Pr(T < t < T + dt \mid t \geq Tt) \tag{2.1}$$

In the job-duration model, the time interval *dt* is normalized to one month. Three types of transitions may take place: moving into another job, becoming unemployed, or becoming a non-participant. Therefore, the hazard rate out of employment is modelled into three possible competing risks. The impact of several exogenous variables (such as age, sex or income) may vary with respect to these risks.

The competing risks have a proportional (or loglinear) structure (see e.g. Lancaster 1990). b denotes the index of a particular risk (b = 1,2.. B). Thus, the risk into b at time t can be described as:

$$\theta b (t \mid y_t , X_t) = \exp [\alpha_b y_t + \beta_b X_t + \Psi (t)] \tag{2.2}$$

with $b = 1,2,3$,

in which y_t equals one if the individual is a homeowner at time t (and zero if one rents a home), and X_t is a matrix representing individual covariates that may change over time t. Some of these characteristics do not vary over time, but are defined at the beginning of the duration spell. Obviously, the most relevant variable— that of the housing state y— is time-dependent. Ψ denotes the impact of duration dependence. In the estimation of the model, we use a (nonparametric) step function for Ψ. Further, note that the variables that change over time only do so on a calendar-year basis. Residential transitions may thus coincide with job movements within a calendar year, whereas the exact sequence of events is unknown.

2.3.2 The housing model

We assume the housing state y to follow a Logit specification:

$$\Pr (y_t = 1 \mid X_t , h_t) = \frac{\exp[\gamma X_t + \Phi(t) + \delta h_t]}{1 + \exp[\gamma X_t + \Phi(t) + \delta h_t]} \tag{2.3}$$

$$\Pr (y_t = 0 \mid X_t , h_t) = 1 - \Pr (y_t = 1)$$

As becomes apparent from (2.3), we assume the housing probability to be driven by the same time-varying covariates as the job-duration model, X_t. In addition to this, we use the regional homeownership rate h_t as an instrumental variable, affecting only the housing status. In our data, we have 538 regions. Also, since h_t pertains to average group behaviour, it should be noted at this point that the assumptions for identification here are stronger than in models where instruments are measured on an individual basis (see Manski 1993). These assumptions are discussed in detail in Section 2.5, when we

come to the estimation results. Further, similar to (2.2), $\Phi(t)$ denotes a step function describing the impact of job tenure.

2.3.3 Unobserved heterogeneity

The IPR data we use provide us with a limited number of registered individual information. Obviously, more characteristics may be relevant in explaining the differences in e.g. the risk of unemployment, or that of moving to another home. In particular, job commitment — which is approximated by the job-tenure variable — may be measured imperfectly. The more important the impact of such unobserved heterogeneity, the larger the potential biasing impact of endogeneity effects. Endogeneity may arise if the choice of buying or renting a home is correlated with the risk of job transitions, becoming unemployed or becoming a non-participant.

Within the context of duration models, several methods have been developed to allow for unobserved heterogeneity. To minimize the impact of distributional assumptions, we adopt a nonparametric method that was introduced by Heckman and Singer (1984). They assume that a sample consists of two (or more) (unobserved) subsamples with different levels of time-invariant unobservable effects. Then, for all subsamples the corresponding weights are estimated, as well as the impact of unobserved differences on the hazard. This mass-point methodology is also used for the housing model. The unobserved differences in both models can then be linked, so as to allow for cross-correlation.

To allow for the presence of unobserved heterogeneity, we specify the risks (with index b) as a so-called Mixed Proportional Hazard (MPH) structure. The mixing is with respect to v, which can be interpreted as a time invariant random effect:

$$\theta_b(t \mid y_t, X_t, v_b)\exp[\alpha_b y_t + \beta_b X_t + \Psi(t) + v_b, \tag{2.4}$$

where $b = 1, 2, 3$.

We also extend the housing model with random effects, u:

$$\Pr(y_t = 1 \mid Z_t, u) = \frac{\exp[\gamma X_t + \Phi(t) + \delta h_t + u]}{1 + \exp[\gamma X_t + \Phi(t) + \delta h_t + u]} \tag{2.5}$$

$$\Pr(y_t = 0 \mid Z_t, u) = 1 - \Pr(y_t = 1)$$

To correct for endogeneity bias, we allow v_1, v_2, v_3 and u to be correlated. Similar to Heckman and Singer (1984), we do this by modelling K combinations of mass points for $\{ v_1, v_2, v_3, u \}$, with probability weights, P_1, P_2 .. $1 - P_1 - .. - P_{k-1}$, respectively.

Thus, the unknown distribution of { v_1, v_2 , v_3 , u } is represented by a nonparametric distribution with a finite number of points of support. The first point of support is normalized to {0, 0, 0, 0}. Thus, in this specification one has to estimate the parameters {α, β, γ, P_1, $P_{2..}$ P_{K-1}} as well as K-1 combinations of {v_1, v_2 , v_3 , u}. We do this by using Maximum Likelihood estimation. We start by estimating the model without unobserved heterogeneity (K=1; where there is only one point of support and P_1=1). Subsequently, we increase the number of points of support K iteratively, so as to improve the fit of the model. We perform a Likelihood Ratio test to determine the optimal K: that is, the number of points of support where the inclusion of an additional point of support { v_1, v_2 , v_3 , u }, together with an additional weight, improves the likelihood significantly.

Correlation between the v's and u is not explicitly specified in the model, but follows from the combination of mass points. In principle, 4^{K-1} points of support allow for all possible forms of correlation between the four random effects. However, this makes the empirical model computationally rather burdensome. Therefore, with increasing K, we add a fixed point of support for { v_1, v_2 , v_3 , u }. For K=2, this means that we only allow the random effects of the v's and u to be fully correlated. For $K > 2$, however, the model becomes more flexible. The mass-point methodology we use resembles that of Abbring (1997) and Holm (2002), who both estimate a bivariate model with limited dependent or duration data. Abbring (1997) studies the impact of punitive sanctions on the job-finding rate of unemployed employees. Both the job-finding process and the risk of being sanctioned are influenced by random effects that may be correlated. Analogously, Holm (2002) studies the effect of training on search durations. He also uses a random-effect approach, in both the training-allocation model and the hazard-rate model of finding a job.

2.3.4 The likelihood

As stated before, if we do not allow for time-invariant (unobserved) heterogeneity, the likelihood function of the model consists of two model parts that can be estimated separately. For ease of exposition, we first derive these two likelihood contributions, conditional on the unobserved components { v_1 , v_2 , v_3 , u }. Next, we integrate with respect to the unobserved mass points, so as to obtain the joint likelihood of the model.

Basically, our model explains two types of information:

Elapsed job durations:

T = the elapsed job duration, starting from the moment of inflow in the IPR sample.
d = a censoring indicator, which equals one if the job duration is right censored, and zero otherwise.

b = the destination that follows the job duration spell. This destination can be another job (v = 1), unemployment (v = 2), or non-participation (v = 3).

Housing state:

y_t = a dummy indicator, which equals one if a employee is a homeowner at time t, for t = 1..T.

We assume that the censoring times are stochastically independent of the corresponding job durations (i.e. we assume that censoring is independent). Since the job durations are exponentially distributed, conditional likelihood of $\{T, b\}$ of a particular individual can be described as:

$$f_T\,(T, b \mid y, X, v)\exp[\,-\,\Sigma_t^T\,\{\,\theta_1(t) + \theta_2(t) + \theta_3(t)\,\}\,] \times \qquad (2.6)$$
$$\times \quad [\theta_1(T)^{I(b=1)} \times \theta_2(T)^{I(b=2)} \times \theta_3(T)^{I(b=3)}]^{(1-d)},$$

where I (b = 1,2,3) is an indicator function of the event between parentheses. In particular, this concerns the destination following the jobs spell. The first part of (2.6) represents the survival probability. Within the context of our model, this is the probability of not having found another job, having become unemployed or having become a non-participant, up to time T. If T is censored (=1), then the likelihood of $\{\,T, b\,\}$ equals the survival probability. If T is uncensored (=0), then equation (8.6) consists of two parts: the probability of survival until T and the likelihood of a transition, into either another job (b=1), unemployment (b=2), or non-participation (b=3).

The individual conditional likelihood of y (which consists of a sequence of housing states over the job spell of an individual) that follows from the (panel) Logit model (2.5) is:

$$\Pr(\,y \mid X, h, u) = \Pi_t^T \;\; \Pr(\,y_t = 1 \mid X_t, h_t, u)^{I(y(t)=1)} \qquad (2.7)$$
$$\times \;\; \Pr(\,y_t = 0 \mid Z_t, h_t, u)^{I(y(t)=0)}.$$

The joint, individual likelihood of the observed variables — given the unobserved variables v and u — is obtained by multiplying (8.6) and (8.7). For the unobserved variables, we have K combinations of mass points for $\{\,v_1, v_2, v_3, u\,\}$, with probability weights, $P_1, P_2 .. 1 - P_1 - .. - P_{k-1}$, respectively. Thus, the joint, integrated likelihood can be written as:

$$L = \Sigma_i^K \;\; [\;\; P_i \times f_T(\,T, b \mid y, X, \boldsymbol{v}_i) \times \Pr(\,y \mid X, h, u_i\,)\;\;], \qquad (2.8)$$

where i indicates the mass-point combination. This expression is maximized with respect to $\{\,\alpha, \beta, \gamma\,\}$, as well as K mass points of $\{\,v_1, v_2, v_3, u\,\}$. Obviously, more

combinations of mass points may help in increasing the fit of the model. As stated before, we use a likelihood ratio test to determine the optimal number of combinations.

2.4 Data

The IPR database consists of a sample of about 75,000 individuals that are followed yearly by tax authorities, over the period 1989-1998. The IPR distinguishes between a number of possible housing and labour market states. The states for the labour market are based on individual income states, such as social assistance (SA) benefits, unemployment insurance (UI) benefits, income and no income. From these income states, one can derive the date at which a person becomes unemployed (SA or UI-benefit), or non-participant (no income or disability benefits). Further, since we know the identity of the employer, it is possible to keep track of job-to-job changes. Moving behaviour can be derived from address changes. Housing-market states consist of rental housing, homeownership, or other types (for example, housing for the elderly). These are observed on a yearly basis. For each individual, we observe a complete or incomplete job spell, together with various individual characteristics.

Our data consist of a flow sample of employees. This means that we select upon individuals entering into a job, avoiding the problem of left censoring. This leaves us with 9,426 observations of individual spells. The construction of a flow sample has one major advantage: for each employee we observe the exact job tenure. Obviously, this variable is crucial to identify the impact of job commitment, particularly the impact of (negative) duration dependence.

We also select upon employees that are either homeowners or tenants during the time span covered by the interviews. Thus, employees living in “other house types” are left out of the sample. As the vast majority of individuals in this category are students or pensioners, this does not reduce the size of our sample (consisting of employees) substantially.

Given the IPR, the following variables are used in the empirical analysis:

1. Age at the moment of entry in the sample.
2. Gender.
3. Higher or university education. This (proxy) dummy variable indicates whether a person has recently received a scholarship for higher or university education at the moment of inflow in the sample. Thus, this level of education is not observed for older employees.
4. Having children that receive child support, or not.
5. Having a partner who earns income, or not.
6. Marital state. Being married, or not.
7. Wage in logs.

Table 2.1 Description of variables (mean and standard deviation)

	Employees	
	Mean (fractions[a])	**Standard Deviation of Mean**
Job duration (including censored; in days)	596.25	7.44
Percentage of right-censored	0.232	0.004
Female	0.475	0.005
Working partner	0.345	0.005
Children	0.31	0.005
High education	0.176	0.004
Age (years)	30.60	0.106
Married	0.41	0.005
Wage	4.47	0.05
Percentage of homeowners	0.53	
Number of observations	9426	

[a]Unless defined otherwise.

Table 2.1 presents the characteristics of employees at the end of 1998. The majority of the employees are male (59%), 40% have a working partner, 31% have children, 7% have studied recently. As we have a flow sample, a large fraction of the sample consists of employees that are more likely to switch jobs, and/or start their working career. Consequently, on average, employees are rather young (34 years), and job durations relatively short (almost twenty months). The mean percentage of homeowners is 53%. In the first year of a job spell, we observe a mean percentage of homeowners of about 25%. Thus, a large portion of employees is observed buying a home during their job spell.

As we have yearly observations of housing state (measured at the end of calendar years) and monthly observations of labour market state, this may cause measurement problems. For example, an employee becoming unemployed may be faced with a drop in income and therefore have to sell his home and move to a rental home. Suppose this employee is registered as being a tenant for the whole year; the new housing state may then be misperceived as having caused an increase in job mobility. Similar problems arise if e.g. an employee decides to move to another region, and only temporarily moves to the rental sector. If then, after a while, the tenant becomes a homeowner again, the new housing state may seem to have caused an increase in job mobility. Thus, measurement errors may occur in some cases. However, there are no strong *a priori* beliefs that this will lead to a strong bias in our estimation results.

2.5 Estimation results

2.5.1 Two separate models

Initially — as previously stated— the job-duration model and the housing model are estimated separately, and without the inclusion of time-invariant random effects. This is the model for K=1. Obviously, no possible interaction exists between the job-duration and housing models when unobserved heterogeneity is not included in the model. Thus, the comparison between the two models helps us to identify the possible impact of endogeneity effects. Endogeneity can be tested by examining the difference in the coefficient estimates of homeownership in the two models — the null hypothesis being that this difference equals zero and there is no endogeneity (see e.g. Wooldridge 2002). At the end of this section, we will employ this endogeneity test.

We first assume that the hazard of leaving a job is not affected by duration in a job. Then, as we have a flow sample of employees, we allow for the presence of (negative) duration dependence in both models. The results of these two model versions are presented in the first two columns of Table 2.2.

The first column allows us to conclude not only that homeowners indeed experience fewer job-to-job transitions, but also that they have a smaller risk of becoming either a non-participant, or unemployed. Obviously, as will be shown in the sequel, these findings may be biased for various reasons. Further, most coefficients are in line with economic intuition. That is, the probability of job-to-job transitions decreases with age and the wage level. Also, we find that both women and married employees show less job-to-job mobility than other employees do. The risk into non-participation first decreases, and then increases with age. Students often have temporary jobs, which explains the relatively high inflow into non-participation of younger employees. On the other hand, older employees often enter into disability insurance, or into pre-retirement schemes. Remarkably, we find the 'higher education' dummy to have a positive impact on the risk of becoming a non-participant. This reflects the fact that this dummy is measured only for employees that are students, or have studied in the recent past. Again, this group often works in temporary jobs.

Less pronounced effects are found for the risk of moving into unemployment. Here, the (negative) impact of homeownership appears to be substantial, compared to the other variables. The higher the wage that is earned, the lower seems to be the probability of becoming unemployed. Employees with children have a significantly higher risk of becoming unemployed. These employees may, perhaps, work more often in part-time jobs to combine formal and informal labour activities, and are more vulnerable for unemployment.

Generally, the estimation results of the housing model are in line with economic intuition: the probability of being a homeowner increases with job duration, age and the

wage level. In addition to this, individuals who have children, are married or have a working partner are more likely to own a home. Students often live in rental homes. Remarkably, women are more likely to live more in owned homes than man are. Perhaps the female coefficient captures a difference in the education level— which we observe only to some extent— between men and women. In the Netherlands, the labour participation of women is still relatively low, compared to other countries, and the women that do participate are, on average, educated more highly than their male counterparts. As a result, the coefficient of women may be overestimated.

2.5.2 Duration dependence and job commitment

Until now, we have abstracted from the role of job tenure. Obviously, job commitment is crucial in understanding the decision of buying a home, as well as labour mobility. As job commitment and job security grow, individual employees will have a lower risk of becoming unemployed. Also, they will increasingly be faced with the risk of losing the returns to job-specific investments. Thus, less time will be spent searching for other jobs. The attachment to a job also reduces the probability of moving, which makes buying a home more attractive.

The results in the first and second columns of Table 2.2 illustrate the importance of job tenure as a proxy of job commitment, which is included as a (nonparametric) step function. The fit of the model increases dramatically, and all risks show that the job hazard strongly declines with tenure. A similar pattern is found in the housing model: the larger the job commitment, the more likely it is that one owns a home. This indicates that the decision of buying a home is strongly influenced by job commitment. Using job tenure as a control variable helps in reducing the estimation bias: we no longer find a significant impact of homeownership on job-to-job mobility. Also, the risk of non-participation is no longer affected by the homeownership dummy. For the risk of moving into unemployment, we still find a (smaller) significant negative impact. These findings suggest that the housing market is affected by the labour market— particularly the tenure of workers— rather than the reverse.

The result that there is no impact of homeownership on the risk of job changes may be quite strong for densely populated areas, where people can change jobs without changing residence. Also, moving costs may have been relatively low for homeowners. In the Netherlands, housing transactions are taxed by about 6%, but it may well be that— in the time span covered by the data— these costs were compensated by strong increases in housing prices. From the perspective of tenants, particularly those in the social renting sector, the costs of moving are often high: rental prices are kept artificially low, leading to long waiting lists. Once a new job in another region is accepted, and one has to move to another region, one may be faced with much higher rental prices in the private sector.

Thus, it seems that individual employees decide to change jobs without changing residence. In contrast to this, we do find a negative coefficient describing the effect of homeownership on the risk of becoming unemployed. In a way, this is not surprising: the consequences of this event may lead to a far more substantial and unanticipated decrease in income. Homeowners are not entitled to Social Assistance if they have own capital, and therefore have to break into their housing equity. Also, tenants are (partially) insured against loss of income, as they may receive higher rent subsidies to compensate for this. Thus, homeowners have higher incentives to prevent unemployment by investing more in job-specific capital.

2.5.3 The simultaneous model

Clearly, the inclusion of duration dependence helps in obtaining a better understanding of both labour market dynamics and the role of the housing market. It also helps us in disentangling duration dependence and the mixing distribution. If unobserved effects are important in the duration model, then the impact of genuine duration dependence is overestimated.

As becomes apparent from the third column of Table 2.2, unobserved time-invariant effects indeed are important. The simultaneous model, which is estimated with three points of support (up to $K=3$, the likelihood of the model increases significantly), again shows a dramatic increase of the fit of the model. Note, however, that this increase is almost fully confined to the housing model; random effects are important in explaining the housing state. This becomes apparent from the size and the significance of the coefficients of the parameters u_1 and u_2, the random effects in the housing model. Following the estimation results, three types of employees can be distinguished (at the three points of support), having unobservable characteristics that make them more or less likely to own a home. As a result of these characteristics, 32% is very likely to own a home (P_2) and 29% very unlikely to own a home (P_1).

Table 2.2 The (simultaneous) job-duration model and housing model — without and with unobserved heterogeneity (N=9426).

	Without unobserved effects; no job tenure included		Without unobserved effects; job tenure included		With unobserved effects; job tenure included	
	Estimates	Std. error.	Estimates	Std. error.	Estimates	Std. error.
Parameters job-duration model:						
Risk of job changes						
Constant	-0.8905	0.0302	-0.1830	0.0406	-0.1747	0.0550
Homeowner	-0.3460	0.0374	0.0397	0.0459	-0.0084	0.0555
1-2 years tenure			-1.7229	0.0583	-1.7199	0.0585
3-5 years tenure			-2.2921	0.0660	-2.2853	0.0661
More than 5 years			-2.7514	0.1365	-2.7302	0.1356
Age 25-35 years	-0.0575	0.0395	-0.2032	0.0512	-0.1903	0.0521
Age 35-45 years	-0.3181	0.0522	-0.4333	0.0667	-0.4333	0.0678
Age > 45 years	-0.5873	0.0691	-0.8013	0.0838	-0.8046	0.0849
Women	-0.1929	0.0310	-0.0988	0.0393	-0.0974	0.0395
Children	-0.2055	0.0380	-0.1682	0.0476	-0.1741	0.0478
Working partner	-0.0061	0.0389	-0.0482	0.0483	-0.0369	0.0484
High education	0.2504	0.0412	0.1184	0.0546	0.1139	0.0549
Log wage	-0.3727	0.0152	-0.1769	0.0182	-0.1757	0.0183
Married	-0.0356	0.0454	-0.0748	0.0562	-0.0727	0.0563
Random effects:	2nd point of support: v_{21}				0.0893	0.0624
	3rd point of support: v_{31}				-0.0820	0.0733
Risk into non-participation						
Constant	-1.6860	0.0455	-0.9838	0.0543	-0.9509	0.0758
Homeowner	-0.3392	0.0553	0.0119	0.0630	0.0529	0.0800
1-2 years tenure			-1.8735	0.0841	-1.8745	0.0841
3-5 years tenure			-2.2942	0.0941	-2.2983	0.0943
More than 5 years			-2.5341	0.1765	-2.5410	0.1774
Age 25-35 years	-0.1669	0.6430	-0.2977	0.0737	-0.3073	0.0749
Age 35-45 years	-0.4199	0.0800	-0.5153	0.0919	-0.5267	0.0932
Age > 45 years	-0.1159	0.0878	-0.2640	0.1042	-0.2774	0.1062
Women	-0.0449	0.0443	0.0455	0.0515	0.0454	0.0515
Children	-0.0271	0.0514	0.0230	0.0607	0.0222	0.0608
Working partner	-0.1483	0.0584	-0.1505	0.0664	-0.1536	0.0664
High education	0.3523	0.0553	0.2045	0.0653	0.2075	0.0656
Log wage	-0.5847	0.0172	-0.4100	0.0201	-0.4103	0.0201
Married	0.1658	0.0708	0.1185	0.0807	0.1134	0.0809
Random effects:	2nd point of support: v_{22}				-0.0813	0.0838
	3rd point of support: v_{32}				-0.0580	0.1018

Table 2.2 (continued)

	Without unobserved effects; no job tenure included		Without unobserved effects; job tenure included		With unobserved effects; job tenure included	
	Estimates	**Std. error**	**Estimates**	**Std. error**	**Estimates**	**Std. error**
Risk into unemployment						
Constant	-2.2779	0.0655	-1.5910	0.0722	-1.3931	0.0926
Homeowner	-0.8687	0.0785	-0.5837	0.0844	-0.3745	0.1173
1-2 years tenure			-1.6169	0.1051	-1.6199	0.1051
3-5 years tenure			-2.1531	0.1211	-2.1690	0.1214
More than 5 years			-3.3230	0.3584	-3.3640	0.3585
Age 25-35 years	0.2200	0.0802	0.0958	0.0868	0.0365	0.0885
Age 35-45 years	0.1971	0.0960	0.1342	0.1042	0.0431	0.1078
Age > 45 years	0.2077	0.1137	0.0447	0.1232	-0.0628	0.1275
Women	-0.0387	0.0646	0.0480	0.0692	0.0495	0.0694
Children	-0.0600	0.0746	-0.0247	0.0807	-0.0344	0.0810
Working partner	-0.2873	0.0786	-0.2796	0.0835	-0.2838	0.0836
High education	-0.0782	0.0960	-0.2122	0.1038	-0.1984	0.1045
Log wage	-0.2840	0.0383	-0.0941	0.0401	-0.0926	0.0402
Married	0.0366	0.0855	0.0180	0.0925	-0.0073	0.0926
Random effects:	2nd point of support: v_{23}				-0.3365	0.1119
	3rd point of support: v_{33}				-0.4086	0.1224
Unobserved heterogeneity: probability masses						
P_1 : 1st point of support					0.2863	0.0055
P_2: 2nd point of support					0.3184	0.0099
P_3 : 3rd point of support					0.3953	0.0100
Parameters of housing model:						
Constant	-3.2909	0.0175	-3.3851	0.0179	-9.1951	0.0904
1-2 years tenure			0.3334	0.0513	0.4922	0.0616
3-5 years tenure			0.7746	0.0297	1.4827	0.0475
More than 5 years			1.5174	0.0367	3.3260	0.0768
Age 25-35 years	0.3752	0.0103	0.4036	0.0104	1.1249	0.0327
Age 35-45 years	0.9179	0.0112	0.9332	0.0113	2.1337	0.0458
Age > 45 years	0.9872	0.0123	1.0296	0.0124	2.5575	0.0558
Women	0.3133	0.0075	0.2991	0.0076	0.3186	0.0252
Children	0.1062	0.0079	0.1008	0.0079	0.0219	0.0329
Working partner	0.6068	0.0073	0.6115	0.0074	0.6808	0.0297
High education	-0.2631	0.0155	-0.2315	0.0157	-0.4934	0.0352
Log wage	0.2885	0.0038	0.2446	0.0039	0.1837	0.0132
Married	0.9347	0.0087	0.9405	0.0088	1.4555	0.0395
% homeowners	2.7560	0.0264	2.7399	0.0267	1.7655	0.0935
Random effects:	2nd point of support: u_2				7.6423	0.0685
	3rd point of support: u_3				4.8388	0.0585
Mean log likelihood	-7.1992		-6.8322		-5.0056	

In contrast to this, the impact of unobserved time-invariant characteristics in the job-duration model is mostly found to be small. All coefficients, except for those of the risk into unemployment (which are denoted by v_{23} and v_{33}), are found to be insignificant. Moreover, for all risks the pattern of duration dependence seems to be unaffected. Not surprisingly, the estimated coefficients of the homeownership dummy remain almost unchanged. Thus, following a Hausman test on the difference between the coefficients for the two model versions, the null hypothesis that there is no endogeneity cannot be rejected (with P-values of 0.252 and 0,343 for the homeownership coefficient of the risks of job changes and into non-participation, respectively). These findings suggest that the potential biasing impact of unobserved, time invariant characteristics is not important.

Random effects however do matter with respect to the risk into unemployment. Employees with hidden characteristics that make them less (more) vulnerable for unemployment or non-participation, have a higher (lower) probability of owning a home. This seems to result in endogeneity effects: comparing the homeownership coefficients for the unemployment risk in the two models, we find (weak) evidence that the difference is significant (P = 0,074) — suggesting the presence of endogeneity effects. The intuition behind this result is that the lower the risk of a decrease in income, the higher the possibilities of buying a home. This effect may be reinforced by banks' selection criteria to grant mortgages. However, we still do find a significant (negative) impact of homeownership on the risk of becoming unemployed. This means that the unemployment risk is affected negatively by homeownership. As explained earlier, this can be driven by the stronger incentives homeowners have to invest in their jobs.

2.5.4 The regional homeownership rate as an instrumental variable

In our model, the instrumental variable, regional homeownership, serves as an important variable for identification, particularly for the simultaneous model. This rate is observed for 538 regions in the Netherlands. We find the regional homeownership rate to have a strong impact on the individual housing status: the higher the regional proportion of homeowners, the higher the individual probability of being a homeowner. However, there still are some conditions to be met for this variable to be used as a proper instrument. The regional proportion of homeowners is clearly a variable pertaining to average group behaviour. As shown by Manski (1993), using these variables to identify causality effects may be problematic for various reasons. Three types of effects that may lead to estimation biases are endogenous effects, exogenous effects and correlated effects.

Endogenous effects occur when the propensity of an individual to behave in some way is influenced by the behaviour of the group. Within the context of our model, individual homeowners may compare their social status with that of other homeowners

in their neighbourhood, and thus tend to invest in their careers. As a result, labour mobility of the individual homeowner may be small, as well as the unemployment risk. In that case, the regional proportion of homeowners would not be a valid instrument that is fully exogenous. However, in our model, such endogeneity effects are not likely to be important, as the proportion of homeowners is measured at the regional level, and not at the (relevant) neighbourhood level.

Exogenous (or contextual) effects occur if the propensity of an individual to behave in some way varies with exogenous characteristics of the reference group. Within the context of our model, these effects may result from individuals having a strong labour market position and earning a high income, moving to regions with high homeownership rates. To a great extent, these exogenous effects are controlled for in our model, by the income variable. Still, to the extent that some exogenous effects are not fully captured in our model, it is likely that most variation is between individuals within regions, and not between regions themselves. Thus, exogenous effects will be considerably smaller for the instrumental variable.

Correlated effects arise if individuals in the same group tend to behave similarly because they face similar institutional settings. In the context of our model, this would mean that unobserved neighbourhood characteristics affecting job mobility are correlated with the homeownership rate. In particular, good employment prospects may be concentrated in rich regions with a high proportion of homeowners. These effects are largely taken into account (by using income as a control variable) by the heterogeneity in our model. Further variation in job mobility between regions may be associated with differences in regional institutional settings (such as property taxes set by local authorities), but these are not very likely to be related to the proportion of homeowners.

None of the three types of effects thus seem to be substantial, as homeownership is measured at the level of communities, and not (smaller) neighbourhoods. The homeownership rate, to a great extent, also seems to be regulated by local authorities — and we control for various variables in order to avoid exogenous or correlated effects. We thus conclude that this variable can be used as a valid instrument for identification.

2.6 Conclusions

To sum up, our estimation results suggest that the housing decision is strongly affected by job commitment; the estimated impact of homeownership decreases strongly if we control for this effect. Thus, the housing market is affected by the labour market, rather than the reverse. In particular, we do not find evidence of homeownership affecting the risk of either job changes or the risk of non-participation. Also, and not surprisingly, endogeneity effects are not likely to be important for these risks. Individual employees decide to change jobs, irrespective of their housing status, for various reasons. First, given the population density in the Netherlands, people often change jobs without changing residence. Second, strong increases in housing prices may have compensated

the moving costs of homeowners. And third, the regulation of the social rental sector may result in high moving costs for tenants.

Similar to the risk of job mobility, we find no impact of homeownership on the outflow of the labour force. To a great extent, this concerns employees getting pensioned, or becoming disabled. It seems that these transitions are not driven by the housing state, and do not (directly) affect moving behaviour.

In contrast to job-to-job changes and the probability of becoming a non-participant, we do find a negative effect of homeownership on the probability of becoming unemployed. The explanation for this is that the decrease in income that comes with unemployment is far more substantial for homeowners than for tenants. In principle, homeowners are not eligible for Social Assistance and have to break into their housing equity. Moreover, tenants are (partly) insured against loss of income, due to the rent subsidy system. Thus, homeowners have a higher incentive to reduce the risk of becoming unemployed, particularly by investing more in job-specific capital.

To conclude, homeownership seems to stimulate job commitment in one way (lower risk of unemployment), but not at the cost of less job-to-job mobility. However, these findings alone will not allow us to conclude that homeownership does not affect labour market mobility at all. Institutional arrangements in the rental sector — particularly rental subsidies, and low prices in the social rental sector — may discourage labour mobility. From that perspective, labour mobility may be too low, both for homeowners and tenants.

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3 The importance of income and housing wealth shocks for residential mobility

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3.1 Introduction

This chapter shows that lenders' expectations about prepayment in home mortgage lending may have significant consequences for a borrower's cost of housing. We concentrate on prepayment as a result of residential mobility. One of the main consequences of moving residence is that it terminates the current mortgage contract prior to maturity. As a result, the mortgage lender may be left with additional costs of prepayment. Its funding of the current mortgage loan no longer matches the incoming flow of interest payments, necessitating a potentially costly reinvestment of its portfolio, while the interest rate for reinvestment may have decreased (see Dattatreya and Fabozzi 2001). The mortgage lender would like to pass on the actual costs of prepayment to the household, and the household would include the costs of prepayment in its decision to move. However, in the Dutch mortgage market, which is investigated in this chapter, the mortgage lender, instead of the borrower, incurs the costs of prepayment associated with unexpected residential mobility at the moment of prepayment (see Mercer, Oliver and Wyman 2006).[1]

Lenders in the mortgage market are forward looking. When setting the lending rate, they include considerations about possible prepayment of the household. Hence, Dutch mortgage lenders transfer the expected costs of prepayment to the mortgage borrower when writing up the mortgage contract. This leads to a mark-up on the lending rate, which depends on the expected residential mobility of the mortgage borrower prior to maturity. A higher expected mobility of the household gives a higher probability of prepayment and, hence, a higher mark-up on the lending rate. Its drawback is that the lender's expectations formation about residential mobility is based on imperfect

[1] In the UK, Spain, and Portugal, borrowers incur the costs of prepayment due to residential moves at the time of prepayment. This is not allowed in e.g. Denmark, France, Germany, Italy and the Netherlands.

information about the individual household. It leads to a distortion of the mark-up on the lending rate, so that pricing in the mortgage market does not fully reflect individual prepayment. Consequently, the user's cost of housing may not be at the optimal level, rendering the housing market less flexible.

This chapter considers explicitly the lender's perspective of prepayment. More specifically, its aim is to quantify the size of the mark-up on the lending rate, as a result of the lenders' expectation about prepayment due to mobility in the housing market. Residential changes may be affected by the borrower's loan-to-income ratio (liquidity constraint) as well as his loan-to-value ratio (collateral constraint). However, both constraints may change during the term of the mortgage contract. First, the household may have unexpected income shocks, resulting in changes in the loan-to-income ratio. Second, the value of the house may change, leading to a different loan-to-value ratio. The main unresolved question in the literature is whether households are more likely to move (and thus to prepay) in case of a relaxation of the liquidity constraint due to a growth in household income or in case of a less stringent collateral constraint due to an increase in housing wealth (as a result of rising house prices).

The chapter is related to two important strands of literature. First, it is related to studies that investigate the effect of (financial) constraints in the mortgage market on residential mobility. Cameron and Muellbauer (1998) recognize that ceilings on loan-to-income ratios could hamper migration between regions in the UK. Henley (1998) and Chan (2001) show that a low or negative housing equity impedes moving. Böheim and Taylor (2002) and Van Ommeren and Van Leuvensteijn (2005) show that changes in income and (regional) house prices may increase residential mobility. Second, this chapter is related to studies of the effect of financial constraints on the probability of prepayment. Ortalo-Magné and Rady (2006) show that credit constraints and income shocks are important factors behind the decision to prepay. Archer et al. (1996), Alink (2002) and Charlier and Van Bussel (2003) show that prepayment is largely driven by collateral and liquidity constraints. The novelty of this chapter is that it gives an estimate of the costs to lenders associated with expected residential mobility. It provides the mark-up on the lending rate that a household has to pay when it is expected to be relatively more mobile in the housing market.

Although many studies have been published on the determinants of the mortgage lending rate that individual households have to pay (see, for instance, Hendershott and Van Order 1987; Duca and Rosenthal 1994; Nothaft and Perry 2002; Archer et al. 2003; and Gary-Bobo and Larribeau 2004), there are no studies that estimate the mark-up to (the costs of) prepayment due to unforeseen residential mobility. The main identification problem is that the mark-up on the lending rate may be due to both the risk of prepayment and the risk of default. An additional complication is that a higher risk of default reduces the risk of prepayment. Usually, both risks cannot be disentangled empirically, due to a lack of suitable instrumental variables. This chapter applies a unique setting in which lenders do not face the risk of default, as they are insured against this event. We were able to control for default risk of households by

using administrative information of mortgagors who were covered for this risk by the Dutch National Mortgage Guarantee (NMG). All of the costs associated with default (such as delayed interest payments and the costs of auction) are reimbursed by this organisation (NMG 2004). Hence, mortgage lenders face only the costs of prepayment.

The chapter proceeds as follows. Section 3.2 describes the relevant Dutch institutions. Section 3.3 gives a theoretical model and Section 3.4 the empirical model. Section 3.5 describes the data. Section 3.6 provides the estimates. Section 3.7 concludes.

3.2 Dutch institutional setting

In the Netherlands, there are various types of mortgages (annuity mortgages, escrow mortgages, endowment mortgages, repayment mortgages, and a type for which there is no repayment). For all of these mortgages, the interest payments are fully tax-deductible, rendering it unprofitable to prepay the mortgage.[2] This chapter focuses on endowment mortgages, which was the most commonly used mortgage in our period of investigation.[3] Specific for this type of mortgage is that households build up financial capital during the lending term, by paying a monthly fixed amount of money.[4] In addition, households receive interest on their financial capital that is equal to the mortgage-lending rate. The accumulated financial capital equals the mortgage loan at maturity, so that borrowers can repay the full mortgage loan at the end of the lending term.

Usually, the lending term of an endowment mortgage is a period of 25 or 30 years. Within this term, the lending rate is fixed for a specified period at the discretion of the borrower. Frequently used fixation periods for endowment mortgages are one, two, five, ten, 15 or 20 years. When a period of a fixed lending rate ends and the mortgage loan has not yet been repaid, a new lending rate is set for a specific period. Typically, the government bond rate is used as a benchmark for mortgage lending rates.

Dutch households may prepay (part of) the loan before the end of the fixed lending-rate term. Basically, mortgage lenders can respond to prepayment in two different ways. First, they can respond ex post by charging a penalty for actual prepayment. Second, they can anticipate ex ante by setting a mark-up on the lending rate that depends on the expected (costs of) prepayment. The penalty ex post is more efficient, as it depends on

[2] Tax savings can be quite substantial. In the highest income tax bracket, 52 percent of the interest payments of mortgage loans are tax deductible. Or as Girouard et al. (2006) put it "Dutch households have strong incentives to maintain mortgages at high levels given the extremely favourable tax treatment of debt-financed owner-occupied housing."

[3] About 65 percent of the Dutch mortgage transactions involved an endowment mortgage.

[4] Part of this transfer is used to pay for the payment of an insurance premium. The lender requires a life insurance on part of the financial capital that has not yet been built up (the difference between the mortgage loan and the financial capital).

the actual behaviour of an individual borrower. However, a penalty implies switching costs for the borrower, rendering the lender less attractive than its competitors. All in all, a mortgage lender faces a trade-off between the ex post prepayment penalty and the ex ante mark-up on the lending rate.

Most lenders opt for a prepayment penalty. The prepayment penalty then is calculated as the difference between the discounted flow of remaining interest payments for the remaining period of the fixed lending rate and the discounted flow of interest payments at the current lending rate. Hence, households will be less inclined to prepay when the remaining term of the fixed lending rate is large or when there is a minor difference between their mortgage lending rate and the current market-lending rate.

Basically, there are five clauses that exempt borrowers from having to pay a prepayment penalty. 1) Destruction of the house. 2) Death of the borrower. 3) Adjustment of the lending rate to the current market rate at the end of fixed lending-rate term. 4) An annual prepayment of less than 10 to 20 percent of the original loan (the actual threshold may differ across lenders). 5) Selling of the home that serves as collateral due to the borrower moving residence. Hence, for each of these events, the mortgage lender incurs all costs of prepayment.[5]

We claim that it is not likely that there is prepayment for other reasons than residential change. In other words, in our empirical analysis the fifth clause is the main reason for prepayment for the endowment mortgages that we investigate. Home destruction can be ruled out, as it is a random and rare occasion (clause 1). Survival hazards of the household do not need to be accounted for, as we control for the age of the (head of the) household in the regression equation (clause 2). Furthermore, we focus on a set of mortgage contracts with a fixed lending rate of ten years, which does not allow households to reset the interest rate (clause 3). It is very costly for a household to prepay an endowment mortgage within the first 15 years of the contract (clause 4), since the household will not be exempted from tax payments if it prepays during this period for reasons other than residential change. Finally, the benefits of prepaying endowment mortgages are minor, as lower interest payments result in higher endowment payments to compensate for the lower discount rate. Overall, within the context of this study, residential change is the most likely reason for prepayment and is therefore the lender's greatest concern when setting the mortgage interest rate.

3.3 Theory

In the literature on optimal residential mobility, residential moves are assumed to be the result of long-term planning based on evaluations of permanent income, expected household composition, wealth formation and aging (see e.g. Amundsen 1985; Englund 1985; and Hardman and Ioannides 1995). Given the household's income, and the prices

[5] During the period 1996-2001 it was not common to keep the mortgage when moving.

of housing services and other goods, the household's objective is to determine the optimal housing duration and the optimal consumption of housing services (and other goods). The price of housing services depends on the mortgage's interest rate, r_0, agreed upon at $t=0$. In this section, we abstract both from demographic characteristics of the household (such as age) and from observed characteristics of the home.

Residential mobility can be described by a housing duration variable D, which is a function of the vector Z_t and X_t:

$$D = \theta(Z_t, X_t) \tag{3.1}$$

with $Z_t = (L_t / Y_t, L_t / H_t, Y_t)$, which is a vector that contains the loan-to-income ratio (L / Y), the loan-to-value ratio (L / H) and the gross household income (Y), and X_t is a vector of observed household-specific effects. L denotes the size of the mortgage loan and H indicates the house value. Usually, Dutch mortgage lenders apply the criterion that the maximum of L / Y is 4.5 and that the maximum of L / H is 1.25.[6] Home duration D depends positively on (L / Y) and (L / H). For a household that has one of these ratios close to the maximum, it is harder to find another house within the same regional housing market that has better characteristics and for which both constraints are still below the maximum.[7] Generally, borrowers can be constrained by a high L / Y and L / H at $t = 0$. Both constraints may be relaxed over the period of the loan, because of either an increase in household income (Y) or an increase in the value of the collateral (H). The third argument in equation (3.1) is that an increase in Y raises the likelihood to move and limits the housing duration. Higher-income households tend be further in their residential career and are therefore less likely to move.

We consider the costs of prepayment to the lender due to unforeseen residential mobility of the borrower at $t = 0$.[8] At $t = \theta(Z)$ there will be prepayment due to a residential change, and at $t = T$ the term of fixed lending rate expires. In addition, the lending rate in the market upon prepayment is $r_{\theta(Z)}$. The lender incurs a loss when $r_{\theta(Z_t)} < r_0$. This loss is taken over the remaining term of lending between $t = \theta(Z)$and $t = T$.

[6] Compared to other European countries, homeowners in the Netherlands can borrow against relatively high loan-to-value ratios. The maximum loan-to-value ratio for Dutch residences amounts to 125% of the property value. In France, the UK and Spain, the maximum loan-to-value ratio ranges between 100 and 110%, and in Germany and Italy it is around 90% (see Mercer, Oliver Wyman 2003).

[7] In addition, the buyer of a house has to pay an ad-valorem buyer transaction tax in the Netherlands (Van Ommeren and Van Leuvensteijn 2005).

[8] Basically, this loss to the lender is equal to the penalty a household has to pay in case of the prepayment being higher than 10-20% of the loan (the exact value differs between borrowers). See Section 2.2.

The mark-up on the lending rate at $t = 0$ is the loss over the period [$\theta(Z_t),T$], as expressed in:

$$Markup_0 = r_0 - r_{\theta(Z_t)} \tag{3.2}$$

The mark-up on the lending rate depends negatively on *L / Y* and *L / H*. As stated before, home duration *D* depends positively on *(L / Y)* and *(L / H)*. A change in income, Y, has a positive impact on the housing duration *D*. An increase in household income, Y, may improve the lending position of the household relative to other households; it thus may lead to an increase in the probability of moving.

So far, studies have estimated equation (3.1) only. Archer et al. (1996) show that households with a high payment-to-income ratio are less likely to prepay their mortgage, although the option to prepay would have a positive return. The advantage of equation (3.2) is that it gives a quantification of the perceived costs of prepayment by banks in relation to both constraints.

3.4 Empirical model

The purpose of this study is to quantify the effect of *L / Y* and *L / H* on the mark-up in the lending rate (equation (3.2)). The model we estimate is:

$$r_{ijt} - r^b_{ijt} = \alpha_i + \tau_t + \beta_1 \log(L_{ijt} / Y_{ijt}) + \beta_2 \log(L_{ijt} / H_{ijt}) + \beta_3 \log(Y_{ijt}) + \gamma' X_{ijt} + \varepsilon_{ijt} \tag{3.3}$$

where subscript *i* refers to the *i*-th lender, subscript *j* to the *j*-th borrower and subscript *t* to the *t*-th month. The dependent variable is the difference between the nominal lending rate of the mortgage loan, *r*, and government bonds' interest rate, r^b (both measured at the day the mortgage contract is formally signed). In this respect, the bond has the same term as the mortgage loan (in our analysis a period of ten years). We will refer to the difference $r - r^b$ as the spread. We include a dummy variable for the *i*-th lender, α_i, as well as a dummy for the *t*-th month (τ_t). *X* is a vector of observed household-specific effects, and the vector γ contains the corresponding parameters. ε is a stochastic error term that is identically and independently distributed.

The vector *X* contains the remaining control variables: five dummy variables for the age class of the household, and three dummy variables for apartment, overdue maintenance of the home and newly built homes. These variables may capture one of the other reasons for prepayment: destruction of the home. The effect of age can be twofold. First, it is included to control for the lower survival rate of older people, so that they have a higher probability to prepay. Second, older people may have a longer housing duration, so that they have a lower probability to prepay. Alink (2002) finds

that older people have a lower probability to prepay. Likewise, Charlier and Van Bussel (2003) find that older borrowers have a reduced probability to prepay, although the effect is hardly significant. A dummy for apartment is introduced, because Alink (2002) finds a positive effect of apartment on prepayment for five-year fixed interest rate mortgages with interest-only. Charlier and Van Bussel (2003) find a positive effect of apartment on prepayment risk for endowment mortgages. A home with overdue maintenance (that is determined by the borrower) has an increased risk of deterioration, with a concomitant loss in value. We therefore expect houses with back repair to have a higher interest rate. A dummy for new home is used to pick up the fact that new homes have a lower lending rate than existing homes.[9]

3.5 Data

Basically, the mortgage transactions we analyse are free of default risk. The data were provided by the NMG. This guarantee was set up by the Dutch government in the mid-1990s in order to stimulate homeownership for the lower segment of the Dutch housing market. In the Netherlands, buyers of a home may opt to insure their risk of default with the NMG. For a small insurance premium (0.15 percent of the mortgage loan) to be paid at the date of the mortgage transaction, they receive a discount on the lending rate in return (0.2 – 0.5%-points)[10], since they nullify the risk of default to the mortgage provider. Thus, part of the risks is covered by the NMG, but the prepayment risk for the lender remains. The criteria of eligibility for this guarantee are not particularly stringent.[11] First, the value of the mortgage has to be below 420,000 guilders in 2000 and 2001.[12] Thus, our analysis concentrates on the lower segment of the Dutch mortgage market. Furthermore, 12 percent of the maximum value of the loan is reserved for transaction costs such as transfer taxes and intermediation and notary fees.[13] The advantage of this dataset is that the information is free of measurement error, as it was used by the NMG to assess the eligibility of individual households.

We concentrated on endowment mortgages with a fixed lending rate of ten years at the start of the contract; we selected mortgages that were not used to refinance the

[9] In the Netherlands, it is common practice to have a discount on the interest rate on newly built homes that were constructed in the same building project (and purchased by different homeowners). Fixed costs are lower to the lender so that they can ask for a lower lending rate. These reductions can be substantial, around ten base points.

[10] The size of the discount is positively related to the mark-up that compensates for risk of default, so that households with a higher risk of default have a higher discount of the lending rate.

[11] These criteria are more stringent than the criteria for mortgages usually set by lenders. The maximum mortgage loan depends on the gross income of both the head of household and the partner. Furthermore it depends on the house value (NMG 2004).

[12] 1 Dutch guilder (DFL) is worth 0.45 euro.

[13] In 2002, the NMG required that the maximum share of gross income spent on housing is 28-37%.

home.[14] Furthermore, all lenders were required to be experienced in judging prepayment risk through transactions in this segment on a regular basis. We selected a subset of lenders that had mortgage loans in this segment in all months of the period of investigation (January 1996 – October 2001). We excluded 58 lenders and retained information on 66,698 borrowers from 14 lenders.

Table 3.1 provides the descriptive statistics of the variables that we use in the analysis. The average lending rate is 6.03 percent. The spread (the difference between the lending rate and the ten-year bond rate) is on average 0.80 percent. Borrowers are concentrated in the younger age cohorts, with about 20 percent being younger than 25 years, and about 70 percent being between 25 and 40 years of age. 17 percent of the mortgages are used for newly built property and 19 percent for apartments. About 4 percent are used for overdue maintenance. The household's gross annual income is about 76,000 guilders.

The value of the loan is on average 240,000 guilders, and the house value 237,000 guilders. For most of the mortgages, the loan-to-value ratio exceeds one. The dummies of this ratio indicate that it is skewed to the right. The loan-to-income ratio, the other financial constraint, is skewed to the right also. For about 22 percent of the mortgages, the loan-to-income ratio exceeds 3.75. Thus, a large number of households borrow close to their maximum loan capacity.

[14] This selection had the advantage that mortgages are homogenous in this respect. A period of ten years is the most commonly used period in our dataset. Households that expect to prepay at the end of the fixed lending-rate period will select themselves into a shorter term.

Table 3.1 Descriptive statistics; sample January 1996 – October 2001

Variable	Mean	Standard deviation	Minimum	Maximum
Lending rate	6.030	0.686	3.250	10.000
Spread (lending rate–ten-year bond's interest rate)	0.798	0.449	-1.970	4.370
Dummy variables for Age				
Dummy age ≤ 25 years	0.185	0.388	0.000	1.000
Dummy 25 < age ≤ 30 years	0.398	0.489	0.000	1.000
Dummy 30 < age ≤ 35 years	0.220	0.414	0.000	1.000
Dummy 35 < age ≤ 40 years	0.104	0.306	0.000	1.000
Dummy 40 < age ≤ 45 years	0.054	0.227	0.000	1.000
Dummy age > 45 years	0.039	0.193	0.000	1.000
Dummy newly built property	0.169	0.375	0.000	1.000
Dummy apartment	0.192	0.394	0.000	1.000
Dummy overdue maintenance of the home	0.042	0.200	0.000	1.000
Annual gross income of household (in HFL 1.000)	76.462	110.293	11.802	282.000
Value of mortgage loan (in HFL 1.000)	239.606	72.626	15.950	420.000
House value (in HFL 1.000)	236.691	69.041	36.000	826.391
Log(income of household)	11.192	0.308	9.376	17.153
Log(value of mortgage loan)	12.337	0.324	9.677	12.948
Log(house value)	12.329	0.313	10.491	14.662
Log(loan-to-value)	0.009	0.154	-2.358	0.511
Log(loan-to-income)	1.145	0.226	-4.439	2.142
Dummy variables for Loan-to-value ratio				
Loan-to-value ratio ≤ 0.75	0.057	0.232	0.000	1.000
0.75 < Loan-to-value ratio ≤ 0.80	0.023	0.149	0.000	1.000
0.80 < Loan-to-value ratio ≤ 0.85	0.031	0.175	0.000	1.000
0.85 < Loan-to-value ratio ≤ 0.90	0.039	0.193	0.000	1.000
0.90 < Loan-to-value ratio ≤ 0.95	0.047	0.213	0.000	1.000
0.95 < Loan-to-value ratio ≤ 1.00	0.084	0.278	0.000	1.000
1.00 < Loan-to-value ratio ≤ 1.05	0.110	0.313	0.000	1.000
1.05 < Loan-to-value ratio ≤ 1.10	0.369	0.482	0.000	1.000
Loan-to-value ratio > 1.10	0.240	0.427	0.000	1.000
Dummy variables for Loan-to-income ratio				
Loan-to-income ratio ≤ 2.75	0.239	0.427	0.000	1.000
2.75 < Loan-to-income ratio ≤ 3.00	0.119	0.324	0.000	1.000
3.00 < Loan-to-income ratio ≤ 3.25	0.137	0.344	0.000	1.000
3.25 < Loan-to-income ratio ≤ 3.50	0.144	0.351	0.000	1.000
3.50 < Loan-to-income ratio ≤ 3.75	0.140	0.347	0.000	1.000
Loan-to-income ratio > 3.75	0.224	0.417	0.000	1.000
Number of lenders	14			
Number of borrowers	66,698			

3.6 Estimates

3.6.1 All lenders

This sub-section discusses the estimation results of equation (3.3) presented in Table 3.2. It gives the estimated effect of the liquidity constraint and the collateral constraint on the spread, while controlling (among other things) for household income. We also consider a more flexible specification of equation (3.3), in which the collateral and liquidity ratios are replaced by dummy variables. For all estimated parameters we report heteroskedasticity-adjusted robust standard errors, which are clustered towards the lender.[15]

In the first specification, the estimated coefficient on the (log of the) loan-to-value ratio is statistically insignificant, whereas the (log of the) loan-to-income ratio has an estimated coefficient of –0.126. An increase of this ratio by 10 percent decreases the spread by 1.26 basis points.[16] It implies that households that are seriously constrained with respect to liquidity are less likely to prepay. Consequently, they have to pay a lower mark-up on the lending rate. In contrast, collateral constraints do not influence the mark-up on the lending rate. Interestingly, these estimates make it possible to consider the effect of loan and income on the spread. We can reformulate equation (3.3) as:

$$r_{ijt} - r_{ijt}^{b} = \alpha_i + \tau_t + \eta_1 \log(L_{ijt}) + \eta_2 \log(H_{ijt}) + \eta_3 \log(Y_{ijt}) + \gamma' X_{ijt} + \varepsilon_{ijt},$$

where $\eta_1 = \beta_1 + \beta_2$; $\eta_2 = -\beta_2$, *and* $\eta_3 = \beta_3 + \beta_1$. The estimated coefficients on the value of the loan, the value of the home and household income (all in logarithm) are $\hat{\eta}_1 = -0.115$ (t-value: –10.70), $\hat{\eta}_2 = -0.011$ (t-value: –0.82), and $\hat{\eta}_3 = 0.082$ (t-value: 4.05), respectively. The other explanatory variables remain unaffected.

[15] The variation of the lender dummies suggests that lenders have market power as a result of imperfect information of borrowers.

[16] 100 base points equals 1%-point.

Table 3.2 Estimates of equation (3.3)

Dependent variable: Spread (lending rate – ten year bond's interest rate)	**Parameter**	**t-value**	**Parameter**	**t-value**
Dummy variables for Age[a]				
25 < Age ≤ 30 years	-0.018	*-2.88	-0.012	-1.13
30 < Age ≤ 35 years	-0.011	-2.05	-0.007	-0.73
35 < Age ≤ 40 years	-0.010	-1.29	-0.007	-0.81
40 < Age ≤ 45 years	0.001	0.17	0.003	0.61
Dummy newly-built property [b]	-0.106	**-5.48	-0.012	**-4.57
Dummy apartment[c]	0.007	1.47	0.000002	0.00
Dummy overdue maintenance of the home[d])	0.012	*2.52	0.012	*2.02
Log(income of household)	-0.044	**-3.02	-0.040	**-3.14
Log(loan-to-value)	0.011	0.82	-	
Log(loan-to-income)	-0.126	**-7.34	-	
Dummy variables for Loan-to-value ratio[e]				
Loan-to-value ratio ≤ 0.75	-		-0.009	-1.03
0.75 < Loan-to-value ratio ≤ 0.80	-		-0.005	-0.57
0.80 < Loan-to-value ratio ≤ 0.85	-		0.007	0.93
0.85 < Loan-to-value ratio ≤ 0.90	-		-0.006	-0.68
0.90 < Loan-to-value ratio ≤ 0.95	-		-0.009	-1.08
0.95 < Loan-to-value ratio ≤ 1.00	-		-0.009	*-2.55
1.00 < Loan-to-value ratio ≤ 1.05	-		-0.018	*-2.20
1.05 < Loan-to-value ratio ≤ 1.10	-		-0.013	*-2.85
Dummy variables for Loan-to-income ratio[f]				
Loan-to-income ratio ≤ 2.75	-		0.087	**6.48
2.75 < Loan-to-income ratio ≤ 3.00	-		0.071	**6.87
3.00 < Loan-to-income ratio ≤ 3.25	-		0.056	**5.15
3.25 < Loan-to-income ratio ≤ 3.50	-		0.051	**5.67
3.50 < Loan-to-income ratio ≤ 3.75	-		0.035	**5.69
Intercept	1.582	**9.07	1.341	**9.30
Monthly dummies (68 dummies)	F(66604,68) = 942**		F(66593,68) = 941**	
Lender dummies (13 dummies	F(66604,13) = 303**		F(66593,13) =299**	
Adjusted R^2	0.514		0.514	
Number of explanatory variables	93		104	
Number of lenders	14		14	
Number of borrowers	66,698		66,698	

[a].Reference group: age over 45 years.
[b] Reference group: not newly-built homes.
[c] Reference group: remaining homes, other than apartments.
[d] Reference group: no back repair of home.
[e] Reference group: Loan-to-value ratio > 1.10.
[f] Reference group: Loan-to-income ratio > 3.75.
* Statistically different from zero at 5% level, ** Statistically different from zero at 1% level.

Next, we consider a more flexible specification with the eight dummy variables for the loan-to-value ratio and five dummy variables for the loan-to-income ratio (see the second column of Table 3.2). The loan-to-value dummies are jointly significant (F-statistic: 5.76; critical value: 5.65). However, only the dummy variables in the range 0.95 – 1.10 are individually significantly different from the reference category (loan-to-value ratio > 1.10). With respect to the reference category, the spread is 0.9 basis points (loan-to-value ratio: 0.95 – 1.00) and 1.8 basis points (loan-to-value ratio: 1.00 – 1.05) lower. It implies that borrowers in the reference category have a higher spread than the borrowers in the categories with lower loan-to-value rates.

The estimated coefficients on the dummy variables for loan-to-income ratio are jointly statistically significant at the 5%-level (F-statistic is 83.9). Their economic significance is quite substantial. There is a negative effect of the loan-to-income ratio on the spread. At maximum (for the loan-to-value ratio below 2.75), the spread is 8.7 basis points higher than the reference category (which is the loan-to-income ratio > 3.75).

With respect to the other control variables, we find that age has no influence on the spread.[17] Newly built homes have a spread that is 1.2 basis points smaller than that of other homes. Furthermore, the fact that a household has purchased an apartment does not affect the mortgage interest rate, partly because we have corrected for both borrower age and house value. This is in line with other empirical studies that show that the fact that a home is an apartment does not affect prepayment risk (see, for instance, Alink 2002). When maintenance of the home is overdue (a situation that is determined by the borrower), the spread increased by 1.2 basis points. Finally, we find that household income reduces the interest-rate mark-up significantly. A 1 percent higher income reduces the interest rate by 4.4 basis points (ceteris paribus on the loan-to-income ratio).[18] High-income households have a longer housing duration and are thus less likely to prepay (Abrahams 1997).

3.6.2 Robustness checks

This sub-section considers two robustness checks. First, from the 14 lenders we selected the six with the largest market share in this specifiek segment of the mortgage market. This selection reduces the sample by 27 percent to 49,967 observations. The first two columns of Table 3.3 present the estimates. They give the same impression as the overall sample.

[17] It is remarkable that age has a negative effect on the dependent variable in the first equation. The second, more flexible specification picks up the effect that starters in the housing market have mortgage loans closer to the maximum constraints of the loan-to-value ratio and the loan-to-income ratio.

[18] However, the marginal effect of the spread with respect to log(Y) is 0.082. This positive marginal effect of log(Y) is a composite of the negative effect of $\log(L/Y)$ (-0.126; see Table 3 2) and the negative effect of log(Y) (-0.044; see Table 3.2), the latter effect being weaker than the former.

Table 3.3 Estimates of equation (3.3), robustness checks

	Sample: 6 largest lenders				Included a dummy for increasing bond rates			
Dependent variable: Spread (lending rate– ten-year bond's interest rate)	**Parameter**	**t-value**	**Parameter**	**t-value**	**Parameter**	**t-value**	**Parameter**	**t-value**
Dummy variables for Age[a]								
Log(income of household)	-0.045	**-2.25	-0.040	**-2.30	-0.044	**-3.02	-0.038	**-2.99
Log(loan-to-value)	0.012	0.62	-		0.011	0.82	-	
Log(loan-to-income)	-0.120	**-5.34	-		-0.126	**-7.34	-	
Dummy variables for Loan-to-value ratio[b]								
Loan-to-value ratio ≤ 0.75	-		-0.002	-0.22	-		-0.002	-0.34
0.75 < Loan-to-value ratio ≤ .80	-		-0.010	-0.79	-		-0.001	-0.12
0.80 < Loan-to-value ratio ≤ .85	-		0.015	**2.31	-		0.015	**3.29
0.85 < Loan-to-value ratio ≤ .90	-		-0.008	-1.01	-		-0.004	-0.54
0.90 < Loan-to-value ratio ≤ .95	-		0.001	0.21	-		-0.002	-0.49
0.95 < Loan-to-value ratio ≤ 1.00	-		-0.003	-0.46	-		-0.003	-0.6
1.00 < Loan-to-value ratio ≤ 1.05	-		-0.008	-1.29	-		-0.008	-1.84
1.05 < Loan-to-value ratio ≤1.10			-0.007	-1.83			-0.007	**-2.61
Dummy variables for Loan-to-income ratio[c]								
Loan-to-income ratio ≤ 2.75	-		0.076	**5.15	-		0.082	**6.83
2.75 < Loan-to-income ratio ≤ 3.00	-		0.064	**6.74	-		0.067	**8.27
3.00 < Loan-to-income ratio ≤ 3.25	-		0.052	**4.39	-		0.053	**5.66
3.25 < Loan-to-income ratio ≤ 3.50	-		0.042	**5.16	-		0.047	**6.29
3.50 < Loan-to-income ratio ≤ 3.75	-		0.030	**7.24	-		0.032	**7.31
Dummy for period of increasing interest rate on government bonds					-0.116	**-2.47	-0.118	**-2.48
Monthly dummies (68 dummies)	F(49873,68) = 3383**		F(49873,68) = 3383**		F(66603,68) = 3300**		F(66603,68) = 3300**	
Lender dummies (13 dummies)	F(49873,13) = 35**		F(49873,13) = 35**		F(66603,13) = 62**		F(66603,13) = 62**	
Adjusted R^2	0.509		0.509		0.514		0.515	
Number of explanatory variables	93		104		94		105	
Number of lenders	6		6		14		14	
Number of borrowers	49,967		49,967		66,698		66,698	

[a] Estimated coefficients on five age dummies, dummy newly-built property, dummy apartment, dummy overdue maintenance of home and intercept are not reported.
[b] Reference group: Loan-to-value ratio > 1.10.
[c] Reference group: Loan-to-income ratio > 3.75.
** Statistically different from zero at 1% level.

The first column of this table shows that the loan-to-value ratio has no significant effect on the spread, whereas the loan-to-income ratio has about the same effect as in Table 3.2. The second column shows that both the dummies for loan-to-value (F(49951,8) = 11.8) and the dummies for the loan-to-income ratio (F(49951,5) = 114.3) are jointly significant. For the loan-to-income ratio below 2.75, the spread is 7.6 basis points higher than that of the reference category (ratio above 3.75).

As a second robustness check, we included a dummy variable for an increase in the government bond rate during the previous three months. The reason for doing so is that it may take some time between the offer of the mortgage lender (in terms of the size of the lending rate as well as further lending conditions) ($t=0$) and the signing of the mortgage deed at the notary ($t=1$). In case of a fall in the government bond rate during this period, the lending rate in the contract at the notary would be corrected for the decrease of the market lending rate at time $t=1$. However, in case the government bond rate increased in the previous three months, the lending rate in the contract would be equal to the offered lending rate at time $t=0$. As it usually takes about three months between tender and signing of the contract, we created a dummy that would equal one in case of an increase in the government bond rate during the previous three months and would equal zero in all other cases. The estimates in the last two columns of Table 3.3 show that the introduction of a dummy for a rise in government bond rates makes little difference compared with the outcomes presented in Table 3.2.

3.7 Conclusion

This chapter has considered the consequences of expected residential mobility for the lending rate of home mortgages. Residential mobility reflects the adjustment process between demand and supply in the housing market. Although a flexible housing market is beneficial for society, residential mobility also inflicts costs on the financial sector, due to the early (unexpected) termination of mortgages. In the Netherlands, the lenders incur these concomitant costs at the moment of prepayment, i.e. at the moment when properties are sold. Consequently, lenders want to be compensated for the risk of prepayment, by requiring a higher lending rate in advance, upon the moment of writing the mortgage contract.

This chapter has analysed how lenders valuate the importance of liquidity and collateral constraints for residential changes. We were able to address this issue due to the availability of a special dataset of the Dutch National Mortgage Guarantee with information on lending rates of endowment mortgages without the risk of default. For this specific type of mortgage, prepayment is mostly due to moving; this made it possible to analyse the consequences of the lender's expectation of residential mobility for the size of the mark-up.

The estimates of this chapter indicate that the liquidity constraint has a negative influence on the mark-up that is associated with prepayment. In other words,

households that are more constrained with respect to income have a lower risk of prepayment, so that they have a lower mark-up on the lending rate. Households with a loan-to-income ratio below 2.75 pay 8.7 basis points more than households with a loan-to-income ratio above 3.75. In contrast, the collateral constraint has very little effect on the mark-up.

This empirical outcome has wider implications. Since the variation in prepayment premiums in lending rates is strongly related to moving behaviour of households, we can relate the lending rate to lenders' expectations about residential mobility. Residential mobility can be the result of both an income shock and a shock in wealth due to an increase in the house value. Shocks in income are generated mostly at the household level. For example, heads of a household may improve their income by changing jobs. Partners may decide to participate in the labour force or they may quit their job to take care of the children. Shocks in income occur more frequently than shocks in wealth and are therefore considered a higher risk. Furthermore, shocks in housing wealth occur mostly at a regional economic level. These shocks can be substantial. In the period 1995-2005, real estate prices in the Netherlands more than doubled (NVM 2006). Although there are differences across regions, increases in house prices are likely to be very similar at the municipal level. Since most of the residential mobility takes place within a municipality (Everaers and Davis 1993), changes in housing wealth have no significant effect on the decision to move. This makes sense, because income changes may improve the relative position of households in the housing market. In contrast, overall increases in housing wealth due to a rise in real estate prices do not improve their relative position. All in all, lenders seem to consider a change in income a far greater risk to residential mobility than a change in the property value.

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4 Measuring transparency and pricing power in the Dutch mortgage market

4.1 Introduction

This chapter is an empirical study of the transparency of the Dutch mortgage market, focussing in particular on transparency in relation to the role of mortgage brokers or middlemen. Transparency is an important issue, as a lack of it impedes competition in the mortgage market; we therefore also analyse whether non-transparency in markets results in diminished competition and increased pricing power for lenders.

The chapter is in line with earlier literature on competition in the Dutch loan market (e.g. Den Butter *et al*. 1977; Fase 1995; Swank 1995; Toolsema 2002). Den Butter *et al.* (1977) is partly related to this chapter, as it gives an econometric model of the Dutch mortgage market with a demand- and interest-setting equation. Fase (1995) focuses on the uncertainty of measuring the loan rate and concludes that his empirical analysis supports the intuitive feeling that the rate of interest for bank credit is of great importance as an instrument to control aggregate credit supply. Swank (1995) concludes that the mortgage market still has an oligopolistic structure in the Netherlands, although competition has intensified significantly in recent years. Toolsema (2002), on the other hand, finds indications for perfect competition among banks in the Dutch consumer credit market.

Our empirical analysis of transparency is based on a simple model. Because of imperfect information about lending rates, consumers looking for a mortgage loan have to incur search costs. Consequently, lending rates may become dispersed across lenders, even when the mortgages are homogeneous. In addition to the search costs borne by consumers, lenders may incur agency costs, as they have imperfect information on the creditworthiness of borrowers. Banks may have lower agency costs than other lenders (insurers and pension funds), especially when borrowers have been their clients for an extended period of time. Imperfect information renders mortgage markets less transparent; the size of dispersion in lending rates across lenders provides an indication of the lack of transparency of a market.

This chapter may be considered as a follow-up study of Fase (1995), who states explicitly that lending rates may be dispersed across households. This chapter

introduces a new type of analysis of the Dutch mortgage market, by performing an empirical study of dispersion of the lending rate within and across mortgage suppliers.

We are able to exploit a dataset that contains administrative information on lending rates. We measure price dispersion for a homogeneous set of residential mortgages (endowment mortgages with a fixed lending rate for ten years) across lenders (banks, insurers and pension funds) for an extended period (January 1996 – September 2001). In addition, we focus on a market segment for which the borrowers are rather homogeneous with respect to risk of the mortgage. Our data are from mortgages in the lower segment of the Dutch mortgage market and pertain to borrowers who acquired insurance against default risk from the Dutch National Mortgage Guarantee (NMG). We selected the mortgages that are not used to refinance the home. As we focus on a homogeneous type of mortgage for a specific market segment, the advantage of our empirical analysis is that measurement problems do seem less pronounced than they usually are in related studies.

We find that lending rates are highly dispersed across lenders and that the within-lender dispersion across borrowers is relatively small. From these findings, we conclude that the mortgage market is not transparent. Prices remain dispersed after controlling for the government bond rate and characteristics of the individual borrower and the region. We find that prices at the lender level are more dispersed for mortgages sold by insurers and pension funds than for mortgages sold by banks. This result may be due to imperfect information on the side of borrowers (difference in transparency) and on the side of lenders (difference in agency costs between types of lender).

As lending rates are highly dispersed across lenders, this would indicate that a large proportion of customers are not well informed. Since this could impede competition in the mortgage market, we test the hypothesis that non-transparency results in less competition and more pricing power for lenders. For this hypothesis we need lender-level data. Therefore, we will use the averages for each lender by month. We estimate two models. First, we use market shares as an indicator for market power in order to test whether lenders with large market shares have higher interest rates. This would indicate pricing power. Second, a good indicator for pricing power of lenders is the price elasticity of the demand for mortgage loans. Lenders have pricing power when they are confronted with price-inelastic demand for loans. In that case, lenders have room for rises in the interest rate without losing market share to other lenders. Therefore, we estimate the price elasticity of the demand for mortgage loans. Given that we have found that price dispersion across banks is smaller in comparison to that of non-banks, we test whether the demand for loans provided by banks is more price-elastic than the demand for loans provided by non-banks.

This chapter is organised as follows. Section 4.2 gives a theoretical background and describes the empirical models. Section 4.3 provides detailed information on the dataset used. Section 4.4 examines the variation of the lending rates across borrowers and lenders over time. Section 4.5 gives the estimates. Section 4.6 concludes.

4.2 Theoretical background and empirical model

4.2.1 Transparency

Our starting point is the set-up of Fase (1995), who models the demand for short-term bank credit at the macro level. The model of Fase (1995) contains three equations; the first is a demand equation, in which the stock of outstanding bank credit depends on (transformations of) the volume of expected sales, the yield on long-term government bonds and the (unobserved) lending rate of the bank loan. Second, his model contains a lending-rate-setting equation, which has as explanatory variables the cost of capital and capital market conditions, because lenders operate in an oligopolistic setting. Basically, the lending rate for short-term bank loans depends on:

$$r^* = g(M), \tag{4.1}$$

where r^* is the unobserved lending rate at the macro level and M is a vector of variables (transformations of the discount rate, the yield obtainable on alternative earning assets, and the proportion of short-term deposits of the domestic sector in the banking system's total liabilities). Equation (4.1) is a macro equation, which relates aggregate phenomena in the capital market to the price setting of banks (see also Swank 1995). Fase (1995) includes in his model influences at household level on the lending rate at the macro level. To that end, he introduces a third equation that contains idiosyncratic effects on the lending rate that result from differences in lending opportunities among individual households.

Our empirical model for the mortgage market is based on the same principles, but the emphasis is reversed. In explaining the lending rate of mortgages, the major focus of our empirical model focuses on specific influences of individual lenders and borrowers, while allowing for macro influences. In this way, we are able to analyse empirically the dispersion of mortgage lending rates across lenders. We follow Fase (1995) by modelling a zone around the unobserved mortgage rate (r^*):

$$r_j = r^* + u_j, \tag{4.2}$$

where r is the observed mortgage lending rate. Subscript j refers to the j-th household. The spread of the zone is captured by the variation of u, which is an error term.

We extend equations (4.1) and (4.2) in the following way. First, equation (4.1) is modelled parsimoniously, by including a bond rate at the date of transaction of the mortgage (r_b), for which the maturity is equal to that of the mortgage (i.e. both have the same fixed term). It serves as a benchmark, as it is an interest rate without the normal risks of a mortgage. It can also be interpreted as an approximation of the lender's opportunity costs of extending a mortgage loan. In this respect, we follow Den Butter *et*

al. (1977) and Swank (1995), who include the bond rate in the lending-rate equation. Second, we allow for the possibility that mortgage lenders may set different lending rates for individual borrowers, as observable borrower characteristics reflect differences in risk. Hence, equations (4.1) and (4.2) become:

$$r_j = \gamma r_b + \beta' X_j + v_j, \tag{4.3}$$

where $u_j = \beta' X_j + v_j$. X_j is a vector of observable characteristics of the household, the home and the regional home market. Sub-section 4.5.1 motivates these variables in further detail. γ is a parameter; β is a vector of parameters related to X; v is an i.i.d. error term with standard deviation σ_v. We extend equation (4.3) by allowing for differences in the lending rate across lenders, which will be motivated below. The lending-rate equation then becomes:

$$r_{ij} = \alpha_i + \gamma r_b + \beta' X_j + \upsilon_{ij} \quad , \tag{4.4}$$

where subscript i refers to the i-th lender; α_i is a lender-specific effect. The standard deviation of α_i is referred to as σ_a. It is a measure of the between-lender variation of the lending rate, conditional on r_b and the vector X. We will explore the variation of α_i in greater detail below.

Transparency of the market

The first aim of the empirical analysis is to estimate dispersion of the lending rate across lenders as a measure of transparency in the mortgage market. The variation of α_i across lenders will be limited when consumers' search costs are zero and the mortgages in equation (4.4) are homogeneous (for similar mortgages with a lending rate for the same fixed term). In that case, variation, if any, is likely to be small and limited to differences in operating costs across lenders.

There is a vast literature that explains the equilibrium price dispersion for homogeneous products by differences in consumers' search costs. When all consumers have equal search costs, then the equilibrium is the monopoly price (Diamond 1971). However, when consumers are heterogeneous with respect to their search costs, there will be an equilibrium price distribution (e.g. Salop and Stiglitz 1977; Lach 2002). It is expensive for borrowers to get an exhaustive overview of the lending rates for all lenders that operate on the mortgage market. Generally, consumers are not experienced buyers of mortgages; it is expensive for consumers to learn through frequent transactions from which lender they should purchase at the lowest lending rate. We argue that there are no indications that borrowers have equal search costs, which

implies that lending rates may be dispersed due to a lack of transparency of the mortgage market.

Middlemen

Next, we consider the role of middlemen and their influence on transparency in the mortgage market. Basically, there are two types of information channels in the Dutch mortgage market. As in other countries, banks, insurance companies and pension funds are suppliers in the Dutch mortgage market (Merriken 1988). A striking difference between insurance companies and pension funds, on the one hand, and banks, on the other, is the distribution channel used to sell mortgages. The former sell mortgages mainly through middlemen, whereas the latter sell relatively more by direct face-to-face contacts at the desk. De Haas *et al.* (2000) find that in 1999 large banks used middlemen as a distribution channel for only 20 percent of their transactions in mortgages. For small banks, this percentage was at most 70 percent. According to NERA (1999), insurers distribute up to 79 percent of their products through intermediary channels, such as affiliated agents, brokers, and even banks (10 percent).

One could argue that middlemen increase the transparency in the mortgage market, so that dispersion of the lending rate across lenders is limited. Middlemen may provide borrowers with information about lending rates for a large part of the lending market (insurance companies, pension funds and banks), thus forcing mortgage lenders towards limited price dispersion across lenders. Hence, we expect that dispersion in the mortgage market cannot be very large.

However, there are two major drawbacks to the use of middlemen. First, middlemen may be disinclined to provide exhaustive information on lending rates because of bonuses, provisions and discounts they may receive from certain lenders. As a consequence, price dispersion of lenders that make use of middlemen is likely to increase.

Second, banks may have more extensive and adequate information about borrowers than middlemen have. It is more difficult to screen borrowers for creditworthiness through middlemen than by means of face-to-face contact at the desk. Middlemen provide limited information about the borrower, while lenders who meet clients at the desk are able to acquire more specific information. A bank may also have access to additional information about the borrower if that person has been the bank's client (e.g. by having an account or a credit card) for an extended period. The testable implication is that σ_a will be smaller for banks that make use of additional information channels than for insurers and pension funds that make use of middlemen only.[1]

[1] This is an indirect way of testing the role of middlemen. We have no additional information about middlemen to test the hypothesis directly.

Homogeneous mortgages

We consider dispersion of the lending rate for a set of homogeneous mortgages. This refers both to the fixed term of the lending rate and to the type of mortgage. An additional complication is that there may be a measurement error, due to the lapse of time between the offer of the fixed lending rate and the formal signing of the mortgage contract at the notary. However, offers of fixed lending rates usually contain a clause to the effect that the actual lending rate at the date of signing the contract will be entered in the mortgage contract when it is below the initial offer rate, while the official offer rate is used when actual market rates have meanwhile increased. These changes are usually due to capital market developments that can be measured by changes in the rates of government bonds. Hence, lending rates may be contaminated by measurement error in times of an increase in the official mortgage rates of lenders, as they may refer to the lending rate offered some months ago, for which the dates differ across borrowers. In contrast, the lending rates in periods of price decrease are free of measurement error, since they refer to the actual lending rate at the transaction date of the mortgage loan.

4.2.2 Pricing power

The second aim of the chapter is to test for differences in pricing power between banks and non-banks. According to the seminal papers by Klein (1971) and Monti (1972) on banks' interest-rate-setting behaviour, banks can exert a degree of market pricing power in determining loan rates. The Monti-Klein model demonstrates that interest rates on bank products with smaller demand elasticities are priced less competitively. The Monti-Klein model can be interpreted as a model of imperfect (Cournot) competition between a finite number of lenders (see Freixas and Rochet 1997). Consider the case of N lenders (indexed by n=1,….,N) that have the same cost function:

$$C_n(D,L) = \varphi_D D + \varphi_L L \qquad n=1,\ldots,N , \tag{4.5}$$

where cost, C, depends on the total amount of deposits, D, and the total amount of loans, L, and their respective average costs, φ_D and φ_L . A Cournot equilibrium of the banking sector is then equal to a N-tuple of vectors $(D_n^*, L_n^*)_{n=1,\ldots,N}$ such that for every n, (D_n^*, L_n^*) maximizes the profit of bank *n*, taking the volumes of deposits and loans of other lenders as given. Each lender maximizes its profits, π, and this results in the following equation:

$$\text{Max } \pi = \{(r(L_n + \textstyle\sum_{m\neq n} L_m^*) - r_b) + r_b(1-\alpha) - r_D(D_n + \textstyle\sum_{m\neq n} D_m^*)\, D_n - C_n(D_n,L_n)\} \tag{4.6}$$

$$(D_n, L_n) ,$$

where α stands for the compulsory reserves as percentage of deposits D.
The first-order condition to loans, L, becomes:

$$\partial \pi_n / \partial L_n = r'(L^*) L^* / N + r(L^*) - r_b - \varphi_L = 0. \tag{4.7}$$

Now the elasticity of the demand for loans, e_L, is introduced:

$$e_L = r L'(r) / L(r) < 0. \tag{4.8}$$

Lenders set their loan interest rates by solving equation (4.7):

$$r - (r_b + \varphi_L) / r = 1 / (N e_L(L)) \tag{4.9}$$

Equation (4.9) is simply the adaptation of the banking sector to the familiar equality between Lerner indices (price minus cost divided by price) and inverse elasticities. The greater the market power of the bank on loans, the smaller the elasticity in absolute terms and the higher the Lerner Index. Using this model, we estimate the following two equations:

$$r_{it} = \lambda_t + \delta' X_{it} + \varphi\, r_b + \varepsilon_{it} \tag{4.10}$$

$$log(D_{it}) = \eta_i + \kappa\, \varepsilon_{it} + \tau\, r_b + \mu_{it}\ . \tag{4.11}$$

In these equations, the demand for loans, D_{it}, depends on the residual of equation (4.10), ε_{it}, the bond's interest rate, and lender effects, η_i. We test whether κ for banks is smaller than the κ for non-banks. As an increase in the interest rate curbs demand for mortgage loans, we expect κ to be negative.

4.3 Data

Our empirical analysis is based on a specific part of the Dutch mortgage market, as we make use of data provided by the National Mortgage Guarantee (NMG) ('Nationale Hypotheek Garantie'). The Dutch government set up this guarantee in the mid-1990s in order to stimulate homeownership for the lower segment of the Dutch home market. In the Netherlands, homebuyers may opt to insure the risk of default with the NMG. They pay a small insurance premium (0.15 percent of the mortgage loan) at the date of transaction of the mortgage and receive a discount on their lending rate in return (0.2 to 0.5%-points), since they pose no risk of default to the mortgage provider. Thus, the risk of default is covered by the NMG, but the repayment and prepayment risks remain for

the lender. The eligibility criteria for this guarantee are not stringent.[2] The value of the mortgage had to be below 420,000 guilders in 2000 and 2001, and the loan-to-value ratio could not exceed 88 percent.[3] [4] Thus, our analysis concentrates on the lower segment of the Dutch mortgage market.

The NMG provides a guarantee against the risk of default. In case of default of the homeowner, the NMG is liable for the remaining debt. The NMG will make arrangements with the homeowner to pay back this sum to the NMG over an extended period of time. Between 1995 and 2001, about 393,000 households obtained an NMG guarantee; of these, 194 (about 0.05 percent) defaulted in those years. In the same period, the guarantee of the NMG gained nearly countrywide coverage.[5] The NMG estimated that in 1997 25 percent of the total mortgage market actually acquired an NMG guarantee. In 2001, this percentage had increased to 26 percent (NHG 2002). The potential market share is based on the value of the home, taking into account the additional costs that must be made to acquire the home and that must be financed by mortgages.

We have access to data from the NMG over the period January 1995 – October 2001. Our dataset contains all transactions of homeowners who received the guarantee by the NMG in this period. The NMG data serve an administrative purpose, as they were used to assess the eligibility of individual households. Each case contains information on the borrower's characteristics, which includes gross annual income (distinguished by head of household and partner), address of the home, all necessary aspects of the mortgage contract (name of mortgage lender, lending rate, type of mortgage, size of the loan, and date of transaction), and some household characteristics (date of birth of head of household and partner, type of home, and number of homeowners). The date of transaction of the mortgage loan is the first day on which the borrower starts paying interest payments to the lender.

We linked our data on households with two other datasets: a dataset pertaining to the municipality and data with daily information on the ten-year government bond rate.[6] The municipality data, collected by Statistics Netherlands, were available for 1999 only.[7] We used municipality-level information on the population density, the number of inhabitants in the municipality, and the average value of homes in a municipality as

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[2] These criteria are more stringent than the criteria for mortgages that are usually set by lenders. The maximum size of the mortgage loan depends on the gross income of both the head of household and the partner. Furthermore, the maximum size depends on the value of the home (NMG, 2002).

[3] In 2002, the NMG required that a maximum of 28-37 percent of gross income (depending on household income and interest rate) was spent on housing.

[4] 1 Dutch Guilder (DFL) is worth 0.45 euros.

[5] A few large municipalities joined the NMG during our period of investigation: Groningen in January 1999, Rotterdam in January 2000 and Arnhem mid 2001. The NMG reached full countrywide coverage in 2001.

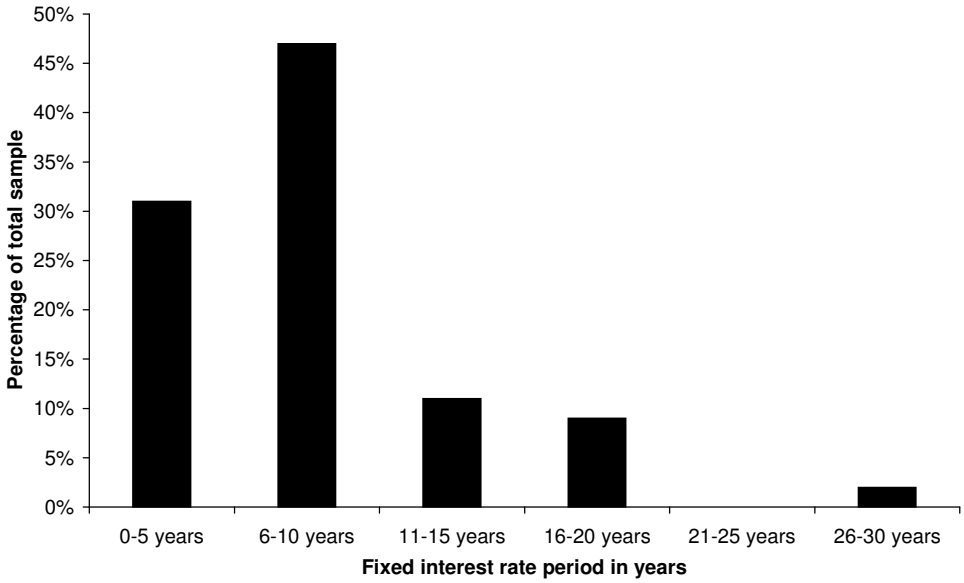
[6] Statistics Districts and Neighbourhoods 1999.

[7] Except for the average WOZ value, which is available for January 1st 1995.

used by the tax authorities (in Dutch: "WOZ-waarde"). The value used by the tax authorities is on average considerably lower than the market value. The daily data on the ten-year government bond rate were collected by Dutch Central Bank. We matched the government bond rate with the transaction date of the mortgage loan.[8]

In addition, we determined whether the lender was a bank, insurance company or pension fund. Our categorization of banks is based on the definition of Bankscope (for banks) and the definition of the Pensions and Insurance Supervisory Authority of the Netherlands, the supervising body of insurance companies.

Figure 4.1 Distribution of the fixed interest-rate period (in years), January 1996 – October 2001; N = 386,335



Our gross sample of household data consists of 386,335 mortgages of dwellings covering all maturities. Figure 4.1 gives the distribution of the mortgages' fixed interest-rate period. The largest class of mortgages is that of a ten-year period with fixed lending rates (154,874 cases or 40 percent of the gross sample). We selected these ten-year mortgages. Second, we excluded the cases for which the income of the head of household was not reported as well as the cases for which the mortgages were used to refinance the home. Third, cases observed in 1995 were excluded because not all explanatory variables were available for that year. Finally, cases from October 2001 were excluded because information was missing on the dates at the end of that month,

[8] Statistics T3.8.1 Market interest rates, Table 3.1.3.

which could affect the analyses with the monthly lending rates in Section 4.4. Eventually, our sample was reduced to 130,842 cases, which were observed in the period January 1996 – September 2001 (69 calender months).[9] For these cases, 65 percent of the mortgages are based on endowment, 32 percent are other mortgages (including escrow mortgages) and 3 percent are annuity mortgages. In order to have a homogenous type of mortgage (so that there are no measurement errors due to differences in the type of contract), we restricted our sample to the endowment mortgages. This resulted in a sample of 84,727 cases, which are used in Section 4.4 and Sub-sections 4.5.1 and 4.5.2.

Table 4.1 Mortgages by type of lender

Lender	Number of lenders	Number of borrowers	Percentage of mortgages
Banks	21	59.434	70
Insurance companies	25	10.070	12
Other lenders	26	15.223	18
Total	72	84.727	100

This sample may be distinguished by type of lender, i.e. banks, insurance companies, and other lenders. Table 4.1 gives the mortgage distribution by type of lender in our sample. Banks provide about 70 percent of the mortgages, insurers 12 percent, and the other lenders 18 percent. There are 72 mortgage lenders: 21 banks, 25 insurers and 26 other suppliers (including pension funds).

As indicated above, our sample focuses on the lower part of the Dutch mortgage market. The distribution of mortgages by type of provider in our sample therefore differs from that of the total mortgage market. Statistics Netherlands reports that, overall, banks have about 45% of the market, insurers about 15% and other suppliers about 40% of the market between 1996 and 2001.

We analyse dispersion of the lending rate by type of lender separately. Our analysis in Sub-section 4.3 is based on information of 59,434 mortgages sold by banks and 25,293 mortgages sold by insurers and pension funds. In addition, we distinguish periods in which the bond rate decreased from periods that featured an increase in the bond rate. We constructed a variable that has the value of one when the bonds' interest rate goes up compared with the preceding two months and the value of zero when this interest rate decreased compared with the preceding two months. The bond market interest rate is used as an exogenous variable that indicates whether the market was going up or down, which is in line with Toolsema and Jacobs (2001). Den Butter *et al.* (1977) and Swank (1995) demonstrate the importance of the capital market interest rate for the mortgage rate charged.

[9] In addition, we omitted a few cases that had an outlier in the lending rate (13 cases with a lending rate above 15.0 percent or below 3.0 percent), the income of the head of household (four cases) and the partner (two cases), the number of homeowners (six cases), and the premium deposit (two cases).

Table 4.2 Descriptives

Variable	Mean	Standard deviation	Minimum	Maximum
Characteristics of mortgage				
Lending rate (in percentages)	6.02	0.65	3.25	10.00
Dummy bank	0.70	0.46	0	1
Characteristics of borrower				
Log(value of mortgage)	12.34	0.335	9.68	12.95
Log(gross income of head household)	10.82	0.32	7.48	13.73
Log(gross income of partner + 1)	6.31	5.16	0	13.45
Loan/(value of home)	1.02	0.13	0.09	1.92
Loan/(gross income head + gross income	3.23	0.65	0.01	8.52
Dummy age $\leq$ 25 years	0.19	0.39	0	1
Dummy 25 < age $\leq$ 30 years	0.40	0.49	0	1
Dummy 30 < age $\leq$ 35 years	0.22	0.41	0	1
Dummy 35 < age $\leq$ 40 years	0.10	0.30	0	1
Dummy 40 < age $\leq$ 45 years	0.05	0.22	0	1
Dummy 45 < age $\leq$ 50 years	0.03	0.16	0	1
Dummy age > 50 years	0.01	0.10	0	1
Dummy 1 borrower	0.29	0.45	0	1
Log(instalment payments + 1)	4.96	5.52	0	12.24
Log(premium deposit + 1)	0.81	2.52	0	12.04
Characteristics of home				
Dummy existing home	0.84	0.37	0	1
Dummy apartment	0.20	0.40	0	1
Dummy back repair of the home	0.04	0.19	0	1
Characteristics of municipality				
Population density per square kilometre (in	0.17	0.17	0.03	0.65
Number of inhabitants (in 10,000)	1.08	1.43	0.01	7.27
Log(average value of homes) (in DFL 1000)	5.10	0.22	4.47	6.12
Benchmark interest rate				
Interest on ten-year government bonds	5.24	0.61	3.73	6.58
Median lending rate	6.07	0.63	4.40	7.40
Dummy non-banks	0.56	0.50	0.00	1.00
6-month moving average market share by	0.03	0.05	0.00	0.22
Log(demand for loans) by lender	14.35	1.57	10.98	18.96
Number of observations	84,727			

4.4 Dispersion of the lending rate

This section examines the dispersion of the lending rate and its development over time. We focus on cross-sectional variation within the month of transaction of the mortgage. Even though we use a narrowly defined set of mortgages, we find that the lending rate varies substantially across lenders and borrowers.

Between-lender dispersion

First, we consider the variation in lending rate across lenders. We calculated the average lending rate, $\bar{r}_{it}$, for each of the lenders (subscript *i*) during that month (subscript *t*). For each month, we determined for $\bar{r}_{it}$ a 95 percent interval estimate across all of the lenders. The average width of the interval over all months is 0.96%-point.[10] This provides a first indication that the dispersion of the average lending rate across lenders is quite substantial.

Next, we are interested in the skewness of the distribution of the average lending rate across the lenders, for which we compare the average and the median of the distribution. For each month *t*, we calculated the average of $\bar{r}_{it}$ (across lenders) and the median of $\bar{r}_{it}$ (across lenders) that we refer to as $\bar{r}_t$ and ξ_t^{50}, respectively. The average of $\bar{r}_t - \xi_t^{50}$ over all months equals –0.011%-point, which indicates that the distribution (across lenders) of the average monthly lending rate is slightly, but insignificantly skewed to the right; it has a tail on the left-hand side of the distribution.[11]

Next, as a robustness check of the results presented above we examine the development of the between-lender dispersion of the lending rate over time. In this respect, we use the median lending rate (ξ_{it}^{50}) for each lender and each month. We do not apply the average lending rate, $\bar{r}_{it}$, as the median is less sensitive to outliers. For each month and each lender, we calculated the median lending rate ξ_{it}^{50} across its borrowers. For each month, we determined the 10th, 50th and 90th percentile of the median lending rate ξ_{it}^{50} across the distribution of lenders. Figure 4.2 shows the development of these three percentiles over time. The difference between the 90th and

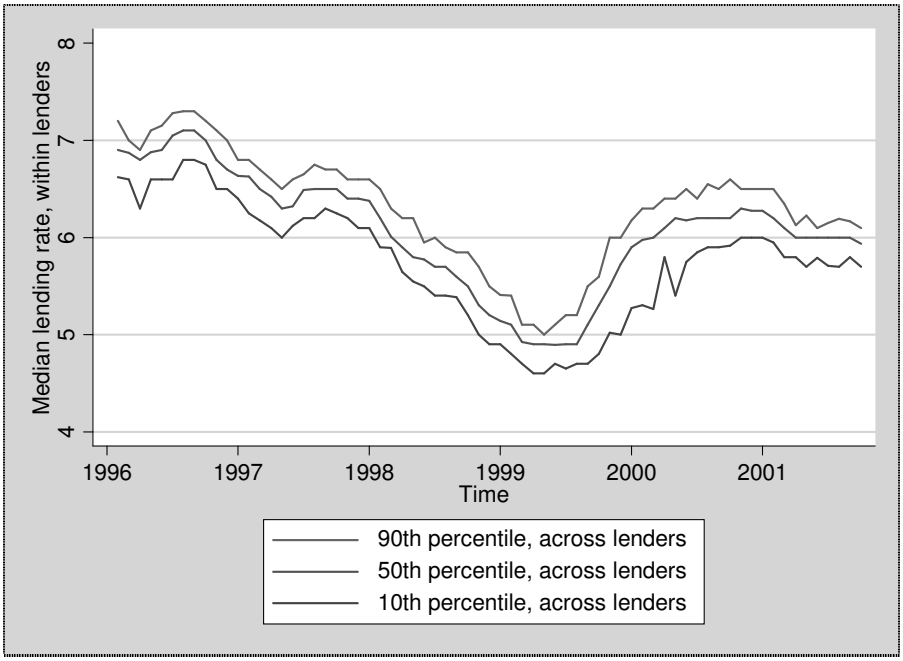
[10] This measure allows us to compare it with the standard deviation of the between-lender dummies in Section 5.

[11] The skewness does not change substantially when we consider different regimes of upward- and downward changes of the bond rate.

the 10th percentiles of the median lending rate is a measure of the between-lender dispersion.[12] The average width of this 80%-interval over all months is 0.56%-point.

The figure shows that the median lending rate decreased from about 7 percent to about 5 percent over the period January 1996 – July 1999. July 1999 is a turning point; from then on the median lending rate increased by about one percentage point to six percent in a few months. From January 2000 onwards, the median lending rate remained stable at the six-percent level. With respect to the difference of the 90th and the 10th percentile, we notice two regimes. In the first regime of decreasing lending rates (until July 1999), the average 80% interval was 0.52%-point. This interval increased to 0.64%-point in the second regime of an increasing rate at the market level. The widening of the dispersion indicates greater non-transparency in times of increasing lending rates.

Figure 4.2 Dispersion of monthly median lending rate; 10th, 50th and 90th percentile (across lenders).

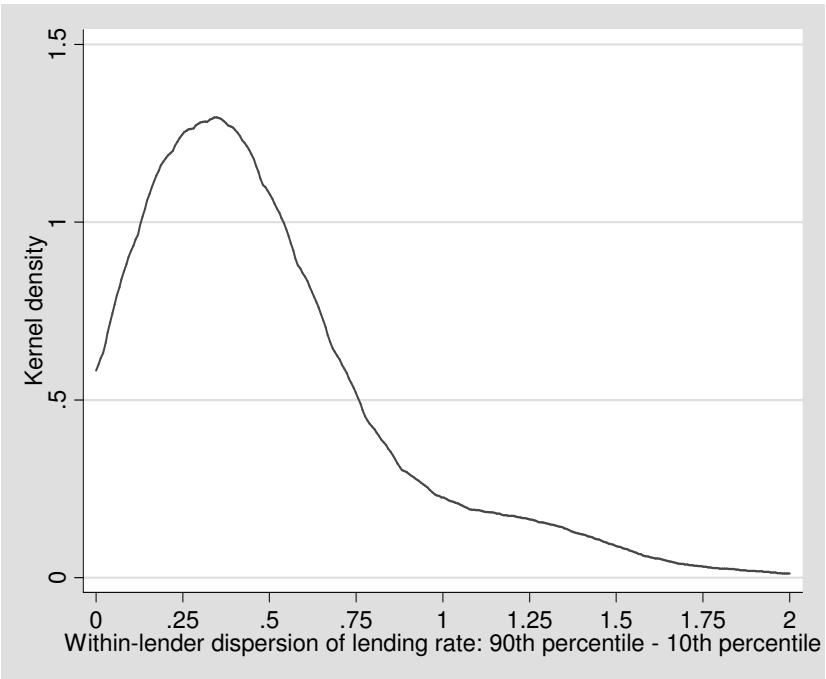


[12] We did not include the minimum and maximum of the median lending rate, so that the outcomes are less sensitive to outliers.

Within lender-dispersion

Next, we consider the dispersion of the lending rate at the borrower level. For each month and each lender, we calculated the difference of the average lending rate and the median lending rate ($\bar{r}_{it} - \xi_{it}^{50}$). The average of this difference across all lenders and months is relatively small but negative (-0.0046%-point for 3087 observations; it remains about the same when we distinguish between regimes of upward- and downward changes of the bond rate). It implies that the distribution of the lending rate within lenders is not symmetric; the distribution has a tail on the left-hand side.

Figure 4.3 Kernel estimate of monthly within-lender dispersion of lending rate; at least two borrowers per month[a]



[a] Explanatory note: We applied an Epanechnikov density Kernel (see Footnote 13).

We consider the difference between the 90th and the 10th percentile of the lending rate across the borrowers, ($\xi_{it}^{90} - \xi_{it}^{10}$) for each lender and each period. It gives us a measure of the within-lender dispersion. Figure 4.3 provides an estimate of the distribution of

the within-lender dispersion across the lenders. We applied a Kernel estimator,[13] for which we used those monthly observations for which the lender had at least two borrowers during the month (2547 observations). It appears that the modus of the within-lender dispersion $\xi_{it}^{90} - \xi_{it}^{10}$ is about 0.3%-point. A comparison of the between-lender dispersion (Figure 4.2) and the within-lender dispersion (Figure 4.3) indicates that the dispersion on average is smaller within lenders (among borrowers) than between lenders, but extreme dispersion occurs more within lenders than between lenders.

Figure 4.4 Development over time of monthly within-lender dispersion of lending rate; at least two borrowers per month.

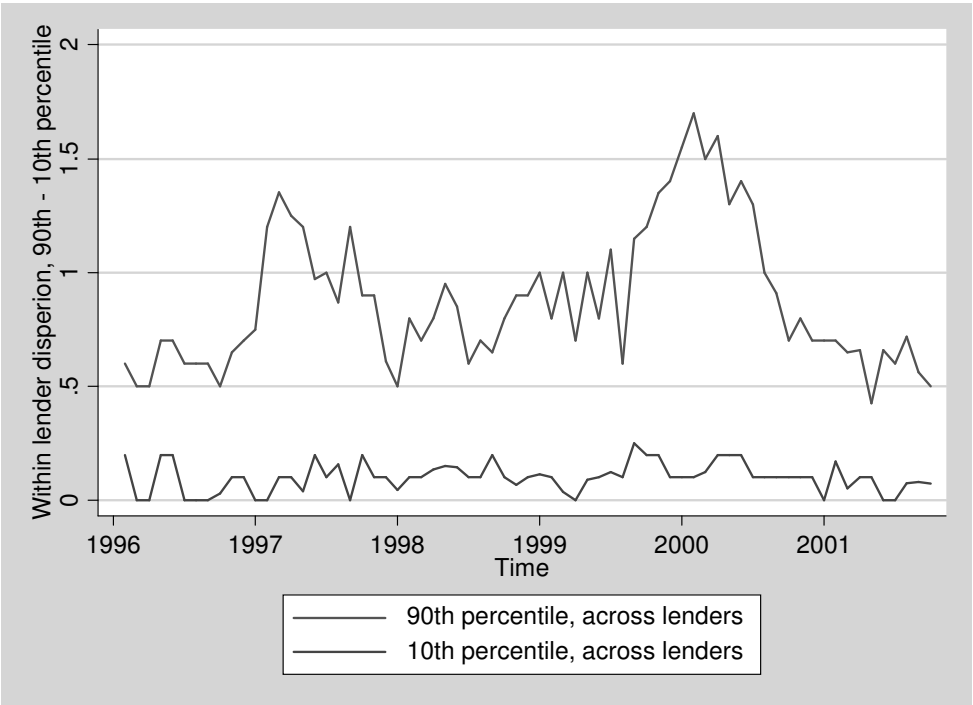


Figure 4.4 shows the development of the within-lender dispersion over time. We are interested in two percentiles across the distribution of lenders: the lenders that have a relatively small or large within-dispersion of the lending rate. For each month, we

[13] The Kernel density estimator is a nonparametric density estimator (e.g. Cameron and Trividi 2005, pp. 298-306). We applied an Epanechnikov Kernel, with a range of 0 – 2.0%-point and a bandwith of 0.125%-point.

determined the 10th percentile and the 90th percentile of the within-lender dispersion, using the same monthly observations as in Figure 4.3. Remarkably, the within-lender dispersion fluctuates substantially over time. In particular, around 2000, when there was a rapid increase in the lending rate (see Figure 4.2), the dispersion of $\xi_{it}^{90} - \xi_{it}^{10}$ becomes substantially larger. The same phenomenon occurred to a lesser extent in 1997.

Table 4.3 Descriptives by type of lender

	Banks		Insurance companies and pension funds	
Variable	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Characteristics of mortgage				
Lending rate (in percentages)	5.93	0.65	6.23	0.60
Characteristics of borrower				
Log(value of mortgage)	12.33	0.31	12.29	0.30
Log(gross income of head household)	10.82	0.33	10.79	0.31
Log(gross income of partner + 1)	6.27	5.17	6.41	5.13
Loan/(value of home)	1.022	0.129	1.022	0.126
Loan/(gross income head + gross income partner)	3.271	0.655	3.139	0.620
Dummy age $\leq$ 25 years	0.19	0.39	0.18	0.39
Dummy 25 < age $\leq$ 30 years	0.39	0.49	0.41	0.49
Dummy 30 < age $\leq$ 35 years	0.21	0.41	0.23	0.42
Dummy 35 < age $\leq$ 40 years	0.10	0.31	0.10	0.30
Dummy 40 < age $\leq$ 45 years	0.05	0.23	0.05	0.21
Dummy 45 < age $\leq$ 50 years	0.03	0.17	0.02	0.14
Dummy age > 50 years	0.01	0.11	0.01	0.09
Dummy 1 borrower	0.30	0.46	0.26	0.44
Log(instalment payments + 1)	5.31	5.63	4.13	5.39
Log(premium deposit + 1)	0.98	2.72	0.41	1.90
Characteristics of home				
Dummy existing home	0.83	0.38	0.86	0.35
Dummy apartment	0.20	0.40	0.19	0.40
Dummy back repair of the home	0.05	0.21	0.03	0.16
Characteristics of municipality				
Population density per square kilometre (in 1000)	0.17	0.17	0.18	0.17
Number of inhabitants (in 10,000)	1.07	1.43	1.10	1.42
Log(average value of homes) (in DFL 1000)	5.09	0.22	5.11	0.21
Benchmark interest rate				
Interest on ten-year government bonds	5.15	0.59	5.44	0.60
6 months moving average market share by lender	0.06	0.06	0.01	0.01
Log(demand for loans) by lender	15.10	1.81	13.96	1.28
Number of observations	59,434		25,293	

Table 4.4 Estimates of equation (4.4)

Dependent variable: lending rate	Parameter	t-value
Explanatory variable		
Characteristics of borrower		
Log(income of head household)	-0.033	**-8.50
Log(income of partner + 1)	-0.003	**-8.43
Log[Loan/(value of home)]	-0.117	**-19.52
Log[Loan/(gross income head + gross income partner)]	0.009	1.14
Dummy age ≤ 25 years [a]	0.002	0.16
Dummy 25 < age ≤ 30 years	-0.010	-0.86
Dummy 30 < age ≤ 35 years	-0.007	-0.63
Dummy 35 < age ≤ 40 years	-0.005	-0.47
Dummy 40 < age ≤ 45 years	0.001	0.05
Dummy 45 < age ≤ 50 years	-0.010	-0.75
Dummy more than one borrower [b]	-0.015	**-3.99
Log(instalment payments + 1)	0.001	**7.36
Log(premium deposit + 1)	0.003	**7.18
Characteristics of home		
Dummy existing home [c]	0.103	**35.33
Dummy apartment [d]	0.002	0.63
Dummy back repair of the home [e]	0.007	1.47
Characteristics of municipality		
Population density per square kilometre	0.047	**5.59
Number of inhabitants	0.001	0.88
Log(average value of homes)	0.007	1.22
Benchmark interest rate		
Interest on ten-year government bonds	0.070	**5.18
Intercept	6.812	**70.93
σ_α	0.152	
σ_ν	0.294	
F-test on age class (6 dummies)	**3.40	
F-test on calendar month (68 dummies)	**1090	
F-test on lender effects (71 dummies)	**140	
R-square	0.766	
Number of observations	84,727	

[a] Reference group: age over 50 years.
[b] Reference group: one borrower.
[c] Reference group: new homes.
[d] Reference group: remaining homes, other than apartments.
[e] Reference group: no back repair of home.
**Statistically different from zero at 1% level.

4.5 Estimates

4.5.1 Explanatory variables

It could well be that the figures on interest-rate dispersion across lenders as presented above can be fully attributed to, for instance, differences in characteristics of borrowers. These figures may thus give us the wrong message with respect to price dispersion across lenders. This section therefore aims to estimate the between-lender dispersion of the lending rate, conditional on the observed characteristics of the borrowers, their property and the opportunity costs of investment. Basically, it boils down to estimating the size of the between-lender variation from equation (4.4). This sub-section motivates the inclusion of the explanatory variables in the vector X in equation (4.4). The choice of our explanatory variables is based on the micro-econometric studies of Duca and Rosenthal (1994), Chiang and Chow (2002) and Nothaft and Perry (2002). The descriptive statistics of the explanatory variables are given in Table 4.2. As motivated in Section 4.3, we make use of the data of endowment mortgages (84,727 observations). For these data, the average lending rate is 6.02 percent. 70 percent of the borrowers purchased their mortgage from a bank.

We first discuss the characteristics of the borrowers. Inclusion of the value of the home, the gross income variables and the value of the mortgage jointly (all of these variables in logarithms) may lead to problems of multicollinearity, as these variables are strongly correlated. Instead, we included both the (logarithm of the) value of the mortgage loan relative to that of the home (the so-called loan-to-value ratio) and the (logarithm of the) mortgage loan relative to the gross household income (referred to as the loan-to-income ratio). Moreover, we included the (logarithm of the) gross household income both for the head of household and for the partner. Both the loan-to-value ratio and the loan-to-income ratio are informative about the risk of prepayment, the risk that a mismatch results between funding and lending due to refinancing or prepaying (a part of) the mortgage before the end of the term (since there is no risk of default, as this is covered by the NMG insurance). We hypothesise that lenders require a higher lending rate when households have a higher risk of prepayment. Given that borrowers with a low loan-to-value ratio are more attractive for competing banks, due to their low default risk, these borrowers can more easily switch lenders. Therefore, lower loan-to-value ratios lead to increases in the risk of prepayment, so that there will be a higher lending rate. A higher loan-to-income ratio leads to a higher risk of prepayment, because borrowers have more to gain from prepayment when the loan is relatively high compared with their income (see also Chapter 3). The average loan-to-value ratio is 1.022; the average loan-to-income ratio is 3.232 (see Table 4.3).

Although the NMG insurance imposes no constraint on household income, the households are from the lower segment of the national income distribution (see Section

4.3). The average value of the mortgage is 237,000 guilders (in logs: 12.34). The average gross income of the head of household is about 52,000 guilders (average of log: 10.82). For the partner of the head of household, the average gross income is about 24,000 guilders (average of log: 6.31). [14] [15]

On average, the homebuyers are young; 59 percent of the borrowers are at most 30 years old. The youth of this group may be due to the segment of the housing market that is the focus of NMG insurance, since young people buy relatively more homes in this segment. 29 percent of the mortgages have one borrower only. The average value of the instalment payments is about 37,000 guilders (average of log: 4.96). The average value of the premium deposit is 930 guilders (average of log: 0.81).[16]

The characteristics of the home provide information on whether the property is new, whether it is an apartment, and whether the home needs back repair. 84 percent of the mortgages are used for existing homes, 20 percent are used for apartments and 4 percent of the mortgaged homes need back repair.

We used various characteristics of the municipality, which refer to the situation on January 1st 1999. On average, there are about 170 inhabitants per square kilometre (so the major part of the households live in non-urbanized areas). On average, a municipality has around 10,800 inhabitants. The average value of the homes in the municipality, on which local taxes are based, is 168,000 guilders (average of log: 5.1) on January 1st 1995. On average, the interest rate on ten-year government bonds is 5.24 percent, which is about 0.8%-point lower than the average lending rate.

Table 4.3 gives the corresponding means and standard deviations of these variables for the mortgages for banks (59,434 cases) and insurers and pension funds (25,293 cases) respectively. The differences between both types of lender seem to be rather small for most of the variables. The nominal lending rate is somewhat lower for the banks than for the insurers and pension funds, but this could be due to different days of observation. Banks and insurance companies and pension funds have an equal difference between the lending rate and the interest on ten-year government bonds.

4.5.2 Transparency of the market

We now estimate equation (4.4) using the explanatory variables discussed in the previous sub-section. Table 4.4 presents the fixed-effect estimates (72 lenders), for

[14] About one-third of the borrowers has no partner with an income; therefore, the difference between the log of the average gross income of the partner and the average of the log is quite substantial.

[15] In this section, the averages of the prices are calculated for the untransformed variables. Table 3 gives the averages of the transformed variables.

[16] About 50 percent of the borrowers have an installment premium; about 30 percent of the borrowers have a premium deposit.

which, additionally, 68 dummies of the calendar month were included.[17] The dispersion of the estimated parameters of the lender-specific dummy variables is quite substantial. The standard deviation of the estimated coefficients on these dummy variables, σ_a, is 0.152. Hence, the dispersion of the lending rate across lenders that we observed in Section 4.4 is still prevalent after correcting for the other explanatory variables. Reformulated, a 95 percent interval estimate of the lender-specific coefficients (across the lenders) is 0.61%-point.[18] This variation is 0.35%-point smaller than the 95 percent interval estimate of the average lending rate (across the lenders), which is 0.96%-point (see Section 4.4). These results are close to the results found by Heffernan (2002), who finds for the UK a price dispersion of 0.45%-point for new borrowers. Her sample includes both banks and non-banks (such as building societies and "community" building societies). Furthermore, she uses interest rates quoted before the actual decision on type of mortgage is made. In that respect, this study is also very comparable to our approach of using one type of mortgage.

Another estimation result is that σ_a (0.152) is smaller than the standard deviation of the error term (σ_v = 0.294), which is in line with our findings of Section 4.4. As σ_v can be interpreted as the within-lender dispersion, this estimation result implies that dispersion of the lending rate across lenders is smaller than the dispersion within lenders.

Ideally, in our regressions we would like to take into account all borrowers' characteristics as observed by the lender. It could be that lenders have information available on the quality of the borrowers (e.g. profession, which is not included in the dataset we used). Although these unobserved characteristics affect price dispersion between borrowers, these characteristics will only affect the price dispersion between lenders if individual lenders would set out to target specific groups of borrowers. For this we have no indication.

Next, we discuss the estimated coefficients on the remaining explanatory variables. The logarithm of the loan-to-value ratio has a statistically significant coefficient. The value of −0.117 indicates that a 10 percent increase of the loan-to-value ratio leads to a decrease of the lending rate by 0.012%-point, so that borrowers who are more restricted have a lower lending rate. In line with our hypothesis, borrowers with a higher loan-to-value ratio have a lower prepayment risk (as mentioned before, the NMG insurance leads to an absence of the risk of default). The loan-to-income ratio is statistically insignificant, but the incomes of the head of household and the partner both have a significant negative effect on the lending rate. A 10 percent increase in the income of the head of household leads to a decrease in lending rate by 0.0033%-point. For the income of the partner, this effect is about 10 times smaller.

[17] We do not include additional lender-specific explanatory variables, as these effects will be picked up by the lender dummies.

[18] Four times the standard deviation of the fixed effect. The standard deviation is measured in terms of %-points.

With respect to the borrower's characteristics, the F-test indicates that the age dummies are jointly significantly different from zero. However, the coefficients on the dummies are individually insignificant, and no clear pattern emerges from the estimated coefficients. There is thus no indication for third-degree price discrimination between age groups.

The home variables may provide some indication about the impact of collateral. The lending rate is 0.103%-point higher for existing homes compared to new ones. For apartments and back repair of the home we find no significant estimated coefficients. These findings imply that the value of the collateral reduces the lending rate. Newly built homes have a higher value. These findings are in line with the results of Wette (1983). Nothaft and Perry (2002) show that neighbourhoods with new homes have lower lending rates. The estimates imply that borrowers in highly populated areas have higher lending rates— but from an economic point of view this effect is very small.

The estimated coefficient on the interest on bonds is 0.07: A 1%-point increase in the interest rate on bonds leads to an increase in the lending rate by 0.07%-point, ceteris paribus on all explanatory variables (including the monthly calendar dummies). This coefficient is very small when we compare it with previous estimates for the Dutch mortgage market, because we have included time-dummies, which take out most of the effect of the interest rate on bonds. Den Butter *et al.* (1977, p. 59) estimate the effect of the bond rate on the lending rate of mortgages (homes and other mortgages), for which they use quarterly data over the period 1960:II-1974:I. The estimated parameter on the bond rate is 0.718. Swank (1995) obtains a value of 0.67 for the effect of the government long-term bond yield on the mortgage lending rate, for which he uses annual data over the period 1957-1990.

When we exclude the 68 calendar dummies, we find an estimated coefficient on the government bond rate of 0.79, which is comparable to the findings of Den Butter *et al.* (1977) and Swank (1995). The other coefficients are only marginally affected.

Table 4.5 Estimates of equation (4.4) for banks and life insurance companies

Dependent variable: lending rate	Banks		Insurance companies	
	Parameter	t-value	Parameter	t-value
Explanatory variable				
Characteristics of borrower				
Log(income of head household)	-0.038	**-8.17	-0.021	**-3.05
Log(income of partner + 1)	-0.004	**-8.53	-0.002	**-2.52
Log[Loan/(value of home)]	-0.124	**-17.17	-0.102	**-9.71
Log[Loan/(gross income head + gross come partner)	0.007	0.71	0.020	1.54
Dummy age ≤ 25 years[a]	-0.009	-0.64	0.033	1.61
Dummy 25 < age ≤ 30 years	-0.023	-1.68	0.025	1.25
Dummy 30 < age ≤ 35 years	-0.019	-1.40	0.025	1.26
Dummy 35 < age ≤ 40 years	-0.021	-1.54	0.037	1.81
Dummy 40 < age ≤ 45 years	-0.009	-0.63	0.025	1.16
Dummy 45 < age ≤ 50 years	-0.019	-1.25	0.015	0.64
Dummy more than one borrower[b]	-0.012	**2.77	-0.019	**-3.12
Log(instalment payments + 1)	0.001	**5.89	0.001	**2.82
Log(premium deposit + 1)	0.003	**6.32	0.003	**3.20
Characteristics of home				
Dummy existing home[c]	0.105	**29.79	0.091	**18.10
Dummy apartment[d]	0.001	0.21	-0.004	-0.72
Dummy back repair of the home[e]	0.004	0.68	0.014	1.42
Characteristics of municipality				
Population density per square kilometre	0.053	**5.07	0.039	**2.83
Number of inhabitants	0.002	1.56	-0.001	-0.62
Log(average value of homes)	0.010	1.47	0.002	0.17
Benchmark interest rate				
Interest on ten-year government bonds (at date of purchase of mortgage)	0.082	**4.93	0.038	1.67
Intercept	6.773	**56.46	5.189	**42.33
σ	0.117		0.162	
σ	0.303		0.267	
F-test on age class (6 dummies)	**3.65		1.55	
F-test on calendar month (68 dummies)	**843		**98	
F-test on lender effects (20 dummies: banks; 50 dummies: other lenders)	**237		**230	
R-squared	0.785		0.805	
Number of observations	59,434		25,293	

[a] Reference group: age over 50 years.
[b] Reference group: one borrower.
[c] Reference group: new homes.
[d] Reference group: remaining homes, other than apartments.
[e] Reference group: no back repair of home.
**Statistically different from zero at 1% level.

4.5.3 Middlemen

We argued in Section 4.2 that banks might have lower agency costs because of better information about borrowers, due to previous contacts. In contrast, agency costs are higher for insurers and pension funds, since they get their information through middlemen only. To test this hypothesis, we estimate equation (4.4) separately for the category banks (21 lenders) and the category insurers and pension funds (51 lenders) (see Table 4.5). We find that σ_a is smaller for banks (0.117) than for insurers and pension funds (0.162). This difference indicates that lenders that employ only middlemen may have higher agency costs. Borrower's information apparently reduces price dispersion for lenders. In contrast, we find that σ_v is larger for banks than for insurers and pension funds (0.303 versus 0.267). A likely explanation for the larger residual variation for banks is that they have applied additional characteristics of the borrower that are not captured by the administrative information that we use in the regression equation. Probably, part of this additional information may be collected through previous contacts with the borrower.

With respect to the effects of the other explanatory variables, the differences between banks and the other lenders are not very substantial, except for the effect of the interest on ten-year government bonds. Our estimates imply that for banks, an increase in the bond rate by 1%-point leads to an increase in the lending rate of 0.082%-point. Since banks attract funds mainly from the bond market, the bond rate represents the marginal costs of attracting funding to finance mortgages for banks. For the insurers and pension funds, the estimated coefficient is not statistically different from zero. The coefficient on the bond rate has a different interpretation for insurance companies, as they mainly invest in the bond market— in contrast to banks, which mainly attract funds from the bond market. Here the bond rate reflects their opportunity costs of alternative investments in bonds (Boshuizen and Pijpers 2000). When we exclude the time dummies, we find an estimated coefficient on the government bond rate of 0.793 for banks and 0.745 for insurers and pension funds. The other coefficients are only marginally affected.

Next, we consider the differences between the lenders for periods of a decreasing lending rate (44 months) and periods of an increasing lending rate at the market level (25 months). Table A1 in Appendix I presents the results for banks, while Table A2 does the same for insurers and pension funds. According to the estimates, σ_a is smaller for banks than for the other lenders when there is a decrease in the lending rate (0.112 versus 0.168%-point, which can be recalculated as a 95 percent interval estimate: 0.45%-point and 0.67%-point, respectively). See the first columns of Tables A1 and A2 in Appendix I.

The estimated error term σ_v is somewhat larger for banks than for the other lenders (0.265 versus 0.296%-point), which may reflect the fact that in their assessment of the creditworthiness of borrowers, banks made use of additional information that is not captured by the administrative information.

4.5.4 Pricing power

Section 4.5.2 showed that price dispersion across banks is smaller than price dispersion between insurers and pension funds. This indicates that the market segment in which banks operate is more transparent than that of non-banks. It raises the question whether this difference in transparency results in stronger pricing power for non-banks than for banks. We analyse this question in two ways. First, we investigate whether lenders with large market shares also charge higher interest rates. Furthermore, we look at the difference between banks and non-banks. Second, we follow the Monti-Klein model presented earlier and estimate the price elasticity of demand of mortgage loans provided by banks and non-banks. A high price elasticity of demand, in absolute terms, would indicate low pricing power for lenders. We test the hypothesis that banks face a higher price elasticity of demand than non-banks. If the hypothesis were accepted, this would indicate that banks are less able to raise interest rate and thus have less pricing power in comparison to non-banks. Because we are interested in differences between lenders, we make use of lender-level data to estimate the above-described models.

Before we turn to the estimations of the price elasticity, we need to correct the lending rate for risk premiums due to specific characteristics of the borrower's population. There is a difference between estimations on borrower-level data and lender-level data. In Table 4.4, the interest rate charged to an individual borrower is explained by characteristics of borrowers and their property. For instance, Table 4.4 shows that differences in income between borrowers partly explain the variation in interest rates between individual borrowers. Table 4.6 presents the estimates of equation (4.10). It is shown that differences in the average income of the borrower's population of the lenders do not explain significantly the variation in interest rates across lenders. Table 4.6 shows that only a handful of customer's population characteristics explain the lender's variation in interest rates. Lenders with a borrower's population that is characterised by a relatively high loan-to-income ratio charge lower interest rates, due to the smaller probability of prepayment. Lenders with a high proportion of multiple borrowers charge interest rates that are 10 basis points lower. Also, lenders charge 15 basis points lower interest rates for new homes compared to existing homes, because new homes maintain their value. Lenders that have mortgages with relatively high instalment payments and premium deposits demand slightly higher interest rates. Estimations for banks, pension funds and life insurance firms separately show more or less the same picture.

Table 4.6 Estimates of the lending rate in equation (4.10)

Dependent Variable: Lending rate	Overall sample Weighted estimation Parameter	z-value[1]	Banks Weighted estimation Parameter	z-value[1]	Insurance companies, pension funds Weighted estimation Parameter	z-value[1]
Log(income of head household)	-0.068	-1.72	-0.231	**-2.97	0.028	0.74
Log(income of partner + 1)	-0.003	-0.94	-0.010	-1.42	-0.001	-0.38
Log(loan-to-value)	-0.005	-0.08	-0.278	-1.98	0.206	** 2.66
Log(loan-to-income)	-0.300	**-5.32	-0.503	**-4.40	-0.209	**-3.65
Fraction age ≤ 25 years a)	-0.096	-0.96	-0.483	-2.52	-0.019	-0.17
Fraction 25 < age ≤ 30 years [a]	-0.102	-1.05	-0.457	-2.38	-0.066	-0.63
Fraction 30 < age ≤ 35 years [a]	-0.098	-0.98	-0.432	-2.28	-0.060	-0.57
Fraction 35 < age ≤ 40 years [a]	-0.094	-0.95	-0.455	-2.41	-0.046	-0.44
Fraction 40 < age ≤ 45 years [a]	0.022	0.22	-0.171	-0.83	-0.048	-0.44
Fraction 45 < age ≤ 50 years [a]	0.048	0.41	-0.208	-1.00	-0.008	-0.07
Fraction more than 1 borrower[b]	-0.104	**-3.07	-0.148	-2.17	-0.064	-1.96
Log(instalment payments + 1)	0.005	** 2.63	0.051	** 5.22	0.006	1.16
Log(premium deposit + 1)	0.028	** 5.74	0.003	0.85	0.0037	1.85
Fraction apartment [c]	0.152	** 4.90	0.053	0.88	0.005	0.17
Fraction existing home [d]	0.063	2.63	0.108	1.83	0.154	** 5.03
Fraction back repair of home [e]	0.089	1.90	0.022	0.20	0.072	1.72
Population density per square kilometre (in thousands)	0.167	1.96	0.187	1.10	0.205	2.48
Number of inhabitants (10,000)	-0.014	-1.37	0.007	0.37	-0.023	-2.48
Log(average value of homes) (in thousands of guilders)	-0.059	-1.09	-0.023	-0.21	-0.033	-0.58
Interest on ten-year government bonds (at date of purchase of mortgage)	0.191	1.62	0.276	1.30	0.067	0.52
Intercept	5.56	**-8.21	8.696	**5.42	6.635	7.58
σ_a	0.137		0.128		0.135	
σ_v	0.201		0.198		0.199	
F-test on age class	1.65		16.35		3.46	
F-test on calendar month	**133.8		**6263.7		**4050.5	
F-test on lender effects	**27.23		**444.7		**814.9	
R-squared	0.967		0.976		0.946	
Number of observations	3087		1057		2030	

[a] Reference group: age over 50 years.
[b] Reference group: one borrower.
[c] Reference group: new homes.
[d] Reference group: remaining homes, other than apartments.
[e] Reference group: no back repair of home.
**Statistically different from zero at 1% level.
[1] The Z-value indicates whether the parameter significantly differs from zero under the normal distribution with zero mean and standard deviation one.

Table 4.7 Estimates of the market shares on the lending rate in equation (4.10)

Dependent Variable: Lending rate	Overall sample Weighted estimation Parameter	z-value[1]	Banks Weighted estimation Parameter	z-value[1]	Insurance companies, pension funds Weighted estimation Parameter	z-value[1]
Market share of banks	0.679	** 8.09	0.712	**6.31		
Market share of non-banks	1.866	** 4.87			2.203	**5.38
Log(income of head household)	0.040	0.51	- 0.260	-2.27	0.214	2.20
Log(income of partner + 1)	0.007	1.07	-0.019	-0.17	0.005	0.71
Log(loan-to-value)	0.045	0.31	-0.037	-0.15	0.127	0.71
Log(loan-to-income)	-0.444	**-3.90	-0.649	-	-0.312	**-2.77
Fraction age ≤ 25 years a)	-0.123	-0.73	-0.698	-2.49	0.203	1.01
Fraction 25 < age ≤ 30 years [a]	-0.025	-0.15	-0.457	-1.64	0.170	0.90
Fraction 30 < age ≤ 35 years [a]	0.058	0.35	-0.428	-1.50	0.248	1.29
Fraction 35 < age ≤ 40 years [a]	-0.016	-0.10	-0.460	-1.63	0.109	0.58
Fraction 40 < age ≤ 45 years [a]	0.195	1.08	-0.174	-0.58	0.240	1.12
Fraction 45 < age ≤ 50 years[a]	0.089	0.42	-0.336	-1.01	0.144	0.59
Fraction more than 1 borrower [b]	**-0.219	-3.31	-0.364	**-3.00	-0.144	-2.12
Log(instalment payments + 1)	-0.002	-0.81	-0.005	-1.09	0.001	0.56
Log(premium deposit + 1)	0.014	1.74	0.021	1.88	0.017	1.87
Fraction apartment [c]	0.098	1.94	0.167	1.98	-0.042	-0.84
Fraction existing home [d]	0.544		0.590	** 8.57	0.400	**6.45
Fraction back repair of home [e]	-0.021	-1.90	0.252	1.79	0.122	1.26
Population density per square	-0.105	-0.69	-0.117	-0.46	-0.109	-0.73
Number of inhabitants (10,000)	0.044	2.72	0.074	** 2.57	0.019	1.09
Log(average value of homes)	-0.059	-1.09	0.262	1.61	0.060	0.55
Interest on ten-year government	0.191	1.62	0.276	1.30	0.067	0.52
Intercept	5.56	**-8.21	5.40	2.30	6.857	1.30
σ_a						
σ_v	0.128		0.086		0.160	
F-test on age class	1.65		**14.8		6.02	
F-test on calendar month	**4624.4		**3925.5		**1816.8	
F-test on lender effects						
R-squared	0.946		0.960		0.898	
Number of observations	1948		785		1163	

[a] Reference group: age over 50 years.
[b] Reference group: one borrower.
[c] Reference group: new homes.
[d] Reference group: remaining homes, other than apartments.
[e] Reference group: no back repair of home.
**Statistically different from zero at 1% level.
[1] The Z-value indicates whether the parameter significantly differs from zero under the normal distribution with zero mean and standard deviation one.

The first column of Table 4.7 shows the first way to analyse the impact of market power on pricing by using kernel-based heteroskedastic and autocorrelation-consistent (HAC) variance estimations. The bandwidth in these estimations is set at two periods and the Newey-West kernel is applied. We test for a positive relationship between the market shares of lenders and the interest rate charged on mortgage loans. We weight the estimations by the number of observations on which the averages are based to acknowledge that averages based on many observations are more reliable than those based on a few observations. Market shares are here defined as the moving average of market shares over the past six months. We add this variable to the right-hand side of equation (4.10). Note that the number of observations is reduced by the moving average of market shares to 1948 observations. We find that both for banks and non-banks the relationship is positive and significant at the 10%-level. The effect for non-banks is significantly larger than for banks. The Chi-quadratic test rejects the null hypothesis of equality for banks and non-banks of the effect of market shares. The value is 10.20, which implies a rejection at the 1%-level. This result indicates that the reduced transparency of markets on which non-banks operate increases the pricing power for these lenders.

We now turn to the second approach to measure pricing power: the price elasticity of the demand for mortgage loans. As mentioned before, the greater the market power of banks on loans, the smaller the elasticity and the higher the Lerner indices. We test the hypothesis that banks have a higher price elasticity compared to non-banks, and thus have less pricing power than non-banks. This time, we use the residual of the estimation in the first column of Table 4.6 without lender-specific dummies, so that the variation in lending rates between lenders also through time is still present in the data, but cannot be attributed to differences in the borrowers' population. Table 4.8 shows the estimation of equation (4.11). We find that the price elasticity of non-banks is significantly higher than that of banks (Chi^2-test = 187.33, implying rejection of the null hypothesis of equality of the price elasticity of banks and non-banks at the 1%-level). This result rejects the hypothesis that non-banks have more market power than banks. However, this result is very sensitive to the specification. When we allow time dummies between banks and non-banks to differ (see the second and third columns of Table 4.8), we see that non-banks seem to operate in a less price-elastic environment than banks do.

Table 4.8 Estimates of the price elasticities of demand for mortgage loans in equation (4.11)

Weighted estimation Dependent Variable: Log (Demand for mortgage loans)	**Overall sample**		**Banks**		**Insurance companies, pension funds**	
	Parameter	**z-value[1]**	**Parameter**	**z-value[1]**	**Parameter**	**z-value[1]**
Residual of equation (4.10) of banks	-0.491	-1.97	-0.883	-1.35		
Residual of equation (4.10) of non-banks	-0.674	**-2.71			-0.503	-2.16
Interest on ten-year government bonds	-1.246	-1.93	-3.640	-1.82	-0.482	-0.85
Intercept	24.460	** 6.07	40.740	** 3.32	19.125	** 5.39
σ_a	--		--		--	
σ_v	1.449		1.745		1.227	
F-test on calendar month	**165.0		89.89		**132.6	
F-test on lender effects	--		--		--	
R-squared	0.1333		-0.002		0.0403	
Number of observations	3087		1057		2030	

**Statistically different from zero at 1% level.

[1] The Z-value indicates whether the parameter significantly differs from zero under the normal distribution with zero mean and standard deviation one.

4.6. Conclusion

The empirical results in this chapter have opened an avenue towards a new type of empirical microeconomic research of the Dutch mortgage market. This type of research registers and explains dispersion of lending rates across lenders. For a narrowly defined set of endowment mortgages (fixed rate for ten years), we find that a 95 percent interval estimate of the monthly average lending rate across lenders is about 0.96%-point. However, dispersion within lenders (across borrowers) is larger than the variation between lenders. In addition, the interval estimate drops to 0.61%-point, after correcting for the underlying borrowers' characteristics, the municipality and the government bond rate.

Price dispersion may hint at the presence of imperfect competition, caused by search costs of borrowers or by agency costs of lenders. In general, this points to a lack of transparency, which impedes competition on the mortgage market. We observe substantial differences in price dispersion between the mortgages of banks, on the one hand, and the mortgages of insurers and pension funds, on the other. After correcting for household and municipality characteristics, we find that the dispersion of the lending rate across lenders is smaller for the banks (95 percent interval estimate: 0.45%-point) than for the other lenders that make use of middlemen only (95 percent interval estimate: 0.67%-point). This difference may be caused by a difference in

agency costs between banks and insurers due to unobserved characteristics of the lenders. Banks are able to screen borrowers more thoroughly, as they have relatively more direct contact with their borrowers, whereas insurers and pension funds make use of middlemen, who may screen the borrowers less effectively.

Finally, we tested whether non-banks have more pricing power than banks. We find indications that non-banks have more pricing power than banks. We tested whether lenders with large market shares also charge higher interest rates. We find that the interest rates on mortgage loans are more sensitive to the market share of the lender for non-banks than for banks. Furthermore, we tested whether banks face a more price-elastic demand than non-banks. A lower price elasticity would indicate pricing power for the lender, because interest rate rises would diminish market shares only slightly. We find that the price elasticity of demand for mortgage loans is larger for non-banks than for banks. This implies that non-banks have less pricing power than banks. However, this result depends strongly on the specification of the estimates. In the end, we have mixed results with respect to the pricing power of banks and non-banks. Although we have some indications that larger market shares for non-banks result in higher interest rates, we also find that non-banks face a more price-elastic demand than banks, providing them with less pricing power. Therefore, we have only limited evidence that less transparency in markets results in greater pricing power for lenders.

This chapter is a first step toward measuring transparency and pricing power in the Dutch mortgage market. We focused mainly on variation between borrowers and lenders. Future research might explore the variation between lenders and within lenders. It would be interesting to investigate to what extent variation in the interest rates can be attributed to individual's characteristics or to characteristics of banks, that are focused on special interest groups.

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Appendix

Table A1 – Estimates of equation (4.4) for banks by change in market lending rate

Dependent variable: Lending rate	Banks		Insurance companies	
Explanatory variable	**Parameter**	**t-value**	**Parameter**	**t-value**
Characteristics of borrower				
Log(income of head household)	-0.033	**-5.72	-0.045	**-5.88
Log(income of partner + 1)	-0.004	**-6.55	-0.004	**-5.30
Log[Loan/(value of home)]	-0.117	**-12.92	-0.134	**-11.36
Log[Loan/(gross income head + gross come partner)	-0.006	-0.48	0.026	1.72
Dummy age ≤ 25 years[a]	0.002	0.12	-0.028	-1.43
Dummy 25 < age ≤ 30 years	-0.015	-0.81	-0.037	-1.93
Dummy 30 < age ≤ 35 years	-0.009	-0.51	-0.037	-1.89
Dummy 35 < age ≤ 40 years	-0.014	-0.73	-0.034	-1.72
Dummy 40 < age ≤ 45 years	-0.002	-0.08	-0.023	*-1.11
Dummy 45 < age ≤ 50 years	-0.002	-0.09	-0.047	-2.13
Dummy more than one borrower[b]	-0.016	**-2.80	-0.007	**-0.89
Log(instalment payments + 1)	0.001	**4.69	0.001	*3.39
Log(premium deposit + 1)	0.004	**6.31	0.002	**2.29
Characteristics of home				
Dummy existing home[c]	0.104	**23.85	0.105	**17.68
Dummy apartment[d]	0.004	0.78	-0.004	-0.61
Dummy back repair of the home[e]	0.002	0.22	0.008	0.85
Characteristics of municipality				
Population density per square kilometre	0.047	**3.76	0.060	**3.32
Number of inhabitants	0.001	0.92	0.003	1.33
Log(average value of homes)	0.013	1.54	0.004	0.38
Benchmark interest rate				
Interest on ten-year government bonds (at date of purchase of mortgage)	0.079	**3.81	0.082	**2.98
Intercept	5.163	**48.24	6.818	**33.54
σ_a	0.112		0.160	
σ_v	0.296		0.312	
F-test on age class (6 dummies)	**3.28		1.44	
F-test on calendar month (43 dummies)	**372		**965	
F-test on lender effects	**172		**75	
R-squared	0.745		0.816	
Number of observations	36,455		22,979	

[a] Reference group: age over 50 years.
[b] Reference group: one borrower.
[c] Reference group: new homes.
[d] Reference group: remaining homes, other than apartments.
[e] Reference group: no back repair of home.
* Statistically different from zero at 5% level; **Statistically different from zero at 1% level.

Table A2 – Estimates of equation (4.4) for non-banks by change in market lending rate

Dependent variable: Lending rate	**Banks**		**Insurance companies**	
Explanatory variable	**Parameter**	**t-value**	**Parameter**	**t-value**
Characteristics of borrower				
Log(income of head household)	-0.019	*-2.32	-0.024	*-2.14
Log(income of partner + 1)	-0.001	-1.89	-0.002	-1.87
Log[Loan/(value of home)]	-0.097	**-7.42	-0.111	**-6.34
Log[Loan/(gross income head + gross come partner)	0.011	0.67	0.038	1.68
Dummy age ≤ 25 years[a]	0.023	0.96	0.047	1.33
Dummy 25 < age ≤ 30 years	0.023	0.95	0.027	0.76
Dummy 30 < age ≤ 35 years	0.023	0.98	0.027	0.75
Dummy 35 < age ≤ 40 years	0.039	1.59	0.033	0.91
Dummy 40 < age ≤ 45 years	0.018	0.71	0.036	*0.97
Dummy 45 < age ≤ 50 years	0.005	0.19	0.026	0.66
Dummy more than one borrower[b]	-0.024	**-3.15	-0.009	**-0.89
Log(instalment payments + 1)	0.001	**2.58	0.001	*1.49
Log(premium deposit + 1)	0.003	**3.14	0.002	**1.22
Characteristics of home				
Dummy existing home[c]	0.092	**14.49	0.087	**10.52
Dummy apartment[d]	0.000	-0.03	-0.012	-1.32
Dummy back repair of the home[e]	0.011	0.87	0.018	1.13
Characteristics of municipality				
Population density per square kilometre	0.047	**2.81	0.027	**1.09
Number of inhabitants	-0.002	-1.20	0.002	0.63
Log(average value of homes)	0.000	-0.01	0.005	0.33
Benchmark interest rate				
Interest on ten-year government bonds	0.031	1.08	0.046	**1.27
Intercept	6.910	**34.39	4.986	**24.50
σ_a	0.168		0.161	
σ_v	0.265		0.268	
F-test on age class (6 dummies)	1.34		1.35	
F-test on calendar month (43 dummies)	**139		**228	
F-test on lender effects (50 dummies)	**276		**25	
R-squared	0.767		0.853	
Number of observations	16,727		8566	

[a] Reference group: age over 50 years.
[b] Reference group: one borrower.
[c] Reference group: new homes.
[d] Reference group: remaining homes, other than apartments.
[e] Reference group: no back repair of home.
* Statistically different from zero at 5% level.
** Statistically different from zero at 1% level.

5 The Boone indicator: Identifying different regimes of competition

5.1 Introduction

A new approach to measuring competition was recently introduced by Boone (2008). His new measure of competition is based on the notion that in a competitive market more efficient companies are likely to gain larger market shares than in a non-competitive market. The price-cost margin (PCM) or Lerner Index is a widely used measure of competition of which the empirical underpinning is provided by Genesove and Mullin (1998). However, Boone's approach gives a superior alternative to the price-cost margin (PCM), because the theoretical foundations of the PCM as a competition measure are not robust. Amir (2000), Bulow and Klemperer (1999), Rosenthal (1980) and Stiglitz (1989), for example, present models in which more intense competition leads to higher instead of lower PCM values. Furthermore, Corts (1999) shows that the estimates of the PCM will typically underestimate the price-cost margin and the level of market conduct itself. Boone (2008) presents a competition measure that is both theoretically robust and does not pose more stringent data requirements than PCM.

Whether the indicator is able to correctly measure competition in practice is as yet an unanswered question. This chapter aims to demonstrate that this new measure performs just as well as a measure of competition empirically, by using data from Genesove and Mullin (1998). These data are of the US sugar industry for the period 1890-1914. This is a very well documented period in terms of competition, due to testimonies before the US Industrial Commission in 1900 and the US Tariff Commission in 1920. These testimonies make it possible to identify periods with different degrees of competition.

There is information available for only one firm, the American Sugar Refining Company (ASRC). The ASRC was the leading company in the sugar industry during the period 1890 -1914. Therefore, estimating the competition level for the overall market is infeasible. Instead, I will measure the competitiveness of one firm in different time periods, while Genesove and Mullin (1998) look at the competitiveness of the sugar industry. Furthermore, this is also in contrast to previous studies that use the Boone indicator, like Bikker and Van Leuvensteijn (2008), where different levels of competition in the market at the same time are measured by estimating the cross

sectional relationship between marginal costs and profits of different firms at one given time. I am estimating the relationship between profits and marginal costs of one firm during different periods of time. The underlying hypothesis is that each period is internally homogenous with respect to the prevailing competition regime, but that regimes differ across periods. The estimate can be used to compare the different levels of competitiveness across time as derived from the testimonies.

Genesove and Mullin (1998) used the same data to test whether the elasticity-adjusted Lerner Index is a viable measure of competition. They estimated this indicator for the market as totality. I will estimate this indicator for the American Sugar Refining Company as such for the different periods mentioned above and compare the results with those of the Boone indicator.

The chapter proceeds as follows. First, I introduce the new approach to measure competition and explain its advantages in Section 5.2. Section 5.3 describes the period 1890-1914 and the different regimes of competition in the US sugar industry according to the public testimonies available. Special attention will be given to the technology of production, which is relevant for the marginal costs. Section 5.4 provides a description of the data as derived from Genesove and Mullin (1998). Section 5.5 describes the empirical model. Section 5.6 estimates both the elasticity-adjusted Lerner Index and the Boone indicator for the different periods that represent different regimes of competition. Finally, some conclusions are drawn.

5.2 The Boone indicator model

Boone's model is based on the notion, first, that more efficient firms (that is, firms with lower marginal costs) gain higher market shares or profits and, second, that this effect is stronger the heavier the competition in that market is. Boone develops a broad set of theoretical models (see Boone, 2000, 2001, 2004 and 2008, Boone *et al.*, 2004, and CPB, 2000). From this broad set of theoretical models, I use the most standard industrial organization model with a linear demand curve to explain the Boone indicator and to examine its properties compared to common measures such as the Herfindahl-Hirschman Index (HHI) and the price-cost margin (PCM). Following Boone *et al.* (2004), I consider an industry in which each firm i produces one product q_i. The firm faces a linear demand curve of the form:

$$p\,(q_i, q_{j\neq i}) = a - b\,q_i - d\,\textstyle\sum_{j\neq i} q_j \tag{5.1}$$

and has constant marginal costs mc_i. It maximizes profits $\pi_i = (p_i - mc_i)\,q_i$ by choosing the optimal output level q_i. I assume that $a > mc_i$ and $0 < d \leq b$. The first-order condition for a Cournot-Nash equilibrium can then be written as:

$$a - 2\,b\,q_i - d \sum_{i \neq j} q_j - mc_i = 0\,. \tag{5.2}$$

When N firms produce positive output levels, I can solve the N first-order conditions (5.2), yielding:

$$q_i\,(mc_i) = [(2\,b/d - 1)\,a - (2\,b/d + N - 1)\,mc_i + \sum_j mc_j] \tag{5.3}$$

$$/[(2\,b + d\,(N-1))(2\,b/d - 1)]\,.$$

I define profits π_i as variable profits excluding entry costs ε. Hence, a firm enters the industry if, and only if, $\pi_i \geq \varepsilon$ in equilibrium. Note that Equation (5.3) provides a relationship between output and marginal costs. It follows from $\pi_i = (p_i - mc_i)\,q_i$ that profits depend on marginal costs in a quadratic way:

$$\pi_i\,(mc_i) = [(2\,b/d - 1)\,a - (2\,b/d + N - 1)\,mc_i + \sum_j mc_j] \tag{5.4}$$

$$/[(2\,b + d\,(N-1))(2\,b/d - 1)]\,(p_i - mc_i).$$

Therefore, in this market, competition can increase in three ways. First, competition increases when the products of the various firms become closer substitutes (that is, d increases (keeping d below b)). In the sugar industry, for example, refined sugar and beet sugar became closer substitutes due to the entry of sugar beet producers. Domestic beet sugar supplied less than 1% of US consumption until 1894. The beet supply rose to 5% by 1901 and 15% by 1914. (Genesove and Mullin 1998, p. 358) Second, competition increases when entry costs ε decline and entry occurs (as was the case, for example, with the entry of new companies like Spreckels and Arbuckle in the sugar industry). Boone *et al.* (2004) prove that profits of more efficient firms (that is, with lower marginal costs mc) increase both under regimes of stronger substitution and amid lower entry costs. Third, changes in b are related to adjustments in preferences of consumers, and thus their willingness to pay for refined sugar. A decrease in b reflects a higher price sensitivity of the demand for sugar and decreases the market power of firm i and all other firms.

The theoretical model above can also be used to explain why widely applied measures such as the HHI and the PCM fail as reliable competition indicators. The standard intuition of the HHI is based on a Cournot model with symmetric firms, where a fall in entry barriers reduces the HHI. However, with firms that differ in efficiency an increase in competition through a rise in d reallocates output to the more efficient firms that already had higher output levels. Hence, the increase in competition raises the HHI.

Another often-used measure of competition, the price-cost margin (PCM), or the so-called Lerner Index, has similar disadvantages. Graddy (1995), Genesove and Mullin

(1998) and Wolfram (1999) estimate the elasticity-adjusted Lerner Index which is the Lerner-Index multiplied by the price-elasticity of sugar demand. They show that the conjectural variation parameter can be interpreted as a measure of competition. Corts (1999) criticises this approach and shows that, in general, efficient collusion cannot be distinguished from Cournot competition using the elasticity-adjusted Lerner Index. Generally, heavier competition reduces the PCM of all firms. But since more efficient firms may have a higher PCM (skimming off part of the profits stemming from their efficiency lead), the increase of their market share may raise the industry's average PCM, contrary to common expectations. As such, the estimates of the PCM will typically underestimate the price-cost margin (PCM) and the level of competition itself.

Boone (2000, 2001 and 2004; Boone *et al.* 2004), and CPB (2000) consider firms in a market with homogenous goods at time t and estimate the cross sectional Boone indicator. This indicator measures competition between firms in the market by measuring the strength of the relationship between profits and marginal costs for different firms at one moment in time. The original formulation of this indicator considers three firms and shows that the competitiveness of one firm can be measured relative to another firm. It is not necessarily that these three firms are compared at the same time. Therefore, I introduce a new element to the Boone indicator as described in Boone (2008), and use the indicator to compare the relative competitiveness of one firm in different periods to its average competitiveness. Then, the Boone indicator is no longer measuring the competitiveness of a market, but can only indicate whether a specific firm in one period is more or less competitive compared to another period. Of course, comparing one firm at different moments in time means that also the circumstances over time may differ under which this firm is operating.

The new indicator for competition looks at the relationship between profits and marginal costs. As said before, this relationship depends on the price elasticity of the demand curve (see equation (5.1)) and the quantity and price set by the firm to maximise profits (see equation (5.2)). However, a general shift of the demand curve, which increases production and increases prices for raw sugar and thus marginal costs, should be corrected for in the measurement of competition, as it is not the direct outcome of competition forces. To circumvent this effect, we estimate the relationship between profits and marginal costs with instrumental variables. This indicator shows the relative competitiveness of one firm at different points in time (see Section 5.5). So equation (5.3) can be rewritten as:

$$q_{1,p}\,(mc_{1,p}) = [(2\,b_p/d_p - 1)\,a_p - (2\,b_p/d_p + N_p - 1)\,mc_{1,p} + \textstyle\sum_j mc_{j,p}] \qquad (5.5)$$

$$/[(2\,b_p + d_p\,(N_p - 1))(2\,b_p/d_p - 1)]\,,$$

where the subscript p denotes different periods with distinct competition regimes. Again, competition over time can increase, because competition increases when the produced (portfolios of) services of the various firms become closer substitutes (that is,

d_p increases (again keeping d_p below b_p)), or due to a fall in entry costs (ε_p) and an increase in the number of firms N_p. Finally, a decrease in b_p reflects a higher price sensitivity of the demand for sugar in period p and leads to increased competition. One firm will be compared at four different periods, p: a period of oligopoly, a period of price war, a period in which the cartel is split up and a period between the last price war and the break-up of the cartel.

Following equation (5.4), I can write the relationship between profits and marginal costs as:

$$\pi_{1,p}\,(mc_{1,p}) = [(2\,b_p/d_p - 1)\,a_p - (2\,b_p/d_p + N_p - 1)\,mc_{1,p} + \sum_j mc_{jp}] \qquad (5.6)$$

$$/[(2\,b_p + d_p\,(N_p - 1))(2\,b_p/d_p - 1)]\,(p_p - mc_{1,p})\,,$$

where price, p_p, stands for the price in the sugar market in period p. The Boone indicator, BI, is the profit elasticity of marginal costs derived from this equation (5.6):

$$BI_{,p} = d\,\pi_{1,p}\,/dmc_{1,p}\,(mc_{1,p}\,/\pi_{1,p}\,) < 0.$$

The expectation is that BI is negative, where $mc_{1,p}$ is the average value of marginal cost in period p and $\pi_{1,p}$ is the average profit in period p.

5.3 The sugar industry

5.3.1 History: 1887 - 1914

To verify whether the Boone indicator properly tracks different regimes of competition, I use the case of the US sugar industry from 1887-1914. Genesove and Mullin (1995, 1997, 1998 and 2006) provide a detailed description of the sugar industry in this period. Based on their work, I identify four different regimes of competition, following Genesove and Mullin (1995, 1998). According to Genesove and Mullin (1998), the sugar industry experienced the following structural changes in the period 1887-1914.

These changes will be mentioned in chronological order. From 1887 until 1889, the sugar industry can be characterised as oligopolistic. The Sugar Trust controlled 80% of the market at that time. In December 1887, the Sugar Trust was formed as a consolidation of 18 firms controlling 80 percent of the industry's capacity. The 20 plants owned by the original trust members were quickly reduced to ten plants. Refined prices increased by 16%.

The high prices attracted a new entrant to the market: Claus Spreckels began production in early 1890[1] (Q1). This led to the first price war. In 1891, the Sugar Trust was reorganised as a corporation, the American Sugar Refining Company (ASRC). The ASRC acquired Spreckel's plant. By April 1892 (Q2), the acquisition ended the price war. Due to the acquisition, ASRC's share of industry capacity rose to 95 percent.

In the next period, from 1892 to 1897, the sugar industry was characterised by high levels of concentration; with a maximum of 95% of the market, the ASRC was an oligopoly. In total, five firms entered the market, each with a single plant, with an average capacity of 1340 barrels of refined sugar per day. The ASRC and associated friendly firms had a capacity of 49,500 barrels of refined sugar a day. By 1896, contemporary publications indicate that American Sugar, leader of the cartel, had an agreement with the new entrants.

In 1898, the next phase of competition began with the construction of a plant by the Arbuckle Brothers, which began initial production in August 1898. The Doscher refinery, another entrant, began production in November 1898. These new plants had a capacity of 3000 barrels per day. This led to a severe price war, marked by pricing at or below cost. As a result, the smaller independent refiners were shut down and one of the new entrants partially left the market. The second price war started in August 1898, with the entry of Arbuckle, and ended in May 1900.

After this price war, competition entered another phase in which the regime of competition and the level of competition was unclear. Competition increased, for instance, in the period 1900 Q2 – end of 1909, compared to the oligopolistic period with the gradual decline of the market share of ASRC. Competitive pressure from abroad was strongly reduced, however, because the American sugar industry was able to produce refined sugar at low cost due to a tariff structure that reduced the price of raw sugar. The tariff structure contained two chief components: the duty on raw sugar (an input) and the duty on refined sugar (the final consumption product). The latter tariff protected the US refining industry from foreign, chiefly European, competition. In 1903, an important preference was granted towards (raw) Cuban sugar. Under the Cuban reciprocity Treaty, Cuban raw sugar was admitted to the US at a tariff rate of 80% of full duty. This lowered the price of raw sugar in New York relative to the price of German raw beet sugar and protected the American sugar industry.

At the same time, antitrust regulation increased competition. Seeking the dissolution of the ASRC in 1910, the federal government filed suit with regard to the antitrust regulation, charging monopolization and restraint of trade. Although this case was not formally resolved until a consent degree was signed in 1922, the government victories in the American Tobacco and Standard Oil cases in 1911 led American Sugar to initiate partial, voluntary, dissolution. In the "Chronicle" of January 1910, the Board of ASRC recognized that the Circuit Court of Appeals gave a much wider interpretation to the

[1] Genesove and Mullin 1997, p. 21, Genesove and Mullin 2006.

competition law in the American Tobacco case than previously. The break-up of the cartel took place between 1910 and 1914.

Given that I have data only from 1890 onwards, only five of these six episodes in the history of the American Sugar industry will be used in the analysis. The two price wars will be taken together, because of their small number of observations. Table 5.1 summarizes these episodes. I define two periods of price war: 1890Q1-1892Q2, with the entry of Claus Spreckels in early 1890 and the subsequent takeover of his plant by ASRC in 1892Q3, and 1898Q4-1900Q2, with the entry of the Arbuckle Brothers. The period of oligopoly is defined as 1892Q3-1898Q3, the period in-between two price wars— a time that ASRC had acquired 95% of the production. From 1900Q3 till 1909, competition for the cartel was increasing due to the rise in raw imports from Cuba, and due to the preferential treatment in tariffs in 1903. The slow break-up of the cartel was in the period 1910Q1-1914Q2, beginning with the first successes in anti-trust regulation against American Tobacco and Standard Oil and the voluntary split-up of the cartel (see also Genesove and Mullin 1995, 1998, 2006).

Table 5.1. Competition regimes

Periods	Competition regimes
1887 -1889	Sugar Trust possesses 80% of the market: oligopoly
1890 – 1892Q1	Spreckels' entry, price war
1892 Q2- 1898Q2	Cartel operation, small-scale entry, acquisition of Spreckels: oligopoly
1898Q3 – 1900 Q2	Entry by Arbuckle Brothers and Doscher, price war
1900 Q3 -1909	Mixed regime of competition
1910 -1914	Government antitrust suit, break-up of cartel: end of oligopoly

5.3.2 Technology of sugar production

The production technology of sugar is a very straightforward process. In this period, raw sugar consisted of 96% pure sugar and 4% water and impurities. To transform raw sugar into refined sugar, all sugar refiners used the same process and the same technology. Therefore, marginal costs are a linear function of the price of raw sugar, P_{raw}, with a fixed coefficient k. In the calculation of the marginal costs of producing refined sugar, variable costs such as labour and other costs must also be included. This leads to the following formula for marginal costs:

$$mc_t = mc_0 + k * p_{raw,t} \tag{5.7}$$

where mc_t, the marginal costs, depend on all variable costs other than the cost of raw sugar, mc_0 and the price of raw sugar, $p_{raw,t}$.

The fixed coefficient, k, is equal to 1.075 according to Genesove and Mullin (1995, 1998), because the production of one pound of refined sugar requires 1.075 pounds of raw sugar. The value of mc_0 is less straightforward. Genesove and Mullin (1998) put as best guess for mc_0: 26 cents. This estimate is based on the testimony of a partner in Arbuckle Brothers (an entrant in the second price war). The true net-of-raw-sugar-costs margin is equal to $p_t - p_{raw,t} * 1.075$, where p_t is the price of refined sugar. In this testimony, it is said that if raw sugar costs 4.5 cents a pound, it will cost somewhere over 5 up to 5.1 cents to produce one pound of refined sugar. Subtracting 4.5*1.075 from a total cost of 5 or 5.1 cents, we obtain a value of mc_0 ranging between 16 and 26 cents (per hundred pounds). The upper limit of these non-raw sugar costs is still small compared to the mean raw price of 3.31 dollars, amounting to 7.5% of the costs. It is possible that larger houses (refining units) can refine at a smaller margin than others, but as a commission merchant for one of the independents testified, "*it is possible that the [larger houses] can refine at smaller margin than the others. …[but] it can [not] amount to a great deal: I suppose 3 to 5 cents a hundred would represent the difference*."(Genesove and Mullin 1995, p. 13) So there could be slight differences in marginal costs between producers depending on the scale of their production capacity. In line with Genesove and Mullin (1998), I use the estimate of 26 cents to calculate the marginal costs of ASRC.

In theory, differences in marginal cost of even 3 to 5 cents per hundred pounds would have been enough to calculate a cross-sectional Boone indicator measuring competition between market participants, at the same time. Different marginal costs lead to differences in profit margins, profits and market shares. Although the differences may seem small, compared to an average profit margin of 22 cents (see Table 5.2 for the average difference between price and marginal cost, mc), 3 to 5 cents represent 13.6% to 22.7% of the profit margin. Unfortunately, data for the competitors of the ASRC are unavailable, so the analysis is limited to a time-series perspective.

5.4 The data

Profits and marginal costs are the key variables used to calculate the Boone indicator. Profits cannot be directly observed from the data of Genesove and Mullin (1998). Moreover, the data could not be directly derived from the profit & loss accounts of the ASRC, because in the period 1890-1906, only the balance sheet of the ASRC was reported (as required under law of the State of Massachusetts). Furthermore, the ASRC admitted that the figures presented in the balance sheet did not accurately describe the real profits of the company. This policy of secrecy was meant to avoid attracting the attention of potential competitors (*NY Times*, March 30, 1908). Even shareholders were misled. Havemeijer, director of ASRC, declared that this was done only to serve their best interests.

In this chapter, a proxy for the profits of ASRC is constructed by using information on market shares quoted *on a yearly basis*, the total production in the market, quoted on *a quarterly basis,* and the difference between the price of refined sugar, p_t, and marginal costs, mc_t. The latter two are also available on *a quarterly basis*. The marginal costs are calculated following the formula of Genesove and Mullin (1998): $mc_t = 0.26 + 1.075 *p_{raw,t}$. The proxy for profits is calculated as the product of the profit margin and the quantities of refined sugar sold. The profit margin is equal to the difference in price *p* and marginal costs, mc. The quantity sold is equal to the total demand in the market times ASRC's market share, Q_i, where subscript i represents firm i. In formula terms, the proxy for profits is (p -mc) Q_i. We use Cuban imports of raw sugar as an instrumental variable. These data are also available on a quarterly basis for the period 1890Q1 -1914Q2.

Table 5.2 presents a number of stylized data characteristics. Originally, we had 98 observations. In total, we use 97 observations. In line with Genesove and Mullin (1998), the observation of 1897Q4 is omitted from the estimation because reported Cuban raw sugar imports are zero in this quarter. These 97 observations are divided into four periods: price war with 17 observations, oligopoly with 24 observations, break-up of the cartel with 18 observations and a period with a mixed regime of competition with 38 observations. The total production of melted sugar, on average and on a quarterly basis, amounted to 0.443 mln long tons of sugar.[2] Average Cuban imported raw sugar was 0.218 mln long tons, on a quarterly basis. Total production reached its highest level after the break-up of the cartel with the entry of more producers. Production was kept low during the period of oligopoly. The sugar price was at its highest level during the price war, 4.51 dollars, due to high prices for raw sugar, and at its lowest level after the break-up of the cartel, 3.45 dollars. This may have been related to the high level of production of refined sugar at the time. The price of refined sugar and raw sugar are both expressed in dollars per hundred pounds. The average market share of ASRC was 63% and moved over time from 91% during the time of oligopoly to 43% after the break-up of the cartel.

Quarterly profits varied strongly over the different periods. They were at their lowest level during the price wars with considerably negative values in some quarters. During the period of oligopoly, the profits reached their highest level, nearly ten times as high as during the price war. After the break-up of the cartel, profits decreased strongly compared with the intermediate period between oligopoly and the break-up of the cartel. Marginal costs were relatively high during the period of oligopoly and price war, due to the high prices for raw sugar. The preferences granted to imports of Cuban sugar decreased marginal costs substantially in the period after the price war and in the period after the break-up of the cartel.

[2] One long ton is 2240 pounds.

Table 5.2 Descriptive statistics

Variable	Observations	Mean	Std. Dev.	Min	Max
Total production in long tons	97	4.43	1.11	2.35	7.80
Cuban imports of raw sugar in long tons	97	2.18	1.73	8.62	7.07
Price of refined sugar (p) in dollars	97	4.03	0.62	2.75	5.51
Price of raw sugar (p_{raw}) in dollars	97	3.30	0.59	2.25	4.87
market share in %	97	63.0	12.0	43.0	91.0
marginal cost (mc) in dollars	97	3.81	0.64	2.68	5.50
Calculating the Boone indicator					
profit_price_war in dollars	17	2.52	12.00	-11.95	36.56
profit_oligopoly in dollars	24	28.12	12.67	3.93	49.51
profit_break-up_cartel in dollars	18	6.58	5.00	0.87	17.20
profit_mixed_regime war in dollars	38	13.35	7.68	-1.65	27.36
mc_price_war in dollars	17	4.47	0.80	3.25	5.50
mc_oligopoly in dollars	24	3.97	0.47	3.27	4.82
mc_break-up_cartel in dollars	18	3.34	0.47	2.68	4.37
mc_mixed_regime in dollars	38	3.63	0.42	3.06	4.74

All prices are reported in dollars per hundred pounds. All quantities are reported in 100,000 of long tons (one long ton is 2240 pound). Profits are in 100,000 dollars.

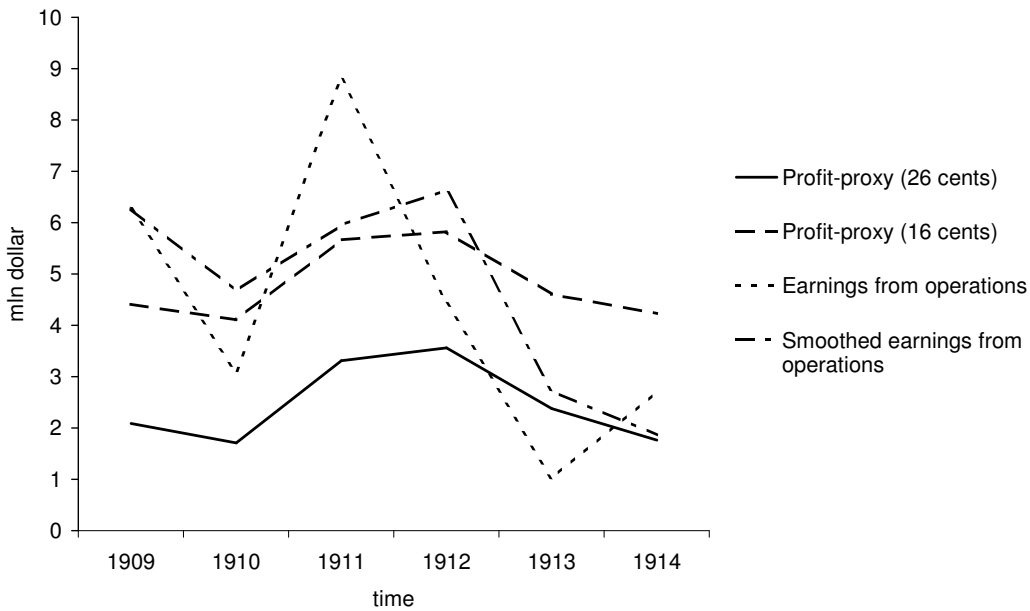
Our calculation of the Boone indicator has two potential weaknesses. First, due to data limitations, I use a proxy for profits that is partially based on information contained in marginal costs. The analysis is therefore vulnerable to the critique that this proxy may not accurately describe actual earnings from operations. Figure 5.1 shows that the proxy for profits follows the same pattern as the earnings from operations. Here, I am able to compare the calculated profit-proxy with the actual earnings on operations as reported in the journal "Chronicle" and in the annual reports of ASRC for the period 1909-1913. From 1890-1906, the ASRC published only balance sheet data and did not provide profit and loss accounts. From 1907-1908, only total earnings are published; they are not split up into earnings from operations and other earnings.

My proxy for profits reasonably describes profits actually earned. Smoothing the earnings figures by calculating a two-year moving average actually provides a very accurate picture of the earned profits. It is reasonable to smooth the data, as some of the reported profits are actually earned in the previous year, but accounted for in the current year. From Figure 5.1, it follows that my profits proxy is lower than the actual reported profits (with 1913 as exception). The correlation between the proxy and the reported earnings on operations is 0.43 (Pearson correlation), and with the smoothed earnings 0.47 for the years 1909-1913. Taking into account the numbers of 1914, of which we have only the first half of 1914, would raise the correlation to, respectively, 0.50 and 0.61. The proxy for profits and the actual (smoothed) figures for earnings from operations clearly move together. Therefore, using the proxy for profits as a representation of earnings of operations is warranted, in my view.

All in all, the comparison shows an overestimation of the marginal costs. Genesove and Mullin (1998) suggest that the additional marginal costs from personnel expenses range between 16 cents and 26 cents. As is shown in Figure 5.1, a profit-proxy in which the additional marginal costs are set to 16 cents indicates a better fit to the earnings data. Also, the Pearson correlation increases to 0.49 for 1909-1913 and 0.54 for 1909-1914. With the smoothed earnings from operations, these correlations are, respectively, 0.51 and 0.60. Therefore, as a robustness check I provide an additional estimate of the Boone indicator using 16 cents as additional marginal costs, mc_0.

The second critique is based on the fact that the proxy for profits is not independent from marginal costs to begin with, as it is calculated using information on marginal costs. As a robustness check, I estimate the relationship between profits and instrumented marginal costs. The estimated value of marginal costs is derived from a regression of marginal costs as dependent variable and lagged values of marginal costs as independent variables. Recall that the proxy for profit used information on marginal costs and not information on the instrumented marginal costs. If the profit-proxy were determined significantly by the instrumented marginal costs, then this would indicate that the relationship between the proxy for profit and marginal costs is not significantly influenced by the fact that profits are partly calculated with information on marginal costs.

Figure 5.1 Profit-proxy compared to earnings from operations[a]



[a]Since we have only the first half of the year, the calculated profit-proxy is doubled.

5.5 The empirical model

Ideally, I would estimate equation (5.6), which shows a nonlinear relationship between marginal costs and profits. However, most parameters would then be insignificant at the 5%-level. From this, the conclusion can be drawn that a nonlinear model was too demanding for the small number of observations available. Therefore, I estimated a linear, model. In this model, profits of firm 1, $\pi_{1,t}$, are related to marginal costs of firm 1, $mc_{1,t}$, in linear form at different moments in time t. Equation (5.6) can be rewritten in an empirical model:

$$\pi_{1t} = \psi_s + \sum \mathrm{d_p}\, \delta_p\, mc_{1t}\,, \tag{5.8}$$

where $\mathrm{d_p}$ is a dummy equal to 1 if *t* is an element in the sub-period p and zero otherwise. I have defined four sub-periods so that p= 1,..,4. The profit of firm 1, π_{1t}, in period t depends on the marginal cost in different sub-periods of period t. The Boone indicator, BI, is equal to $\delta\, mc_{1p}/\, \pi_{1p}$, the elasticity of profits, π, to mc for the sub-period p. The period 1890 -1914 is divided into sub-periods, of price war, oligopoly, the break-up of the cartel and a period with a mixed competition regime. ψ_s is a constant with quarterly dummies, s =0,1..3.

Genesove and Mullin (1998) explicitly test whether the elasticity-adjusted Lerner-Index, PCM times the absolute value of the price elasticity of sugar demand, is able to distinguish between periods of price war and periods with no price war for the sugar industry. To investigate whether the Boone indicator is able to identify the different sub-periods, I use the Wald test to ascertain whether its values in the different sub-periods are significantly different from each other. Given the fact that there are four periods, we have in principle six hypotheses. Of these six, I leave out the hypotheses that test whether competition after the period with a mixed regime was more or less intense than it was during the period of oligopoly or the period of the break-up of the cartel, because it is impossible to have priors on these hypotheses. It is difficult to classify the competition regime of the period 1900 -1909, the period after the Arbuckle war, a period with a mixed regime of competition. The price war was not an outright win over the Arbuckle group. After the price war, the Arbuckle group was incorporated into the cartel. Based on the aforementioned testimonies, it is unclear whether competition had been improved or the degree of competition had returned to pre-price-war days. Therefore, it is hard to set prior beliefs on whether competition during the period 1900-1909 should be higher or lower than during the period of a break-up of the cartel or oligopoly.

These four remaining hypotheses are all one-sided tests. The prior for Hypothesis I is that the value of the Boone indicator, BI, in a period of oligopoly is larger than its value during the break-up of the cartel. Recall that the value of the Boone indicator is always negative or zero. In other words, I expect that competition is fiercer during the period

after the break-up of the cartel compared to the period when the cartel was still intact, because after the break-up of the cartel sugar firms do not collude. Therefore, Hypothesis I is as follows:

$$H0: BI_{oligopoly} \leq BI_{break\text{-}iup}$$
$$H1: BI_{oligopoly} > BI_{break\text{-}iup}$$

Furthermore, following Genesove and Mullin (1998), competition must be fiercer during a price war than in other periods, such as the period during which the cartel was split up. Competition during the price war was very strong, as shown by the drastic reductions in price at the time. Prices were even temporarily lower than marginal costs, resulting in losses for the ASRC. After the break-up of the cartel, ASRC was still making profits, (Genesove and Mullin 2006). Therefore, my prior belief for Hypothesis II is that competition during the price war was heavier than after the break-up of the cartel, which implicates a rejection of H0 of Hypothesis II:

$$H0: BI_{break\text{-}up} \leq BI_{price\ war}$$
$$H1: BI_{break\text{-}up} > BI_{price\ war}$$

Of course, the entry of firms like Spreckels and Arbuckle, and the ensuing price war to fend off these entrants, must have increased the level of competition compared to the period of oligopoly in which the market share of ASRC reached 95%. Thus, hypothesis III is expected to be rejected:

$$H0: BI_{oligopoly} \leq BI_{price\ war}$$
$$H1: BI_{oligopoly} > BI_{price\ war}$$

Based on the testimonies, the Boone indicator should indicate more competition during the periods of price wars than during the period with a mixed regime of competition. Given these considerations, we test only the following hypothesis IV:

$$H0: BI_{mixed\ regime} \leq BI_{\text{price war}}$$
$$H1: BI_{mixed\ regime} > BI_{\text{price war}}.$$

5.6 Results

This section compares the elasticity-adjusted Lerner Index with the new indicator. First, both measures of competition are calculated from the data of the sugar industry. Then, the hypotheses I - IV defined above will be tested for both these measures of competition. There are several reasons why I would like to make this comparison. The first is that Boone (2008) already explained that the Boone indicator is theoretically a

better indicator for competition than the PCM. The elasticity-adjusted Lerner Index is an improved version of PCM, and so the question remains whether the Boone indicator is also empirically a better indicator. The other reasons are more of a practical nature. Genesove and Mullin (1998) calculate the elasticity-adjusted Lerner Index for the overall sugar industry, instead of one firm, which complicates the comparison of my results for the new indicator of competition with those of Genesove and Mullin (1998). The other reason is that Genesove and Mullin (1998) only look at price wars versus nonprice wars. My analysis of different regimes of competition is more demanding. Therefore, Section 5.6.1 presents the results for the elasticity-adjusted Lerner Index and Section 5.6.2 presents those for the Boone indicator. Finally, Section 5.6.3 compares the results.

5.6.1 The elasticity-adjusted Lerner Index revisited

There are two reasons for revisiting the elasticity-adjusted Lerner Index, as it was previously calculated by Genesove and Mullin (1998). First, Genesove and Mullin (1998) test only whether the elasticity-adjusted Lerner Index is able to identify price wars from non-price wars correctly. I test the more elaborate hypotheses of Section 5.5, comparing different periods representing different regimes of competition. To be able to compare the Boone indicator with the elasticity-adjusted Lerner Index, I test whether the latter indicator is able to distinguish between oligopolies, price wars and break-ups of cartels as well. I therefore test the same hypothesis for both the Boone indicator and the elasticity-adjusted Lerner Index. Second, Genesove and Mullin (1998) calculate the elasticity-adjusted Lerner Index for the total sugar market, whereas I am calculating the Boone indicator merely for one company, the American Sugar Refining Company (ASRC). Therefore, I will estimate the elasticity-adjusted Lerner Index for this firm only. The elasticity-adjusted Lerner Index, L_η, is defined as:

$$L_\eta = \eta(p)\,(p\text{-}mc)/\,p\,, \tag{5.9}$$

where (p-mc)/p is the price-cost margin (PCM), and $\eta(p)$ is the absolute value of the price elasticity of demand for sugar. For a monopolist or a functioning cartel, we would expect $L_\eta = 1$, and in a perfectly competitive or Bertrand market, $L_\eta = 0$. We estimate the price elasticity of demand in the following model:

$$D = \gamma_0 + \gamma_1\, Q3 + \sum d_p\, \tau_p\, p_{It}\,, \tag{5.10}$$

where D, total demand in the market, depends on the price set in the market, p, and a dummy for the high season, Q3. Equation (5.10) is again estimated with instrumental

variable, Cuban imports, to distinguish between supply and demand.[3] The standard errors are again heteroskedasticity-robust and autocorrelation-robust by using Newey-West's kernel-based heteroskedastic and autocorrelation consistent (HAC) variance estimations, where the bandwidth was set as before on four periods. This model provides the following results, which appear in Table 5.3. Here, it follows that the parameters of price do not vary significantly among the different regimes of competition. Furthermore, as expected, the demand for sugar during the high season is higher than during the low season.

Table 5.3 Results for the demand for refined sugar

Variable		**IV**	
Demand (production)	**Parameter**		**z-value**
p_oligopoly	-39.68		**-3.32
p_price_war	-39.57		**-3.60
p_break-up_cartel	-35.73		*-2.35
p__mixed_regime	-39.17		**-2.93
Q3	26.64		**5.67
Constant	248.98		**4.99
R^2-adj.		0.139	
Anderson correlation test		12.83	
(p-value)		(0.00)	
Hansen J-statistic		Exactly identified	
Number of observations		97	

* means significance at the 5%-level; ** means significance at the 1%-level.

Elasticity-adjusted Lerner Index

The elasticity-adjusted Lerner Index, L_η has an average value of 0.093, a minimum of 0.027 and a maximum 0f 0.203. It is calculated by the following formula:

$$L_{\eta,p} = \tau_p * (p_p/D_{ip})*(p_p-mc_{ip})/p_p,$$

where p_p is the average price, D_{ip} is the average production of ASRC, $(p_p-mc_{ip})/p_p$ is the average price-cost margin of ASRC (see Table A, in Appendix) and τ_p is the price elasticity of demand (i.e. the parameter of price in equation (5.11), in period p; see Table 5.3). As said before, this calculation of the elasticity-adjusted Lerner Index differs slightly from the version of Genesove and Mullin (1998). They use D_p, the average total production in the market, to calculate the elasticity-adjusted Lerner Index for the total market. I only look at the competitiveness of one firm, the ASRC.

[3] Genesove and Mullin (1998) differentiate between low and high season by estimating different price elasticities for demand. Introducing three quarterly dummies yields positive price elasticities for demand during the price war, due to the small database.

Therefore, I use the production of this company to evaluate the elasticity-adjusted Lerner Index. I assume that all sugar firms face the same demand curve. This assumption is reasonable, given the small quality differences between the firm's products (as sugar is a bulk good). [4]

Figure 5.2 The elasticity-adjusted Lerner Index of ASRC

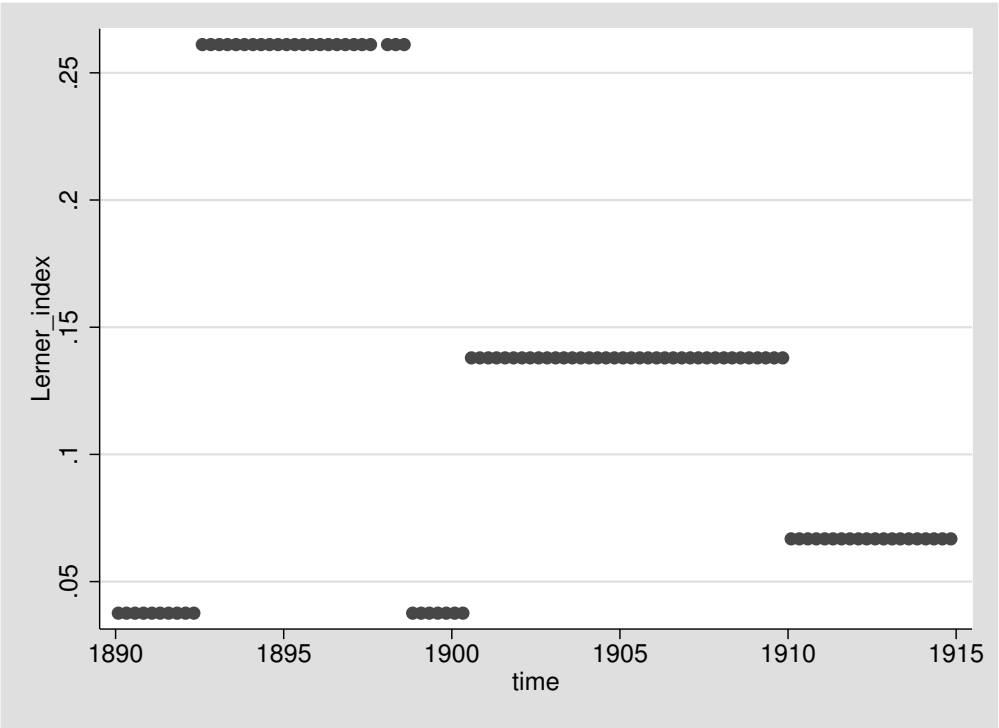


Figure 5.2, which shows the different values of the elasticity-adjusted Lerner Index, reveals that competition was at its highest level during the price war of 1890-1891 and of 1899-1900. The price-cost margin (PCM) was in these periods at its lowest level, as was the elasticity-adjusted Lerner Index. Competition was at its lowest level during the period of oligopoly, 1892-1898. The level of competition increased after the second price war and after the abolishment of the cartel in 1910. The hypotheses tested in Table 5.4 confirm that the differences in the elasticity-adjusted Lerner Index are significant between the regime of price war and the other regimes of competition at the

[4] Had we used total production of the market, the Wald test of Hypothesis II would have been equal to 0.471 with a p-value of 0.77 and would have been rejected at the 10%-level.

1%-significance level, with one exception: the elasticity-adjusted Lerner Index can only identify differences in competition between price war and the break-up of the cartel at the 10%-level.

Table 5.4 Wald tests of the elasticity-adjusted Lerner Index[5]

Hypotheses	**IV**	
	$\chi^2(1)$	**p-values**
Test H0: Lerner _oligopoly <= Lerner_break_up cartel	14.79	0.00
Test H0: Lerner_price war >= Lerner _break_up_cartel	2.50	0.06
Test H0: Lerner _oligopoly <= Lerner_pricewar	10.65	0.00
Test H0: Lerner_price war >= Lerner_mixed_regime	7.35	0.00

5.6.2 The results for the Boone indicator

The second column of Table 5.5 shows the estimations of the linear model using instrumental variables (IV). The standard errors are heteroskedasticity-robust and autocorrelation-robust by using Newey-West's kernel-based heteroskedastic and autocorrelation consistent (HAC) variance estimations, where the bandwidth was set on four periods, as was done by Genesove and Mullin (1998). The estimations are corrected for seasonal effects by introducing quarterly dummies, Q1-Q3. The estimations show that the high season of spring and summer (respectively Q2 and Q3) were more profitable than the low season of winter, Q1, and the benchmark season of autumn.

Marginal costs are determined by the price of raw sugar. This price could increase when the demand curve for sugar shifts to the right and thus indicates increased demand for sugar and an increase in profits. This shift in the demand curve is not related to changes in the competitive environment, and could therefore contaminate our estimates for the Boone indicator. To correct for this endogenous effect, we estimate the same equation with instrumental variables. The IV used is the Cuban import of raw sugar, which most probably diminished the price for raw sugar, but not the demand for sugar and profits of the firm. Genesove and Mullin (1998) point out that the potential endogeneity of Cuban imports depended upon the sources of variation in Cuban production: the seasonality of the yearly production, yearly climate variation, the Cuban Revolution, the subsequent Spanish-American War and a spectacular increase in planting of sugar cane. Only the last factor could be related to demand shocks. This would be possible only if a shock in US demand for sugar induced speculative raw sugar storage in Cuba. The only storage of raw sugar happened at the shipping docks. Storage meant a delay in the cane harvest, which in turn led to the sugar losing some

[5] The Lerner_Arbuckle war indicator was significantly different from the other periods at the 1%-level. The Wald tests are available on request.

sucrose. Postponing the harvest in hopes of receiving higher prices ran the significant risk that the rainy season would begin before all of the cane could be harvested (Genesove and Mullin 1998, pp. 363, 364). Diminished Cuban imports could increase the price of raw sugar. The second column of table 5.6 indicates that the parameter for marginal costs differs significantly from zero at the 1%-level during all periods, with the exception of that of oligopoly. The difference between the parameters of marginal cost is significant only between the period of oligopoly and all the other periods. In all other cases, these differences are not significant.[6]

The parameters of marginal costs, mc, for the sub-period of price war and break-up of the cartel are both significantly different from zero, at the 1%-level. The parameter of marginal costs in the period with a mixed regime of competition is also at the 1%-level significantly different from zero. Marginal costs do not seem to have any relationship with profits in the period of oligopoly. The parameter of marginal costs is at its lowest level during a price war and at its highest during an oligopoly. The parameters of marginal costs during oligopoly and the other periods differ significantly from each other at the 1%-level. There are no significant differences in these parameters in the periods of price war, break-up of the cartel and with a mixed regime of competition. The conclusion is that estimating different parameters for these different regimes of competition only matters for periods of oligopoly.[7]

I performed two robustness checks. In Section 5.4, I pointed out that the proxy for profits is calculated using information on marginal costs and is therefore not independent of marginal costs. As a robustness check I estimate the same equation in General Method of Moments (GMM) with additional instrumental variables, the marginal costs lagged four quarters, to analyse whether the instrumented marginal costs are related to profits in the same way as marginal costs. If this were the case, it would indicate that using a profit-proxy based on marginal costs does not distort the results significantly. The instrumented marginal costs are the residual of the equation in which marginal costs are regressed on the four-quarters-lagged marginal costs. To test for overidentification of the instruments, we apply the Hansen J-test for GMM (Hayashi 2000). The joint null hypothesis is that the instruments are valid instruments (i.e. uncorrelated with the error term). Under the null hypothesis, the test statistic is chi-squared with the number of degrees of freedom equal to the number of overidentification restrictions. A rejection would cast doubt on the validity of the instruments. Only instruments with four periods lagged rejected the Hansen J-statistic with more than 5%-significance. The results, presented in the fourth column of Table 5.5, show the same picture as the first column. The parameters are of the same order of magnitude as those in the first column, and are even more significant. Therefore, I

[6] The Wald tests are available on request.

[7] The estimations presented below use also yearly data for market shares. As a robustness check, I have also used a moving average over four quarters from 1891 onwards for market shares. Using this smoothed version of market share did not change the results significantly.

conclude that the use of a profit-proxy based on marginal costs does not alter the results significantly.

As a second robustness check, I estimate the same relationship in IV, but this time with an estimate for mc_0 of 16 cents, instead of 26 cents, resulting in lower marginal cost and profits. I use 16 cents, as this mimicked the figures for earnings from operations acquired from the Chronicles and annual reports of ASRC the best. Again, the sixth column of Table 5.5 shows that the original estimate does not differ substantially from that with additional marginal costs of 16 cents. Also, there is little difference between the different parameters for marginal costs in the various regimes of competition across the different specifications. This means that the results are insensitive to the choice of additional marginal costs, mc_0.

Table 5.5 Results

mc_0	**26 cents**		**26 cents**		**16 cents**	
Variable	**IV**		**GMM**		**IV**	
Profit	**Parameter**	**z-value**	**Parameter**	**z-value**	**Parameter**	**z-value**
mc_oligopoly	-6.56	-1.83	-8.40	**-3.18	-6.82	-1.83
mc_price_war	-11.43	**-3.49	-14.06	**-5.60	-11.99	**-3.59
mc_break-up_cartel	-14.89	**-3.42	-15.97	**-4.84	-15.65	**-3.45
mc__mixed_regime	-11.76	**-3.00	-13.59	**-4.69	-12.39	**-3.05
Q1	0.04	0.02	0.17	0.09	-0.07	-0.04
Q2	7.25	**3.38	7.41	**3.48	8.52	**3.86
Q3	9.22	**4.43	8.74	**4.28	10.93	**5.00
Constant	51.09	**3.67	57.65	**5.55	57.38	**4.07
R^2-adj.	0.546		0.516		0.562	
Anderson correlation test	32.88		51.71		32.79	
(p-value)	(0.00)		(0.00)		(0.00)	
Hansen J-statistic	Exactly identified		6.712		Exactly identified	
(p-value)			(0.15)			
Number of observations	97		92		97	

* means significance at the 5% level , ** means significance at the 1% level.

The Boone indicator

The Boone indicator, BI, is the elasticity of profits to marginal costs, ie $\delta\ mc_p / \pi_p$. The Boone indicator for the different sub-periods is calculated by multiplying the IV-estimates of the parameter δ of mc in sub-period p from the second column of Table 5.5 with the ratio of average marginal costs, mc_p, and average profits, π_p, in the same sub-period p (as presented in Table 5.2).

Figure 5.3 The Boone indicator of ASRC[8]

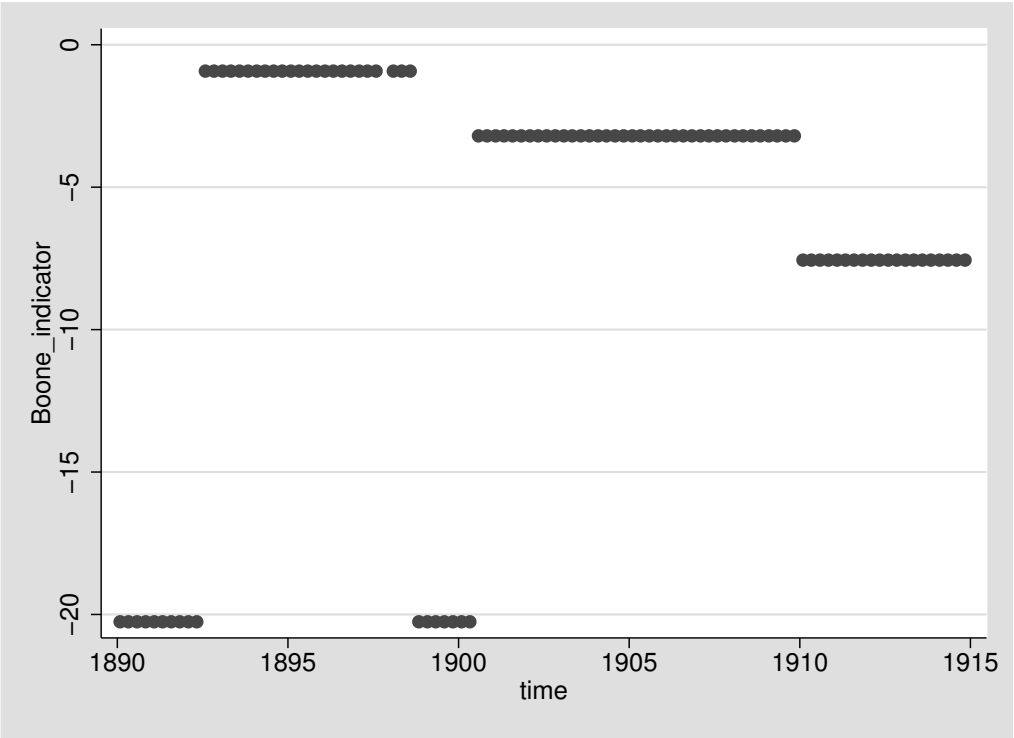


Figure 5.3 presents the values of the Boone indicator for the different regimes of competition. It is shown that competition during the price wars of 1890-1891 and 1899-1900 was very strong compared to other periods, as indicated by its very negative values. The BI was at its highest point (least negative) during the period of oligopoly, 1892-1898. After the break-up of the cartel in 1910, its values became again more negative, indicating that ASRC became more competitive compared to the previous period of oligopoly. The period 1900-1909 shows that competition in the sugar market was moderate during the mixed regime, higher than during the previous period of oligopoly, but lower than during the period after the break-up of the cartel.[9] The next section examines the significance of these differences by testing the hypotheses of Section 5.5.

[8] In line with Genesove and Mullin, observation 1897Q4 is left out of the estimation because the instrumental variable Cuban imports of raw sugar was zero.

[9] The figures of the Boone indicator with the estimates of the fourth and sixth columns of Table 5 are not shown because they are almost identical to Figure 5.2. They are available upon request.

Hypotheses

To test the different hypotheses, I used a Chi-squared distributed Wald test with one degree of freedom to determine whether the Boone indicator was significantly different between two periods. The results are presented in Table 5.6, second column. They show that the Boone indicator during the break-up of the cartel was significantly more negative than the Boone indicator in times of an oligopoly (H0 'Boone_oligopoly > Boone_break_up_cartel'). The null hypothesis I, is thus rejected at the 1%-level. Furthermore, for all the other hypotheses, all of the the null hypotheses is rejected too, which indicates that the BI is fully able to distinguish between the different regimes of competition. Therefore, the new measure of competition could very well be used to measure the different regimes of competition. The fourth and sixth columns of Table 5.6 also show that with instrumented marginal cost or with additional marginal costs of 16 cents, the BI is capable of identifying the different regimes of competition from each other. Again, the conclusion is that the degree to which the Boone indicator is able to identify different regimes of competition is not affected by the fact that the proxy for profits is based on marginal costs.

Table 5.6 Wald tests of the Boone indicator[10]

Hypotheses	**26 cents IV**		**26 cents GMM**		**16 cents IV**	
	$\chi^2(1)$	**p-values**	**$\chi^2(1)$**	**p-values**	**$\chi^2(1)$**	**p-values**
Test H0: Boone_oligopoly <= Boone_break_up cartel	14.87	0.00	27.56	0.00	17.77	0.00
Test H0: Boone_price war >= Boone_break_up_cartel	11.67	0.00	34.07	0.00	10.21	0.00
Test H0: Boone_oligopoly <= Boone_pricewar	13.30	0.00	33.71	0.00	16.95	0.00
Test H0: Boone_price war >= Boone_mixed_regime	12.83	0.00	33.00	0.00	15.09	0.00

5.6.3 Comparison

Above we discussed two measures of competition: the elasticity-adjusted Lerner Index and the Boone indicator. Both measures provide a similar picture with regard to levels of competition. Competition is low in times of oligopoly, and both the elasticity-adjusted Lerner Index and the Boone indicator are high. Competition is most fierce when there are price wars according to both measures of competition: The elasticity-

[10] The $\text{Boone}_{\text{mixed\_regime}}$ indicator was significantly different from the other periods at the 1%-level. The Wald tests are available upon request.

adjusted Lerner Index is close to zero and the Boone indicator has a very negative value.

The Boone indicator provides the same information as the elasticity-adjusted Lerner Index, although the latter indicator did not differentiate significantly between competition levels of price wars and the break-up of the cartel. At the same time, a limitation of the Boone indicator is that there is no benchmark, no absolute value, which indicates the regime of competition. The elasticity-adjusted Lerner Index has such benchmark. For instance, it is possible to test whether, during a price war, competition reaches the level of perfect competition. For that purpose, I use a Wald-test with the H0-hypothesis that the elasticity-adjusted Lerner Index was equal to zero. This H0-hypothesis was rejected at the 1%-level ($\chi^2(1) = 12.94$), meaning that during these price wars there was no perfect competition. This means that the elasticity-adjusted Lerner Index is significantly different from zero.

5.7 Conclusion

This chapter tested whether a new concept to measure competition introduced by Boone (2008) is able to identify empirically significant differences in the level of competition between periods of oligopoly, price war and split-up of cartels. A limitation of the Boone indicator, compared to the elasticity-adjusted Lerner Index, is that it cannot measure the absolute level of competitiveness of the firm. It can only tell us whether the firm in one period is on average more or less competitive than in another period. For this purpose, a linear model is estimated between a proxy for profits and marginal costs by using data of the dominant firm in the sugar industry, ASRC, in the period 1890-1914. These data are derived from Genesove and Mullin (1998). The profit-proxy is based on information on marginal costs. From these estimates, it follows that the Boone indicator indeed is able to identify the different regimes of competition empirically. The results show that during a price war competition is significantly more intense than in a period of an oligopoly. The new indicator further indicates that competition during the break-up of the cartel is also significantly higher than during an oligopoly, just in line with expectation. Finally, the Boone indicator's value during a price war is lower than in the period after the break-up of the cartel, indicating that competition is more fierce in the first period compared to the latter period. Robustness checks with regard to the accurate measurement of profits by the proxy of profits show that my results are insensitive to variation in the specification of the profit-proxy. Estimations with instrumented marginal costs reveal that the results of the Boone indicator are not substantially influenced by the fact that the proxy is based on marginal costs. From a comparison of these results with those of the elasticity-adjusted Lerner Index, it follows that the new indicator performs just as well as the adjusted Lerner Index.

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Appendix

Table A Descriptive statistics for calculating the elasticity-adjusted Lerner Index

	Observations	Mean	Std. Dev.	Min	Max
PCM_price_war (in terms of price)	17	0.01	0.05	-0.04	0.14
PCM_oligopoly (in terms of price)	24	0.10	0.04	0.02	0.15
PCM_break-up_cartel (in terms of price)	18	0.03	0.02	0.01	0.07
PCM__mixed_regime (in terms of price)	38	0.06	0.03	-0.01	0.10
Production_price_war in long tons	17	82.37	15.47	55.54	118.94
Production_oligopoly in long tons	24	83.39	16.64	52.66	122.08
Production_break-up_cartel in long tons	18	124.90	28.65	81.09	165.54
Production_mixed_regime in long tons	38	104.46	17.67	74.26	145.18
Marketshare_price_war (in %)	17	71	8	65	91
Marketshare_oligopoly (in %)	24	78	6	70	91
Marketshare_break-up_cartel (in %)	18	47	3	43	50
Marketshare_mixed_regime (in %)	38	59	5	50	70
Price_price_war (in dollars)	17	4.51	0.68	3.55	5.50
Price_oligopoly (in dollars)	24	4.40	0.412	3.72	5.07
Price_break-up_cartel (in dollars)	18	3.45	0.47	2.75	4.44
Price_mixed_regime (in dollars)	38	3.85	0.44	3.38	5.02

All prices are reported in dollars per hundred pounds. All quantities are reported in 100,000 of long tons (one long ton is 2240 pounds). Profits are in 100,000 dollars.

From Table A, it follows that the price-cost margin as a percentage of price was at its lowest level during the price wars, 1% of the price, and at its highest level during the period of oligopoly, 10% of the price. Furthermore, production increased over time, from around 0.83 million long tons to 0.124 million long tons after the break-up of the cartel, as the entry of firms increased. Market shares declined gradually from 78% on average during the oligopoly period to 47% after the break-up of the cartel. Prices were indeed high during the times of oligopoly, but this was partly due to high prices for raw sugar. Prices reached their lowest levels after the break-up of the cartel.

6 A new approach to measuring competition in the loan markets of the euro area

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6.1 Introduction

This chapter investigates the measurement of competition in the EU banking sector. Competition is a key driver of social welfare, as it may push down prices (i.e. interest rates) and improves services for consumers and enterprises (Cetorelli 2001).[1] Also, competition is pivotal to monetary policy: in a competitive loan market, changes in the policy rates of the European Central Bank (ECB) are passed on more quickly to the interest rates that banks offer their customers. Therefore, we focus our attention to competition in loan markets.

The chapter presents estimates of competition in loan markets of the major EU countries using a new approach, introduced and applied by Boone (2000, 2004), Boone et al. (2004) and CPB (2000) and discussed previously in Chapter 5. So far, this method has not been applied to banking markets.[2] The so-called Boone indicator (BI) measures the impact of efficiency on performance in terms of profits or market shares. The idea behind the BI is that competition enhances the performance of efficient firms in terms of their marginal costs and impairs the performance of inefficient firms, which is reflected in their respective profits or market shares. This approach is related to the well-known efficiency hypothesis, which also explains banks' performances by differences in efficiency (Goldberg and Rai 1996; Smirlock 1985).

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[1] However, as is stressed by Allen *et al.* (2001), there is a conflict between this traditional view, stemming from the industrial organisation literature, and more recent theoretical models of bank competition, which raise the question whether competition between banks is good or bad. See, for example, Cetorelli and Strahan (2006).

[2] Boone applied his indicator to various manufacturing industries and Bikker and Van Leuvensteijn (2008) to the life insurance business.

A well-known problem in the banking industry is that competition cannot be measured directly, as costs and often also price data of single banking products are seldom available. Indirect measures are thus needed. This chapter adds to the competition literature in applying a new competition indicator to the banking sector that improves on widely accepted concentration measures such as the Herfindahl-Hirschmann Index (HHI). The HHI has the disadvantage of not distinguishing between large and small countries. Furthermore, concentration may also be due to consolidation forced by severe competition. Hence, the concentration index is an ambiguous measure.[3]

Our approach to competition is also innovative, in the sense that we can measure competition not only for the entire banking market, but also for various product markets, such as the loan market. An often-applied measure (such as the Panzar-Rosse model) only investigates the competitive nature of the total of all banking activities. Another advantage of the Boone indicator is that it requires relatively little data, different from, e.g. the Bresnahan model, which is very data intensive. This allows the estimation of competition on an annual basis to assess developments over time.

For an overview of different approaches to measure competition, see Chapter 1, the introduction of this thesis. Chapter 6 is structured as follows. As in Chapter 5, Section 6.2 provides a theoretical basis for the Boone indicator as a new measure for competition, and discusses its properties. The data are described in the following section. The econometric method and the results are presented in Section 6.4. Finally, Section 6.5 concludes.

6.2 The Boone indicator model

Boone's model is based on the notion, first of all, that more efficient firms (that is, firms with lower marginal costs) gain higher market shares or profits and, second, that this effect is stronger the heavier the competition in that market is. In order to support this quite intuitive market characteristic, Boone develops a broad set of theoretical models (see Boone 2000, 2001 and 2004, Boone *et al.* 2004, and CPB 2000). We use one of these models to explain the Boone indicator (BI) and to examine its properties compared to common measures such as the HHI and PCM approaches. Following Boone *et al.* (2004), and replacing 'firms' by 'banks', we consider a banking industry where each bank i produces one product q_i (or portfolio of banking products), which faces a demand curve of the form:

$$p\,(q_i, q_{j\neq i}) = a - b\,q_i - d\,\textstyle\sum_{j\neq i} q_j \qquad \forall\, i \tag{6.1}$$

[3] A worldwide study by Claessens and Laeven (2004) found that bank concentration was positively instead of negatively related to competition.

and has constant marginal costs mc_i. This bank maximizes profits $\pi_i = (p_i - mc_i)\, q_i$ by choosing the optimal output level q_i. We assume that $a > mc_i$ and $0 < d \leq b$. The first-order condition for a Cournot-Nash equilibrium can then be written as:

$$a - 2\, b\, q_i - d \sum_{i \neq j} q_j - mc_i = 0 \qquad \forall\, i \tag{6.2}$$

When N banks produce positive output levels, we can solve the N first-order conditions (6.2), yielding:

$$q_i\,(c_i) = [(2\, b/d - 1)\, a - (2\, b/d + N - 1)\, mc_i + \sum_j mc_j] \tag{6.3}$$

$$/[(2\, b + d\,(N - 1))(2\, b/d - 1)] \qquad \forall\, i$$

We define profits π_i as variable profits excluding entry costs ε. Hence, a bank enters the banking industry if, and only if, $\pi_i \geq \varepsilon$ in equilibrium. Note that Equation (6.3) provides a relationship between output and marginal costs. It follows from $\pi_i = (p_i - mc_i)\, q_i$ that profits depend on marginal costs in a quadratic way.

In this market, competition can increase in three ways. First, competition increases when the produced (portfolios of) services of the various banks become closer substitutes (that is, d increases (keeping d below b)). Second, competition increases when entry costs ε decline. Boone *et al*. (2004) prove that market shares of more efficient banks (that is, with lower marginal costs c) increase both under regimes of stronger substitution and amid lower entry costs. Third, changes in b are related to adjustments in the preferences of consumers. An increase in b points to a lower price sensitivity of the demand for loans and increases the market power of all firms.

Equation (6.3) supports the use of the following model for market share, defined as $s_i = q_i / \sum_j q_j$:

$$\ln s_i = \alpha + \beta \ln mc_i. \tag{6.4}$$

The market shares of banks with lower marginal costs are expected to increase, so that β is negative. The stronger the competition is, the stronger this effect will be, and the larger (in absolute terms) this (negative) value of β. We refer to the β parameter as the *Boone indicator*. For empirical reasons, Equation (6.4) has been specified in log-linear terms in order to deal with heteroskedasticty. Moreover, this specification implies that β is an elasticity, which facilitates easy interpretation, particularly across equations.[4] The choice of functional form is not essential, as the log-linear form is just an

[4] The few existing empirical studies based on the Boone indicator have all used a log linear relationship. See, for example, Bikker and Van Leuvensteijn (2007).

approximation of the pure linear form. Section 6.4.2.1 demonstrates how similar the results of the linear model are to those of the log-linear model.

The theoretical model above can also be used to explain why widely applied measures such as the HHI and the PCM fail as reliable competition indicators. The standard intuition of the HHI is based on a Cournot model with symmetric banks, where a fall in entry barriers reduces the HHI. However, with banks that differ in efficiency, an increase in competition through a rise in d reallocates output to the more efficient banks that already had higher output levels. Hence, the increase in competition raises the HHI. The effect of increased competition on the industry's PCM may also be perverse. Generally, heavier competition reduces the PCM of all banks. But since more efficient banks may have a higher PCM (skimming off part of the profits stemming from their efficiency lead), the increase of their market share may raise the industry's average PCM, contrary to common expectations.

We note that the Boone indicator (BI) model, like every other model, is a simplification of reality. We see banks mainly competing on market shares, as in a Cournot model. The price of loans is largely determined by changes in the funding rate by developments in capital markets and monetary policy. Furthermore, efficient banks may choose to translate lower costs into either higher profits or lower output prices in order to gain market share. Our approach assumes that the behaviour of banks is between these two extreme cases, so that banks generally pass on at least part of their efficiency gains to their clients. More precisely, we assume that the banks' passing-on behaviour, which drives Equation (6.4), does not diverge too strongly across the banks. Also, our approach ignores differences in bank product quality and design, as well as the attractiveness of innovations. We assume that banks are forced over time to provide quality levels that are more or less similar. By the same token, we presume that banks have to follow the innovations of their peers. Hence, like many other model-based measures, the BI approach focuses on one important relationship, affected by competition, thereby disregarding other aspects (see also Bikker and Bos 2005). Naturally, annual estimates of β are more likely to be impaired by these distortions than the estimates covering the full sample period. Also, compared to direct measures of competition, the BI may have the disadvantage of being an estimate and thus surrounded by a degree of uncertainty. Of course, other model-based measures, such as Panzar and Rosse's H-statistic, suffer from the same disadvantage. The latter shortcoming concerns the annual estimates β_t rather than the full sample period estimate β.

As the BI may be time dependent, reflecting changes in competition over time, we estimate β separately for every year (hence, β_t). We do not have an absolute benchmark for the level of β. We only know that the more negative β is, the stronger competition must be. Comparing the indicator across regions or countries, or even across industries, may help to interpret estimation results. For that reason, Boone and Weigand in CPB (2000) and Boone *et al.* (2004) apply the model to different manufacturing industries. Since measurement errors – including unobserved country or industry-specific factors –

are less likely to vary over time than across industries, the time-series interpretation of beta is probably more robust than the cross-sectoral one (that is, comparison of β for various countries or industries at a specific moment in time). Therefore, Boone focuses mainly on the *change* in β_t over time within a given industry, rather than comparing β between industries.

Because marginal costs cannot be observed directly, CPB (2000) and Boone *et al.* (2004) approximate a firm's marginal costs by the ratio of average costs and revenues. As dependent variable in Equation (6.4), CPB (2000) uses the *relative* values of profits and as explanatory variable the ratio of variable costs and revenues, whereas Boone *et al.* (2004) consider *absolute* instead of relative values.

We improve on Boone's approach in two ways. First, we calculate marginal costs instead of approximating this variable with average variable costs. We are able to do so by using a translog cost function, which is more precise and more closely in line with theory. An important advantage is that these marginal costs allow us to focus on segments of the market, such as the loan market, where no direct observations of individual cost items are available. Second, we use market share as dependent variable instead of profits. The latter is, by definition, the product of market share and profit margin. We have prior beliefs on the impact of efficiency on market share and its relation with competition, supported by the theoretical framework above, whereas we have no a priori knowledge about the effect of efficiency on the profit margin. Hence, a market-share model will be more precise. An even greater advantage of using market shares is that they are always positive, whereas the range of profits (or losses) includes negative values. A log linear specification would exclude negative profits (losses) by definition, so that the estimation results would be distorted by sample bias.

In order to be able to calculate marginal costs, we first estimate, for each country, a translog cost function (TCF) using individual bank observations. Such a function assumes that the technology of an individual bank can be described by one multiproduct production function. Under proper conditions, a dual cost function can be derived from such a production function, using output levels and factor prices as arguments. A TCF is a second-order Taylor expansion around the mean of a generic dual cost function with all variables appearing as logarithms. It is a flexible functional form that has proven to be an effective tool in explaining multiproduct bank services. The TCF has the following form:

$$\begin{aligned} ln\, c_{it}^{h} = \alpha_0 &+ \textstyle\sum_{h=1,..,(H-1)} \alpha_h\, d_i^h + \sum_{t=1,..,(T-1)} \delta_t\, d_t + \sum_{h=1,..,H} \sum_{j=1,..,K} \beta_{jh}\, ln\, x_{ijt}\, d_i^h \\ &+ \textstyle\sum_{h=1,..,H} \sum_{j=1,..,K} \sum_{k=1,..,K} \gamma_{jkh}\, ln\, x_{ijt}\, ln\, x_{ikt}\, d_i^h + v_i \;, \end{aligned} \tag{6.5}$$

where the dependent variable c_{it}^{h} reflects the production costs of bank i (i = 1, .., N) in year t (t = 1, .., T). The sub-index h (h = 1, .., H) refers to the type of the bank, that is, commercial bank, savings bank or cooperative bank. The variable d_i^h is a dummy variable, which is 1 if bank i is of type h and zero otherwise. The variable d_t is a

dummy variable, which is 1 in year t and zero otherwise. The explanatory variables x_{ikt} represent three groups of variables (k = 1, .., K.). The first group consists of (K_1) bank output components, such as loans, securities and other services (proxied by other income). The second group consists of (K_2) input prices, such as wage rates, deposit rates (as price of funding) and the price of other expenses (proxied as the ratio of other expenses to fixed assets). The third group consists of (K-K_1-K_2) control variables (also known as 'netputs'), e.g. the equity ratio. In line with Berger and Mester (1997), the equity ratio corrects for differences in loan portfolio risk across banks. The coefficients α_h, β_{jh} and γ_{jkh}, all vary with h, the bank type. The parameters δ_t are the coefficients of the time dummies and v_{it} is the error term.

Two standard properties of cost functions are linear homogeneity in the input prices and cost-exhaustion (see e.g. Beattie and Taylor 1985; Jorgenson 1986). They imply the following restrictions on the parameters, assuming – without loss of generality – that the indices j and k of the two sum terms in equation (6.5) are equal to 1, 2 or 3, respectively, for wages, funding rates and prices of other expenses (disregarding the sub-index h):

$$\beta_1 + \beta_2 + \beta_3 = 1,\ \gamma_{1,k} + \gamma_{2,k} + \gamma_{3,k} = 0 \text{ for k = 1, 2, 3, and } \gamma_{k,1} + \gamma_{k,2} + \gamma_{k,3} = 0 \text{ for } k = 4,.., K\,. \tag{6.6}$$

The first restriction stems from cost exhaustion, reflecting the fact that the sum of cost shares is equal to unity. In other words, the value of the three inputs is equal to total costs. Linear homogeneity in the input prices requires that the three linear input price elasticities (β_i) add up to 1, whereas the squared andcross- terms of all explanatory variables ($\gamma_{i,j}$) add up to zero. Again without loss of generality, we also apply the symmetry restrictions $\gamma_{j,k} = \gamma_{k,j}$ for j, k = 1, .., K.[5] As equation (6.5) expresses the fact that we assume different cost functions for each type of bank, the restrictions (6.6) apply to each type of bank.

The marginal costs of output category $j = l$ (of loans) for bank i of category h in year t, $mc_{ilt}^{\ h}$ are defined as:

$$mc_{i1t}^{\ h} = \partial\, c_{it}^{\ h} / \partial\, x_{i1t} = (c_{it}^{\ h} / x_{i1t})\ \partial\, ln\, c_{it}^{\ h} / \partial\, ln\, x_{ilt}\,. \tag{6.7}$$

The term $\partial\, ln\, c_{it}^{\ h} / \partial\, ln\, x_{ilt}$ is the first derivative of equation (6.5) of costs to loans. We use the marginal costs of the output component 'loans' only (and not for the other K_1 components), as we investigate the loan markets. We estimate a separate TCF for each individual sector in each individual country, allowing for differences in the production

[5] The restrictions are imposed on Equation (6.5) so that the equation is reformulated in terms of fewer parameters (see appendix I).

structure across bank types within a country. This leads to the following equation of the marginal costs for output category loans (l) for bank i in category h during year t:

$$mc_{i1t}^{h} = c_{it}^{h} / x_{i1t} (\beta_{1h} + 2\ \gamma_{1lh}\ ln\ x_{ilt} + \sum_{k=1,..,K;\ k \neq l} \gamma_{1kh}\ ln\ x_{ikt}\ )\ d_i^h \tag{6.8}$$

6.3 The data

This chapter uses an extended Bankscope database of banks' balance sheet data running from 1992 to 2004. We investigate banking markets of the major euro area countries (i.e. France, Germany, Italy, the Netherlands and Spain), as well as, for comparison, the UK, the US and Japan. The focus is on commercial banks, savings banks, cooperative banks and mortgage banks and, for most countries, ignores specialized banks (such as investment banks, securities firms and specialized governmental credit institutions). For Germany, some specialized governmental credit institutions, that is, the major *Landesbanken*, are included in the sample in order to have a more adequate coverage of the German banking system. In addition to certain public finance duties, these *Landesbanken* also offer banking activities in competition with the private sector banks (Hackethal 2004). For Japan, in contrast to Uchida and Tsutsui (2005), we also include three long-term credit banks, because they traditionally have offered long-term loans to the corporate sector and have increasingly become competitors of the commercial banks, due to the ongoing process of financial liberalisation in Japan, which has eroded the traditional segmentation of the Japanese banking sector (Van Rixtel 2002).

In order to exclude irrelevant and unreliable observations, banks are incorporated in our sample only if they fulfil the following conditions: total assets, loans, deposits, equity and other non-interest income should be positive; the deposits-to-assets ratio and loans-to-assets ratio should be less than, respectively, 0.98 and 1; the income-to-assets ratio should be below 20 percent; the personnel expenses-to-assets ratio and other expenses-to-assets ratios should be between 0.05% and 5%; and finally, the equity-to-assets ratio should be between 1% and 50%. These restrictions reduced the sample by 3,980 observations, mainly due to the equity-to-assets ratio restriction. As the Japanese banking sector experienced a deep crisis during most of our sample period, we relaxed the equity ratio restriction for Japanese banks.

Table 6.1 Number of banks by country and by type in 2002

Country	Commercial banks	Cooperative banks	Long-term credit banks	Real estate banks/ Mortgage banks	Savings banks	Special governmental credit institutions	Total
DE	130	867	0	44	501	28	1570
ES	61	17	0	0	43	0	121
FR	115	83	0	2	30	0	230
UK	80	0	0	57	3	0	140
IT	105	476	0	1	52	0	634
JP	169	676	3	0	1	0	849
NL	24	1	0	4	1	0	30
US	7921	1	0	1	914	0	8837
Total	8605	2121	3	109	1545	28	12,411

As a result, the dataset for 2002 totals 8605 commercial banks (including *Landesbanken*), 2121 cooperative banks, 1545 savings banks and 109 mortgage banks, plus 31 other banks, which yields 12,411 banks in total (see Table 6.1). Over all of the years of the sample, the number of observations is 88,647. German and, particularly, US banks dominate the sample with, respectively, 1570 and 8837 banks (in 2002). Before 1999, the number of US banks was only around one quarter of this number, because Bankscope does not provide information before that date on small savings banks.

Table 6.2 describes one of the key variables, market shares. From Table 6.2, it follows that the median market share ranges from 0.5% in Japan to 4.80% in Spain. Also, the maximum market share in terms of loans of the balance sheet differs strongly between countries. One Italian bank has as maximum market share 7.8%, for example, whereas one Japanese bank has a market share of 28.5%.

Table 6.2 Stylized facts on market share by country for the period 1992-2004 (in %)

	Market share of lending				
Country	Median	Average	Standard deviation	Minimum	Maximum
DE	1.00	0.06	0.40	4.99E-05	17.9
ES	4.80	0.98	0.80	4.99E-05	14.1
FR	3.10	0.41	1.00	4.57E-05	17.5
UK	2.20	0.78	1.50	4.16E-05	20.6
IT	0.50	0.22	0.40	4.16E-05	7.8
JP	3.50	0.25	2.10	4.16E-05	28.5
NL	3.60	3.02	1.80	4.16E-05	13.5
US	3.00	0.01	0.80	7.07E-05	23.6

Table 6.3 summarizes the variables used in the estimations, such as costs, loans, securities and other services, each expressed as a share of total assets, income or funding. Costs are defined as the sum of interest expenses, personnel expenses and other non-interest expenses. Costs, loans and securities are, respectively, 6%, 61% and 25% of total assets. Average market shares differ strongly across countries, due to large differences in the number of banks. The output factor 'other services' is proxied by non-interest income, which is around 12% of total income. Wage rates are proxied by personnel expenses divided by total assets, as for most banks the number of staff is not available. Wages average 1.5% of total assets. The other-expenses-to-fixed-assets ratio provides an input price for this input factor. Finally, interest-rate costs, proxied by the ratio of interest expenses and total funding, run to around 3.1%.

Table 6.3 Mean values of key variables by country for the period 1992-2004 (in %)

	As a share of total assets				As a share of total income	As a share of fixed assets	As a share of total funding
Country	**Total costs**	**Loans**	**Securities**	**Wages**	**Other services**	**Other expenses**	**Interest expenses**
DE	6.44	60	22	1.5	12	227	3.7
ES	6.63	58	14	1.5	16	167	4.1
FR	7.42	54	4	1.5	20	537	4.8
UK	6.29	59	11	0.9	14	885	5.1
IT	6.67	53	26	1.7	16	261	3.5
JP	2.89	58	20	0.1	14	128	0.4
NL	6.59	54	15	0.9	13	340	5.4
US	5.63	63	28	1.6	11	148	2.8
Total	5.82	61	25	1.5	12	203	3.1

6.4 Estimation results

6.4.1 Marginal costs

The first step of our estimation procedure is to calculate the marginal costs of the national banking sectors; we thus estimate equation (6.5) for each of the respective eight countries. For this purpose, we use the explanatory variables described in Section 6.3, namely bank outputs (loans, securities and other services), input prices (wages, funding rates and prices of other non-interest expenses) and the control variable (equity ratio). As an example, Table A.1 in the appendix presents the TCF for Germany.[6]

The development of the marginal costs of loans for all individual countries during our sample period is shown in Table 6.4. These costs have clearly gradually declined

[6] The TCFs for the other countries may be obtained from the authors.

over time, which to a large extent reflects the decrease in funding rates during 1992-2004. However, the speed and magnitude of this decline differ across countries. Thus, differences in country-specific characteristics, such as banking technology, or differences in legislation and supervision play a role in the development of marginal costs. Germany and Spain have relatively high marginal costs compared to the Netherlands, which may be related to population density: A low population density may raise operating costs in relative terms, because it makes the retail distribution of banking services relatively more costly. Table 6.4 also shows that marginal costs in France are the highest of all countries during the second half of our sample period.

Table 6.4. Marginal costs of loans over time, weighted by loans (in % of loans) [a)]

Year/country	DE	ES	FR	UK	IT	JP	NL	US	Average
1992	10.2	15.9	13.8	14.5	13.2	6.0	9.2	–	10.9
1993	9.4	17.2	13.4	11.3	12.0	5.4	8.1	–	9.8
1994	9.2	14.3	11.9	9.8	12.2	5.4	7.4	–	9.1
1995	8.9	15.4	11.7	10.2	11.8	5.6	7.1	–	9.3
1996	8.5	14.3	10.9	9.2	11.3	4.5	6.3	–	8.8
1997	7.4	11.7	10.9	9.0	9.7	5.0	6.4	–	8.2
1998	7.1	11.1	11.2	10.3	7.5	5.1	7.4	–	7.9
1999	6.4	8.8	10.0	7.7	6.7	4.0	6.4	6.8	6.8
2000	7.1	9.9	11.2	8.0	6.7	3.0	6.5	7.4	7.3
2001	7.3	9.6	11.7	7.2	6.6	3.2	6.4	6.9	7.6
2002	7.1	7.8	10.7	6.3	6.1	3.1	5.7	5.6	6.7
2003	6.4	5.9	8.9	5.8	5.3	2.8	4.9	4.9	5.9
2004	6.0	4.8	7.9	5.6	4.9	2.7	4.6	4.5	5.4

[a] Marginal costs are first calculated with equation (6.8) at the individual bank level. Next, the numbers are weighted by the amount of loans on the balance sheet and aggregated by country and by year.

6.4.2 The Boone indicator

Given the estimated marginal costs from the previous section, we are now able to estimate the Boone indicator. To do so, we use for each country the relationship between the marginal costs of individual banks and their market shares as in equation (6.4): [7]

$$\ln s_{ilt} = \alpha + \beta \ln mc_{ilt} + \sum_{t=1,..,(T-1)} \gamma_t d_t + u_{ilt}, \tag{6.9}$$

where s stands for market share, mc marginal costs, i refers to bank i, l to output type 'loans', and t to year t. d_t are time dummies (as in equation (6.5)) and u_{ilt} is the error

[7] As bank types do not play any role here, we do not refer to the index h. (Compare to Equation (6.11)).

term. This provides us with the coefficient β, the Boone indicator (BI). We estimate this equation for, respectively, the overall banking sector in each country (Sections 6.4.2.1 and 6.4.2.2) and for one banking category separately: commercial banks. (Section 6.4.2.3). We present country estimates of β both for the entire period, referred to as full-sample-period estimates, and for each year separately, referred to as annual estimates.

The estimations are carried out using the Generalized Method of Moments (GMM) with as instrumental variables the one-, two- or three-year lagged values of the explanatory variable, marginal costs.[8] To test for overidentification of the instruments, we apply the Hansen J-test for GMM (Hayashi 2000). The joint null hypothesis is that the instruments are valid instruments, i.e. uncorrelated with the error term. Under the null hypothesis, the test statistic is Chi-squared with the number of degrees of freedom equal to the number of overidentification restrictions. A rejection would cast doubt on the validity of the instruments. Further, the Anderson canonical correlation likelihood ratio is used to test for the relevance of excluded instrument variables (Hayashi 2000). The null hypothesis of this test is that the matrix of reduced-form coefficients has rank K-1, where K is the number of regressors, meaning that the equation is underidentified. Under the null hypothesis of underidentification, the statistic is Chi-squared distributed with L-K+1 degrees of freedom, where L is the number of instruments (whether included in the equation or excluded). This statistic provides a measure of instrument relevance, and rejection of the null hypothesis indicates that the model is identified. We use kernel-based heteroskedastic and autocorrelation-consistent (HAC) variance estimations. The bandwidth in the estimation is set at two periods and the Newey-West kernel is applied. Where the instruments are overidentified, 2SLS is used instead of GMM. For this 2SLS estimator, Sargan's statistic is used instead of the Hansen J-test.

6.4.2.1 Degree of competition across countries

This section discusses the full sample period estimates of the Boone indicator. The results in Table 6.5 suggest that competition in the bank loan market varies considerably across countries.[9] The full-sample-period estimates are derived by estimating one single β for the entire period, as in equation (6.9), instead of estimating a β for each year. These full-sample-period estimates can be interpreted as averages of the year-to-year estimates over the entire 1994-2004 period, weighted by the number of observations in each year. The lagged instrumental variables cover the 1992-2004 period. According to the full-sample-period estimates, the loan market in the euro area is less competitive than its counterpart in the US. Note that the sample period for the US covers only the last five years, which may distort comparison with the other countries. Competition in the euro area appears relatively strong compared to the UK

[8] For Germany, the one-, two- or three-year lagged values of the average costs are used.

[9] In order to test the robustness of the model specification, we re-estimated β with a linear model instead of a log-linear one. The changes are limited. For instance, the German coefficient shifts from -3.38 to -2.68.

and Japan. Japanese banks are the least competitive, with, in absolute terms, the lowest β of -0.72.

Among the major countries in the euro area, the BI for Spain, Italy and Germany suggests comparatively competitive banking markets, while the Dutch banking sector takes up an intermediate position. Within the euro area, France has the least competitive banking market. These findings differ somewhat from recent empirical evidence from alternative measures of competition applied to the European banking sector, such as concentration and price-based measures. For example, recent findings by Carbó *et al.* (2006) suggest that on average, banking competition seems to be strong in the UK, followed by the Netherlands and France, while most measures they use suggest a lower degree of competition in Spain, Italy and Germany.[10] At the same time, Carbó *et al.* (2006) find that the correlation between the various competition measures is in general relatively weak. Moreover, they suggest that there is '… little relationship between structural and non-structural (i.e. price-based) measures of banking competition'. As mentioned in Section 6.2, the information on the degree of competition provided by the Boone indicator, on the one hand, and by price-based and concentration-based measures of competition, on the other hand, may differ, as the BI lacks some of the weaknesses of the latter measures (which we identified in Section 6.2). It is therefore hardly surprising if the results of Carbó *et al.* (2006) differ from ours. Comparing our results with the recent estimates of Carbó *et al.* (2006), we find a Pearson correlation coefficient of 0.30, which suggests that a higher number of banks (or lower concentration) correlates positively, if weakly, with a lower value of the Boone indicator (i.e. stronger competition).[11]

Contrary to recent criticism on the functioning of the German banking sector (e.g. IMF 2004), our estimates suggest that this sector is among the most competitive in the euro area. Most likely, this result for Germany hinges in part on the special structure of its banking system, being built on three pillars, namely commercial banks, publicly owned savings banks and cooperative banks (see Hackethal 2004). Contrary to most other euro-area countries, the total market share of the commercial banks in the loan and deposit markets is relatively limited, amounting to a mere 20-30%. Thus, this distinct characteristic of the German banking system may partly explain why competition is found to be strongest in this country, since the Boone indicator is based on the relationship between banks' relative marginal costs (which in Germany, as in most countries, were found to be lower for the non-commercial banks than for the commercial banks) and their market share (which is larger for the non-commercial banks in Germany than for those in other countries). Hence, our results should not be seen as contradicting the concerns of the IMF (see IMF 2004) about the inflexibility

[10] The estimated competition measures in Carbó *et al.* (2006) include the net interest margin, the return on assets ratio, the Lerner Index, H-statistics and the Hirschmann-Herfindahl Index. The sample applied by Carbó *et al.* (2006) is broadly similar to ours, although the number of banks in their study is somewhat smaller.

[11] This is in line with our results.

and distortive effects of the so-called three-pillar system in Germany, but rather as reflecting the structural characteristics discussed above (see also Section 6.4.2.3).

Table 6.5 Estimates of the Boone indicator over 1994-2004 for various countries

	Boone indicator[a)]	z-value[b)]	F-test	Anderson canon. corr. LR-test	Hansen J-test (P-value)	Number of observations
DE[c)]	**-3.38	-10.80	18.03	930.7	0.00	14,534
ES	**-4.15	-3.99	2.87	162.7	1.339 (0.25)	734
FR	**-0.90	-4.89	7.98	1,122.7	1.816 (0.18)	936
IT	**-3.71	-7.77	19.16	1,613.6	1.690 (0.19)	3,419
NL	**-1.56	-3.46	2.59	159.2	1.106 (0.29)	197
UK	**-1.05	-3.12	1.50	1,068.4	0.396 (0.52)	787
US[c)]	**-5.41	-40.49	345.04	9,916.0	0.00	40,177
JP	*-0.72	-2.26	14.08	402.1	4.88 (0.03)	1,423

[a] Asterisks indicate 95% (*) and 99% (**) levels of confidence.
[b] The z-value indicates whether the parameter significantly differs from zero under the normal distribution with zero mean and standard deviation one.
[c] For Germany and the US, 2SLS is used and the equation is exactly identified, so that the Hansen J-test statistic is 0.00.

The results for Spain and Italy seem to be driven mainly by the boost to competition following the deregulation and liberalisation of the banking sector in the two countries in the early 1990s.[12] In the Netherlands, the banking sector went through a process of profound reorganisation and consolidation during the 1980s and 1990s.[13] This development increased concentration in the Dutch banking sector, but may also have led to efficiency improvements. All in all, the Boone indicator suggests that from an international perspective competitive conditions in the Dutch banking sector take up an intermediate position.[14] Finally, the French banking sector is found to be the least competitive of the euro-area countries considered. This finding may in part stem from the fact that although most French banks have now been privatized and the government continues its withdrawal from the banking industry, the role of the state in the French banking sector remains non-negligible, in that some important entities remain state-controlled (see for example: Fitch Ratings 2001; Moody's Investors Service 2004; S&P 2005b).

[12] See, for example, S&P (2004) and Moody's Investors Service (2006). Our results are in line with Maudos *et al.* (2002), who find that profit margins during that decade declined significantly in Spain, especially for commercial banks and, to a lesser extent, for saving banks. For Italy, Coccorese (2005) presents evidence for the largest eight Italian banks (during 1988-2000) that still experienced a considerable degree of competition, despite increased concentration.
[13] See, for example, Moody's Investors Service (2005a).
[14] Our results are in line with other empirical investigations, such as on competition in the Dutch market for revolving consumer credit, which showed that this market is competitive indeed (see Toolsema 2002).

Turning to the non-euro-area countries, the Boone indicator suggests that in the UK, competition in the loan market is weak. This may be because in specific segments of the UK loan market (in particular, mortgage lending), other institutions play an important role.[15] Our results are in line with Drake and Simper (2003), who find that due to the change in the ownership structure of building societies ('de-mutualisation') competition in retail banking activities in the UK declined during 1999-2001. As a matter of fact, the BI for the loan market without the real estate and mortgage banks shows that competition in this segment is significantly stronger.[16]

The US banking sector appears to be the most competitive among the countries in our sample, reflecting the significant changes in the US banking system over the past two decades. While it remains largely bifurcated along metropolitan and rural lines and continues to hinge on the principles of specialisation and regionalism (basically stemming from legislation enacted following the Great Depression), especially the lifting of restrictions on the range of banking activities and of the ban on interstate banking have transformed the US banking system.[17]

Finally, the poor result for Japan is largely driven by the regulation of the banking industry during the 1990s. As shown in the next section, however, competition in the Japanese loan market increased dramatically during the period under investigation.

This section's estimates, based on the entire sample period, may conceal considerable differences over time and across types of banks. We investigate developments in the level of competition over time in the next section.

6.4.2.2 Developments in competition over the years

Table 6.6 shows the BI estimates across countries and over time (usually 1994-2004, depending on the respective country), based on:

$$\ln s_{ilt} = \alpha + \sum_{t=1,..,T} \beta_t \ln mc_{ilt} + \sum_{t=1,..,(T-1)} \gamma_t d_t + u_{ilt}. \qquad (6.10)$$

Note that, in this section, β_t is time dependent. While the above conclusions based on the full-sample-period estimates generally remain valid, there are some notable differences across countries in the development of the Boone indicator during the sample period.

[15] The UK has over a hundred mortgage lenders. See also Moody's Investors Service (2005c).

[16] According to Heffernan (2002), the mortgage market in the UK is relatively competitive, but in other market segments, such as personal loans, there is substantially less competition. Estimation results for the UK of the Boone indicator using a sample with only mortgage lenders can be obtained from the authors upon request.

[17] Overviews of the various legislative changes can be found in Cetorelli (2001), Clarke (2004) and Fitch Ratings (2005), for example. Emmons and Schmid (2000) find evidence that even before most of this new legislation was enacted, banks and credit unions competed directly.

Table 6.6. Developments of the Boone indicator over time for various countries[b]

	Germany[a]		France		Italy[a]	
The Boone indicator	**β_t**	**z-value**	**β_t**	**z-value**	**β_t**	**z-value**
1993					-5.90	-1.18
1994					-7.25	**-3.24
1995	-4.47.	-1.40	-1.28	**-3.36	-4.51	**-3.53
1996	-7.09	**-2.92	-1.28	**-3.56	-5.58	**-3.98
1997	-4.64	**-3.41	-1.11	**-3.55	-5.89	**-4.08
1998	-5.10	**-3.97	-0.79.	*-1.99	-4.60	**-6.08
1999	-2.60	**-4.04	-0.78	*-2.30	-4.05	**-4.39
2000	-2.50	**-4.60	-0.46.	-1.34	-3.32	**-4.39
2001	-3.31	**-7.02	-0.68.	-1.67	-2.66	**-3.62
2002	-4.53	**-4.71	-0.40.	-0.78	-1.59.	-1.82
2003	-2.73	**-5.62	0.27.	0.39	-2.42	**-3.69
2004	-2.66	**-4.15	0.10.	0.12	-1.81	**-2.79
F-test	10.70		5.10		13.23	
Anderson canon corr. LR-	185.2		1,023.7		300.3	
Hansen J-test	0.00		19.69(0.48)		0.00	
Number of observations	14,534		918		4918	

	Spain[a]		the Netherlands		US[a]	
The Boone indicator	**β_t**	**z-value**	**β_t**	**z-value**	**β_t**	**z-value**
1993	-4.21	*-2.49				
1994	-4.80	*-2.28	-1.92	-1.42		
1995	-5.20	-1.92	-4.42	*-2.42		
1996	-9.61	-0.67	-2.09	**-2.58		
1997	-4.36	-1.78	-3.57	-1.70		
1998	-5.40	-0.86	1.04	0.38		
1999	-5.46	*-2.21	-1.44	-0.85		
2000	-3.44	-1.93	-3.26	**-3.00	-6.89	**-20.34
2001	-4.38	**-2.55	-3.91	**-4.71	-6.16	**-20.94
2002	3.88	*-2.09	-2.45	*-2.44	-5.54	**-22.61
2003	-3.42	-1.20	-2.22	-1.80	-4.87	**-22.15
2004	-2.69	**-5.62	-3.09	**-2.85	-4.54	**-25.53
F-test			3.33		3.90	
Anderson canon corr. LR-	38.8		31.7		7,084.3	
Hansen J-test	0.00		20.5 (0.04)		0.00	
Number of observations	1015		241		40,177	

Table 6.6 Developments of the Boone indicator over time for various countries[b] (continued)

	United Kingdom		Japan	
The Boone indicator	**β_t**	**z-value**	**β_t**	**z-value**
1994	0.36	0.55		
1995	-0.95	-1.57	7.30	** 4.93
1996	-0.48	-0.64	13.88	** 6.63
1997	-1.33	-1.52	5.98	** 3.97
1998	-1.87	*-2.17	3.97	** 4.04
1999	-1.52	*-1.96	4.85	** 2.58
2000	-1.56	*-2.05	0.11	0.03
2001	-1.46	*-1.97	-2.52	**-4.04
2002	-1.22	-1.65	-2.63	**-3.73
2003	-0.43	-0.66	-2.90	**-6.56
2004	-0.49	-0.93	-3.63	**-5.95
F-test	1.25		23.48	
Anderson canon corr.				
LR-test	1,468.2		214.8	
Hansen J-test	20.88		34.43	
(P-value)	(0.03)		(0.02)	
Number of observations	912		1476	

Notes: Asterisks indicate 95% (*) and 99% (**) levels of confidence. Coefficients of time dummies are not shown.

[a] 2SLS is used and the equation is exactly identified, so that the Hansen J-test is 0.00.

[b] Equation (6.10) is estimated with the GMM. The number of observations for Italy, Spain, the Netherlands, the UK and Japan is lower than in Table 5.3, due to the use of instrumental variables with lags of higher order.

For some countries, the β_t's never differ significantly from zero. This is the case for France, the UK, the Netherlands and Spain. For the latter two countries, we also observe substantial jumps in the series over time (see Figure 6.1). However, the estimated annual betas generally do not differ significantly from each other. This section discusses only the countries with statistically significant changes over time: Italy, the US and Japan.[18] Figure 6.1 shows the results for the other countries.

The banking sector in Italy, particularly the savings banks, went through a process of deregulation and liberalisation in the early 1990s, fuelled in part by the adoption of various EU directives on financial institutions, which led to a consolidation wave.[19]

[18] For these countries a Wald test with an H_0 hypothesis of no change over time was rejected at the 5%-level of significance.

[19] In the early 1990s, large universal banking groups were established in Italy, as various restrictions on business activities were abolished. See, for example, Fitch Ratings (2002b), Moody's Investors Service (2005d) and S&P (2005a). The process of financial deregulation was brought about in part by Commu-

Whereas the EU legislative initiatives affected all EU banking sectors, their eventual impact on competition was most probably driven by the actual implementation at the national level and by additional country-specific initiatives. In Italy, in particular, these institutional and regulatory changes are likely to have had a catalytic effect on competition, as our estimates suggest strong competition around the mid-1990s (see Coccorese 2005; Gambacorta and Iannotti 2005). In more recent years, the new banking groups formed in the early 1990s may have been able to reconstitute some market power, as our results point to a continuous decline in competition since 1997 (see also Figure 6.2).[20]

Although our estimates of the Boone indicator for the US show a significant increasing trend (indicating a decline in competition),[21] the level of competition remains comparatively high. A possible explanation for this gradual decline of competition is the decrease in the number of banks competing in the loan market (see also Jones and Critchfield 2005).

In Japan, competition seems to have improved significantly (see Figure 6.3). This remarkable increase can partly be attributed to a history of very little or no competition in the mid-1990s. The Wald test rejects the null hypothesis of no change at the 1%- significance level for Japan. In particular, our estimates show that the Japanese banking sector experienced a rather marked transformation from a climate with very little competition in the mid-1990s to a more competitive environment in recent years, to a point where Japan ranked second in 2004, behind the US. This partly reflects the process of financial deregulation and the gradual resolution of the bad loan problems that plagued Japanese banks throughout the 1990s (Van Rixtel 2002). Eventually, this development involved the de-facto nationalisation of the worst-performing institutions and a major wave of consolidations, resulting in the establishment of a small number of large commercial banking groups in 2000 and 2001 (Van Rixtel *et al*. 2004). Our estimates suggest that the profound and structural changes in the Japanese banking sector have helped to foster a competitive environment.

nity legislation such as the Second Banking Coordination Directive; see Angelini and Cetorelli (2003) and Cetorelli (2003). A largely similar development took place in Spain, where important mergers involving the largest commercial banks took place in 1999 and 2000. See, for example, Fitch Ratings (2002a).

[20] In 2005 and 2006, a new wave of consolidation in the Italian banking sector was initiated. However, as our sample ends in 2004, our results do not capture these events.

[21] The Wald test rejects the null hypothesis of no change at the 1%-level of significance.

Figure 6.1 BIs of the countries with no significant change in competition over time

Figure 6.2 BIs of the countries where competition significantly diminished over time

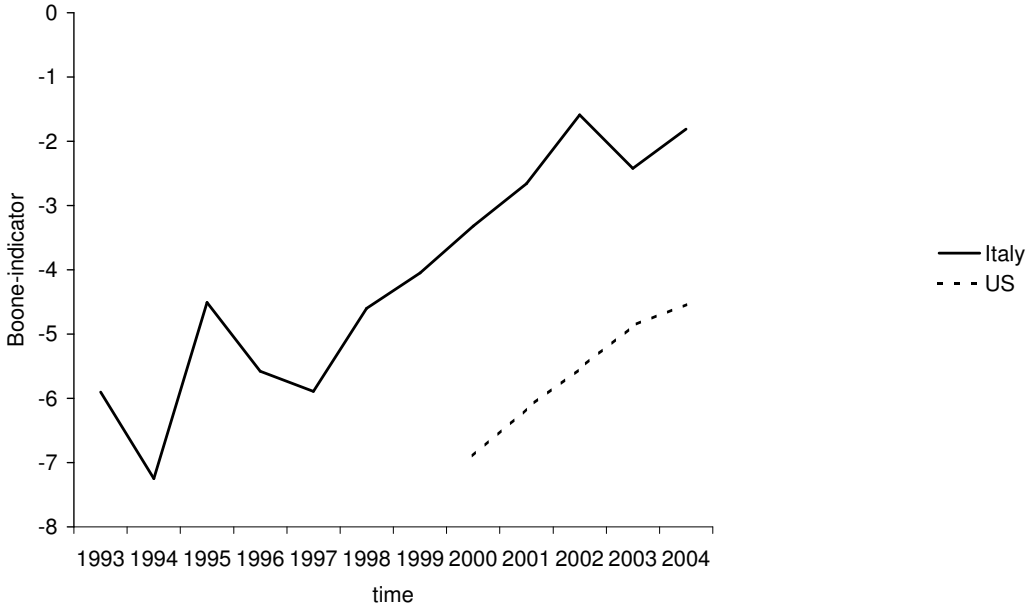
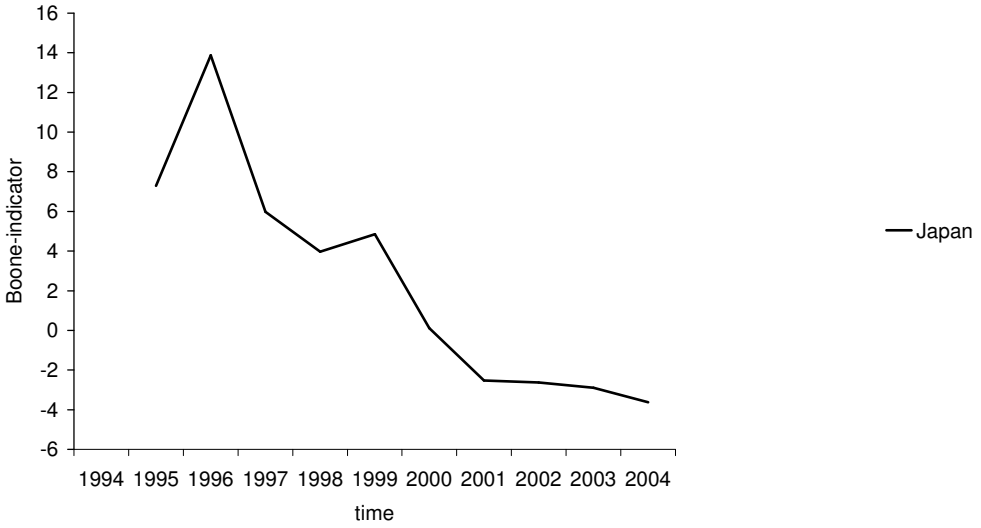


Figure 6.3 The BI of Japan: competition has significantly improved over time



6.4.2.3 Competition for the commercial banks

In countries where banks belonging to a specific bank category compete against each other rather than competing against all the other banks, estimates of competition in such separate bank categories may be more accurate. For some countries, it is probable that small cooperative and savings banks compete mainly in the local market, offering traditional bank products to retail customers and small- and medium-sized enterprises, whereas large commercial banks serve mainly larger firms and wealthy individuals in need of a diversified palette of advanced services. Therefore as robustness check, we estimate separate indicators for the bank category of commercial banks, because they are operating on a country level. We do this robustness check for all countries except for the Netherlands and the UK, as their banking sectors show only minor segmentation, so that estimating indicators for specific bank categories seems irrelevant. For Germany we consider commercial banks and *Landesbanken*, which are assumed to compete with each other (see Hackethal 2004). The results appear in Table 6.7.

In all countries, with the exception of Italy, competition is found to be stronger when measured solely between commercial banks than when the market is defined including cooperative and savings banks, as the BI appears to be above the averages presented in Section 6.4.2.2. This may also indicate that saving banks and cooperative banks are less competitive than the commercial banks.[22] These findings may be explained by the fact

[22] In Italy, cooperative banks are more competitive than commercial banks. As is reported in Fitch Ratings (2002a), cooperative banks fall into two categories: a small group of larger multi-regional cooperative banks and a group of small cooperative banks serving their home regions. It is more likely that the first

that traditionally, savings banks and cooperative banks tend to operate at the local level and have access to a stable and cheap pool of deposits from a loyal customer base. Furthermore, savings and cooperative banks are often partly protected from competition by commercial banks, being unable (either through regulation or by tradition) to compete across regional borders.[23] Commercial banks are typically larger and operate on a national (or at least supra-regional) level where they face competition from other regional and foreign banks. Lacking easy access to a stable pool of deposits, they depend more on costly interbank and market-based funding. They provide loans and services predominantly to larger corporate customers and face competition from the capital markets. These factors may induce commercial banks to behave more competitively than the protected savings and cooperative banks.[24]

Table 6.7 Segmented markets in Germany, Italy, France, Spain, Japan and the US

	Germany		**Italy**	
	Commercial banks and Landesbanken		**Commercial banks**	
Boone indicator	**β_t**	**z-value**	**β_t**	**z-value**
1993			-8.44	-0.60
1994			-9.01	-1.46
1995	-3.01	*-2.44	-2.87	*-2.00
1996	-3.89	*-2.12	-3.73	**-2.68
1997	-4.08	**-2.69	-5.87	**-2.80
1998	-3.11	-3.23	-4.56	**-3.17
1999	-2.54	-1.45	-3.07	*-2.42
2000	-3.61	*-2.45	-2.59	**-2.91
2001	-6.09	**-3.96	-1.69	*-2.39
2002	-9.36	-1.65	-0.95	*-2.37
2003	-6.06	*-2.13	-2.48	**-3.20
2004	-5.41	**-2.66	-1.77*	*-2.48
F-test	3.68		2.30	
Anderson canon corr. LR-test	56.6		28.55	
Hansen J-test	12.7 (0.24)		0.00	
Number of observations	849		1010	

category is more competitive than the commercial banks. They are the new entrants to these multi-regional markets, whereas commercial banks are the incumbents. This process may actually have been beneficial to competition.

[23] This is the case in Germany through the so-called *Regionalprinzip*, or principle of market demarcation within the banking groups (see e.g. Fischer and Pfeil 2004; Fischer and Hempel 2005). In Italy and the US, restrictions to cross-regional competition was effectively lifted during the 1990s, although in practice the majority of the local banks continue to operate predominantly within their historical regional borders.

[24] Furthermore, in Germany these competitive features may be further amplified by the existence of the three-pillar system, which hinders consolidation across the three bank types (see Fischer and Pfeil 2004; IMF 2004).

Table 6.7 Segmented markets in Germany, Italy, France, Spain, Japan and the US (continued)

	France		Spain	
	Commercial banks		Commercial banks[a]	
Boone indicator	β_t	**z-value**	β_t	**z-value**
1993			-4.10	**-2.71
1994			-4.67	**-2.61
1995	-1.45	**-2.76	-5.67	-1.90
1996	-1.82	**-3.18	-8.75	-0.67
1997	-1.59	**-2.98	-4.16	-1.76
1998	-0.85	-0.99	-4.90	-0.85
1999	-0.91	-1.39	-5.10	*-2.14
2000	0.28	0.24	-3.15	-1.75
2001	-0.43	-0.47	-4.18	*-2.48
2002	0.52	0.47	-3.29	*-2.12
2003	0.63	0.61	-2.96	-1.17
2004	-0.03	-0.02	-2.54	**-4.86
F-test	2.48		2.35	
Anderson canon corr. LR-test	378.88		22.8	
Hansen J-test	25.763 (0.17)		0.00	
Number of observations	482		525	

	US		Japan	
	Commercial banks[a]		Commercial banks	
Boone indicator	β_t	**z-value**	β_t	**z-value**
1995			4.30	1.41
1996			14.18	** 7.03
1997			9.09	** 5.37
1998			3.68	** 3.87
1999			5.82	** 6.81
2000	-6.06	**-19.44	13.98	** 1.86
2001	-5.54	**-21.17	-1.01	**-11.40
2002	-4.63	**-24.22	-1.59	**-13.56
2003	-7.01	**-19.81	-2.36	**-19.94
2004	-4.97	**-20.90	-2.20	**-15.50
F-test	177.9		127.55	
Anderson canon corr. LR-test	6541.4		13.55 (0.13)	
Hansen J-test	0.00		6.863 (0.55)	
Number of observations	36,229		63	

Note: * indicates 95% and ** 99% levels of confidence.

[a] 2SLS is used and the equation is thus exactly identified.

6.5 Conclusions

This analysis introduces a new measure for competition, the Boone indicator (BI), which quantifies the impact of marginal costs on performance, measured in terms of market shares. The BI allows us to estimate the degree of competition across countries, across a given country's market segments and over time. We improve the BI approach by calculating marginal costs instead of approximating marginal costs with average variable costs. We applied the new measure to the loan markets of the major countries in the euro area and to the UK, the US and Japan over 1994-2004.

Our findings indicate that the US had the most competitive loan market during this period, whereas Germany and Spain were among the most competitive EU markets. This result for Germany is particularly remarkable, as some observers have suggested that competition in the German banking industry may be rather weak. In Spain, competition remained strong and relatively stable over the entire sample period, indicating the progress that the Spanish banking system has made since the major liberalisation reforms in the late 1980s and early 1990s. The Netherlands occupied a more intermediate position among the countries in our sample, despite having a relatively concentrated banking market dominated by a small number of very large players. Italian competition declined significantly over time, which may be due to the partial reconstitution of market power by the banking groups formed in the early 1990s. French and British loan markets were less competitive overall, possibly owing to the continued existence of market regulations and State intervention in the case of France and to the impact of the 'de-mutualisation' process involving the building societies in the UK. In Japan, competition in loan markets was found to increase dramatically over the years, in line with the consolidation and revitalisation of the Japanese banking industry in recent years.

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Appendix Estimations of translog cost function

Table A.1 Estimations of the TCF for Germany

Dependent variable: ln(costs)-ln(other expenses)	Coefficient	t-value	P>|t|
Outputs			
ln(loans)_comm. banks	0.01	0.43	0.67
$(\ln(\text{loans}))^2$_comm. banks	0.08	45.14	0.00
ln(securities)_comm. banks	0.11	9.32	0.00
$(\ln(\text{securities}))^2$_comm. banks	0.04	39.84	0.00
ln(other services)_comm. banks	0.66	34.45	0.00
$(\ln(\text{other services}))^2$_comm. banks	0.06	24.31	0.00
ln(loans)_savings banks	-0.55	-5.16	0.00
$(\ln(\text{loans}))^2$_savings banks	0.21	20.25	0.00
ln(securities)_savings banks	0.60	10.79	0.00
$(\ln(\text{securities}))^2$_savings banks	0.05	24.39	0.00
ln(other services)_savings banks	0.92	7.93	0.00
$(\ln(\text{other services}))^2$_savings banks	0.07	5.73	0.00
ln(loans)_coop. banks	0.19	6.02	0.00
$(\ln(\text{loans}))^2$_coop. banks	0.11	26.79	0.00
ln(securities)_coop. banks	0.42	27.56	0.00
$(\ln(\text{securities}))^2$_coop. banks	0.04	42.97	0.00
ln(other services)_coop. banks	0.42	14.93	0.00
$(\ln(\text{other services}))^2$_coop. banks	0.05	13.86	0.00
Input prices			
ln(wage)-ln(other expenses)_comm. banks	-0.02	-0.78	0.44
$(\ln(\text{wage}) - \ln(\text{other expenses}))^2$_comm. banks	0.12	26.00	0.00
ln(funding rate)-ln(other expenses)_comm. banks	0.85	28.35	0.00
$(\ln(\text{funding rate})-\ln(\text{other expenses}))^2$_comm. banks	0.15	22.66	0.00
Ln(wage)-ln(other expenses)_savings banks	0.79	5.55	0.00
$(\ln(\text{wage}) - \ln(\text{other expenses}))^2$_savings banks	0.06	2.18	0.03
ln(funding rate)-ln(other expenses)_savings banks	0.14	0.94	0.35
$(\ln(\text{funding rate}) - \ln(\text{other expenses}))^2$_savings banks	0.08	2.91	0.00
ln(wage)-ln(other expenses)_coop. banks	0.15	4.16	0.00
$(\ln(\text{wage}) - \ln(\text{other expenses}))^2$_coop. banks	0.65	15.58	0.00
ln(funding rate)-ln(other expenses)_coop. banks	0.09	15.26	0.00
(ln(funding rate) -ln(other expenses))2_coop. banks	0.10	12.40	0.00
Cross-products between input prices			
(ln(wage) -ln(other expenses))*(ln(funding rate)-ln(other	-0.27	-26.54	0.00
(ln(wage) -ln(other expenses))*(ln(funding rate)-ln(other	-0.15	-2.84	0.01
(ln(wage) -ln(other expenses))*(ln(funding rate)-ln(other	-0.20	-14.82	0.00
Cross-products between outputs			
ln(loans) * ln(securities)_comm. banks	-0.03	-16.25	0.00

Table A.1 Estimations of the TCF for Germany (continued)

ln(loans) * ln(other services)_comm. banks	-0.10	-27.25	0.00
ln(securities) * ln(other services)_comm. banks	-0.03	-15.70	0.00
ln(loans) * ln(securities)_savings banks	-0.21	-20.79	0.00
ln(loans) * ln(other services)_savings banks	-0.21	-10.44	0.00
ln(securities) * ln(other services)_savings banks	0.08	7.58	0.00
ln(loans) * ln(securities)_coop. banks	-0.12	-34.04	0.00
ln(loans) * ln(other services)_ coop. banks	-0.10	-15.55	0.00
ln(securities) * ln(other services)_coop. banks	0.03	9.17	0.00
Cross-products between outputs and input prices			
ln(loans)*(ln(wage)-ln(other expenses))_comm. banks	0.06	13.48	0.00
ln(loans)*(ln(funding rate)-ln(other expenses))_comm. banks	-0.04	-8.27	0.00
ln(loans)*(ln(wage)-ln(other expenses))_savings banks	0.00	-0.11	0.91
ln(loans)*(ln(funding rate)-ln(other expenses))_savings banks	0.02	0.78	0.44
ln(loans)*(ln(wage)-ln(other expenses))_coop. banks	0.10	11.44	0.00
ln(loans)*(ln(funding rate)-ln(other expenses))_coop. banks	-0.08	-8.09	0.00
ln(securities)*(ln(wage)-ln(other expenses))_comm. banks	0.03	11.11	0.00
ln(securities)*(ln(funding rate)-ln(other expenses))_comm. banks	-0.04	-10.00	0.00
ln(securities)*(ln(wage)-ln(other expenses))_savings banks	-0.10	-6.34	0.00
ln(securities)*(ln(funding rate)-ln(other expenses))_savings banks	0.06	3.88	0.00
ln(securities)*(ln(wage)-ln(other expenses))_coop. banks	-0.06	-14.28	0.00
ln(securities)*(ln(funding rate)-ln(other expenses))_coop. banks	0.05	10.49	0.00
ln(other services)*(ln(wage)-ln(other expenses))_comm. banks	-0.05	-9.36	0.00
ln(other services)*(ln(funding rate)-ln(other expenses))_comm.	0.04	6.74	0.00
ln(other services) *(ln(wage)-ln(other expenses))_savings banks	0.07	2.22	0.03
ln(other services)*(ln(funding rate)-ln(other expenses))_savings	-0.06	-1.89	0.06
ln(other services)*(ln(wage)-ln(other expenses))_coop. banks	-0.04	-4.48	0.00
ln(other services)*(ln(funding rate)-ln(other expenses))_coop.	0.03	2.79	0.01
Control variables			
ln(equity/assets)_comm. banks	-0.15	-4.26	0.00
ln(equity/assets)^2_comm. banks	0.01	1.96	0.05
ln(equity/assets)_savings banks	1.11	6.80	0.00
ln(equity/assets)^2_savings banks	0.21	7.86	0.00
ln(equity/assets)_coop. banks	0.51	10.03	0.00
ln(equity/assets)^2_coop. banks	0.10	11.86	0.00
dummy savings banks	2.63	6.12	0.00
dummy coop. banks	-0.15	-13.49	0.00
Intercept	3.07	48.08	0.00
Number of observations	19,551		
F(80, 19,470)	25,462.91		
Adjusted R-square	0.99		

Explanation: Coefficients of time dummies are not shown.

7 Impact of bank competition on the interest-rate pass-through in the euro area

With co-author: Christoffer Kok Sørensen, Jacob A. Bikker and Adrian van Rixtel

7.1 Introduction

This chapter discusses the effects of bank competition on the interest-rate levels of bank loans and, hence, on the monetary policy transmission mechanism. Given the prominent role of the banking sector in the euro area's financial system, it is vital that the ECB is able to monitor the degree of competitive behaviour in the euro-area banking market. A more competitive banking market is expected to drive down bank loan rates, adding to the welfare of households and enterprises. Further, in a more competitive market, changes in the ECB's main policy rates supposedly will be passed through with more speed to banking rates.

This study extends the existing empirical evidence, which suggests that the degree of bank competition may have a significant effect on both the level of bank rates and on the pass-through of market rates to bank interest rates. Understanding this pass-through mechanism is crucial for central banks. Most studies that analyse the relationship between competition and the pricing behaviour of banks apply a concentration index such as the Herfindahl-Hirschman Index (HHI) as a measure of competition.

However, we question the suitability of such indices as measures to capture competition. Whereas the traditional interpretation is that concentration erodes competition, concentration and competition may instead increase simultaneously when competition compels consolidation. For example, in a market where inefficient firms are taken over by efficient companies, competition may strengthen, while the market's concentration increases at the same time. In addition, the HHI suffers from a serious weakness in that it does not distinguish between small and large countries. In small countries, the concentration ratio is likely to be higher, precisely because the economy is small.

The main contribution of this chapter is that it applies a new measure for competition, called the Boone indicator (BI) (see also Boone, 2001; Bikker and Van Leuvensteijn, 2007; Van Leuvensteijn *et al.*, 2007). The basic notion underlying the BI is that in a competitive market, more efficient companies are likely to gain market shares. Hence, the stronger the impact of efficiency on market shares is, the stronger competition will be. Further, by analyzing how this relationship between efficiency and market share changes over time, this approach provides a measure that can be employed to assess how changes in competition affect the cost of borrowing for both households and enterprises, and how competition affects the pass-through of policy rates into loan's interest rates.

Our study contributes also to the pass-through literature, in the sense that it uses a newly constructed dataset on bank interest rates for eight euro-area countries covering the period January 1994 to March 2006. We include data for Austria, Belgium, France, Germany, Italy, the Netherlands, Portugal and Spain.[1] Further, we consider four types of loan products (mortgage loans, consumer loans and short- and long-term loans to enterprises).

We apply recently developed dynamic panel estimates of the pass-through model. Our approach is closely related to that of Kok Sørensen and Werner (2006), on which it expands by linking the degree of competition directly to the pass-through estimates.

Against this background, we test the following four hypotheses:

1. Loan interest rates are lower in more competitive loan markets than in less competitive loan markets.
2. Long-run loan interest-rate responses to the corresponding market rates are stronger in more competitive loan markets than in less competitive loan markets.
3. Bank interest rates in more competitive markets adjust faster to changes in market interest rates than they might in less competitive markets.
4. Interest-rate spreads of banks on loan products are lower in more competitive loan markets than in less competitive loan markets.

This analysis uses interest-rate data that cover a longer period and that are based on more harmonised principles than those used by previous pass-through studies for the euro area. We find that stronger competition implies significantly lower interest-rate spreads for most loan market products, as we expected. Using an error correction model (ECM) approach to measure the effect of competition on the pass-through of market rates to bank interest rates, we likewise find that banks tend to price their loans more in accordance with the market in countries where competitive pressures are stronger. Furthermore, in more competitive markets, bank interest rates appear to respond more strongly and sometimes more rapidly to changes in market interest rates.

[1] For other euro-area countries we had insufficient data to estimate the Boone indicator.

For a discussion on the literature on measuring competition, see Chapter 1. A description of the Boone indicator appears in chapters 5 and 6 (Section 6.2). The structure of this chapter is as follows. Section 7.2 discusses the literature on the bank interest-rate pass-through. Section 7.3 describes the employed interest-rate pass-through model of the error-correction type and the applied panel unit-root and cointegration tests. Section 7.4 presents the various datasets used. The results on the various tests and estimates of the spread model and the error-correction model equations are shown in Section 7.5. Finally, Section 7.6 summarizes and concludes.

7.2 Literature review: competition and monetary transmission

According to the seminal papers by Klein (1971) and Monti (1972) on banks' interest-rate-setting behaviour, banks can exert a degree of market pricing power in determining loan interest rates. The Monti-Klein model demonstrates that interest rates on bank products with smaller demand elasticities are priced less competitively. Hence, both the levels of bank interest rates and their changes over time are expected to depend on the degree of competition. With respect to the level of bank interest rates, Maudos and Fernández de Guevara (2004) show that an increase in banks' market power (*i.e.* a reduction in competitive pressure) results in higher net interest margins.[2] In addition, Corvoisier and Gropp (2002) explain the difference between bank retail interest rates and money market rates by bank's product-specific concentration indices. They find that in concentrated markets, retail-lending rates are substantially higher.

Regarding the effect of competition on the way banks adjust their lending rates, both Cottarelli and Kourelis (1994) and Borio and Fritz (1995), in a cross-country analysis, find a significant effect of constrained competition on the monetary transmission mechanism. Thus, lending rates tend to be stickier when banks operate in a less competitive environment, due to, *inter alia,* the existence of barriers to entry. This finding was confirmed in an Italian setting by Cottarelli *et al.* (1995). Reflecting the existence of bank market power and collusive behaviour as well as potential switching costs for bank customers (or other factors affecting demand elasticities), the degree of price stickiness is likely to be asymmetric over the (monetary policy) interest-rate cycle.[3] Against this background, Mojon (2001) tests for the impact of banking competition on the transmission process related to euro-area bank lending rates, using an index of deregulation, constructed by Gual (1999). He finds that higher competition tends to put pressure on banks to adjust lending rates faster when money market rates are decreasing. Furthermore, higher competition tends to reduce the ability of banks to

[2] Of course, competition is not the only factor determining the level of bank interest rates. Factors such as credit and interest risk, banks' degree of risk aversion, operating costs and bank efficiency are also likely to affect bank margins. See, for example, Maudos and Fernández de Guevara (2004).

[3] See, for example, Neuwark and Sharpe (1992) and Mester and Saunders (1985) for empirical evidence of asymmetric interest-rate pass-through effects among US banks.

increase lending rates (although not significantly), when money market rates are moving up.[4] Similar findings of asymmetric pass-through effects were found by Scholnick (1996), Heinemann and Schüler (2002) and Sander and Kleimeier (2002) and (2004).[5] Moreover, De Bondt (2005) argues that stronger competition from other banks and from capital markets has helped to speed up the interest-rate adjustment of banks in the euro area to changes in market rates.

A number of country-specific studies also provide evidence of sluggish pass-through from market rates into bank rates when competition is weak. For example, Heffernan (1997) finds that the interest-rate adjustment of British banks is compatible with imperfect competition, whereas Weth (2002), by using various proxies for bank market power, provides evidence of sluggish and asymmetric pass-through among German banks. De Graeve *et al.* (2004) estimate the determinants of the interest-rate pass-through on Belgian banks and find that banks with more market power pursue a less competitive pricing policy. In a microeconomic analysis of Spanish banks, Lago-González and Salas-Fumás (2005) provide evidence that a mixture of price-adjustment costs and bank market power leads to price rigidity and asymmetric pass-through. In a cross-country study, Kok Sørensen and Werner (2006) show that differences in the pass-through process across the euro-area countries may to some extent be explained by national differences in bank competition. Finally, in another euro-area-based study, Gropp *et al.* (2006) provide evidence that the level of banking competition has a positive impact on the degree of bank interest-rate pass-through.

7.3 The interest-rate pass-through model

Our analysis of the pass-through of market rates to bank interest rates takes into account the fact that economic variables may be non-stationary.[6] The relationship between non-stationary but cointegrated variables should preferably be based on an error-correction model (ECM), which allows disentangling the long-run co-movement of the variables from the short-run adjustment towards the equilibrium. Accordingly, most of the pass-through studies conducted in recent years apply an ECM, as it allows testing for both

[4] In addition to bank competition, switching costs and other interest-rate adjustment costs, bank rate rigidity may also be due to credit risk factors. For example, in a situation of credit rationing, banks may decide to leave lending rates unchanged and to limit the supply of loans instead; see, for example, Winker (1999). Banks may also choose to provide their borrowers with 'implicit interest-rate insurance' by smoothing bank loan rates over the cycle; see Berger and Udell (1992). Finally, banks sometimes give customers an interest-rate option for a given period. These banks have to recoup the costs of their options, which may reduce the speed of the interest-rate pass-through for outstanding clients.

[5] Sander and Kleimeier (2002, 2004) also take note of the severity of the interest-rate shock (rather than merely its direction) when they model asymmetric responses. This approach aims to take into account menu cost arguments implying that banks tend to pass on changes in market rates of a minimum size only.

[6] In order to avoid spurious results, see Granger and Newbold (1974).

the long-run equilibrium pass-through of bank rates to changes in market rates and the speed of adjustment towards the equilibrium.[7] Using a panel-econometric approach, we test for the impact of banking competition (measured by the Boone indicator) on the long-run bank interest-rate pass-through.

7.3.1 Estimation of the long-run relationship

As a first approach, we test whether the bank interest rates are lower in a more competitive market given the level of the market interest rates. For this purpose, the bank's interest-rate spread, $(BR_{i,t} - MR_{i,t})$, is explained by the Boone indicator (BI) and country dummies, D_i, and monthly dummies, D_t:

$$(BR_{i,t} - MR_{i,t}) = \kappa BI_{i,t} + \rho_i D_i + +\psi_t D_t + u_{i,t}, \tag{7.1a}$$

where $BR_{i,t}$ and $MR_{i,t}$ are the bank interest rate and the corresponding market rate, respectively, in country i (for $i = 1, \ldots, N$) at time t (for $t = 1, \ldots, T$), observed on a monthly basis. For the sake of convenience, the BI is redefined in positive terms, so that an increase in the BI reflects stronger competition. The estimated BI's come from the analysis in the Appendix. We test the following hypothesis:

1. The bank interest-rate spreads are lower on loan products in more competitive loan markets than in less competitive loan markets
   H_0:$\kappa<0$ and H_1: $\kappa\geq 0$.

If bank interest rates and their corresponding market rates are cointegrated, we may analyse their long-run relationship in an error-correction framework. Hereby, we test for three hypotheses by estimating the following two equations for each of the four considered interest rates.[8] In equation (7.1a) we have the underlying restriction that the pass-through from market interest rates, $MR_{i,t}$, to bank interest rates, $BR_{i,t}$ is immediately and complete. We relax this restriction in equation (7.1b), so that $0< \beta < 1$ in equation (7.1b). Furthermore, we introduce the cross-product between MR and BI, reflecting the possibility that the level of competition could affect the pass-through directly.

[7] See, for example, Mojon (2001), De Bondt (2002, 2005), Sander and Kleimeier (2004), and Kok Sørensen and Werner (2006).

[8] Namely, four types of loan products (mortgage loans, consumer loans and short- and long-term loans to enterprises).

$$BR_{i,t} = \alpha BI_{i,t} + \beta_i MR_{i,t} + \gamma BI_{i,t} MR_{i,t} + \delta_i D_i + u_{i,t} \tag{7.1b}$$

$$\Delta BR_{i,t} = \theta_i u_{i,t-1} + \eta_i \Delta MR_{i,t} + \varphi BI_{i,t} \Delta MR_{i,t} + v_{i,t} \tag{7.1c}$$

Equation (7.1b) reflects the long-run equilibrium pass-through, while equation (7.1c) presents the short-term adjustments of bank interest rates to their long-run equilibrium. $BI_{i,t}$ is the Boone indicator of country i at time t. In all estimations, we include the market interest rates for the different countries separately ($\beta_i\ MR_{i,t}$ and $\eta_i\ \Delta MR_{i,t}$, respectively, in the long- and short run) in order to observe country-specific effects. The market rates, $MR_{i,t}$ are multiplied by the Boone indicator ($\gamma\, BI_{i,t} MR_{i,t}$ and $\varphi\, BI_{i,t} \Delta MR_{i,t}$, respectively, in the long and short run) in order to capture the (overall) impact of competition on the pass-through. Furthermore, in the long-run model we account for country effects, by using country dummies (D_i). The short-run model includes the error-correction term ($\theta_i u_{i,t-1}$), the effects of competition on short-term adjustments in market rates ($\varphi BI_{i,t} \Delta MR_{i,t}$) for all countries simultaneously and the change in the market interest rate for each country separately ($\eta_i \Delta MR_{i,t}$).

In Equations (7.1b) and (7.1c), we estimate European-wide (panel) parameters for the various competition effects (α, γ and φ), because the Boone indicator varies insufficiently over time to estimate country-specific effects reliably. The other parameters (β_i, η_i and θ_i) remain country-specific, unless the restrictions that these parameters be equal across all countries considered would be accepted by a Wald test.

The three hypotheses to be tested are:

2. Loan interest rates are lower in more competitive loan markets than in less competitive loan markets H_0: $\alpha + \gamma MR_{i,t} < 0$ and H_1: $\alpha + \gamma MR_{i,t} \geq 0$.[9]
3. Long-run interest rate responses to the corresponding market rates are stronger in more competitive loan markets than in less competitive loan markets
   H_0: $\gamma > 0$ and H_1: $\gamma \leq 0$.
4. More competitive markets adjust faster in the short run to changes in market interest rates than less competitive markets
   H_0: $\varphi > 0$ and H_1: $\varphi \leq 0$.

[9] Note that competition causes a downwards shift in the level of bank interest rates (that is, $\alpha_1 < 0$) as well as a change in the relationship between market rates and bank rates (expressed by $\gamma_1 MR_{i,t}$).

7.3.2 Unit-root and panel cointegration tests

Unit-root tests

As a preparatory step, we first investigate the unit-root properties of the variables.[10] We apply two types of tests based on two different null hypotheses. The Im, Pesaran and Shin (2003) test (referred to as IPS test) is a panel version of the Augmented Dickey Fuller (ADF) test on unit roots. It is based on the following regression equation:

$$\Delta y_{i,t} = \alpha_i + \rho_i y_{i,t-1} + \sum_{j=1}^{p_j} \beta_{i,j} \Delta y_{i,t-j} + \varepsilon_{i,t} \tag{7.2}$$

The interest-rate series under investigation is $y_{i,t}$, and it must be observable for each country i and each month t. The autoregressive parameter ρ_i is estimated for each country separately, which allows for a large degree of heterogeneity. The null hypothesis is H_0: $\rho_i = 0$ for all i, against the alternative hypothesis H_1: $\rho_i < 0$ for some countries. The test statistic Z_{t_bar} of the IPS test is constructed by cross-section-averaging of the individual t-statistics for ρ_i. Rejection of the null hypothesis indicates stationarity.

As a crosscheck, we add results based on Hadri's (2000) test, which is a panel version of the Kwiatkowski, Phillips, Schmidt and Shin (KPSS) test, testing the null hypothesis of stationarity. The model underlying the Hadri test can be written as:

$$y_{i,t} = \alpha_i + \sum_{\tau=1}^{t} u_{i,\tau} + \varepsilon_{i,t} \tag{7.3}$$

The time series $y_{i,t}$ are broken down into two components, a random-walk component $\Sigma_\tau u_{i,\tau}$ and a stationary component $\varepsilon_{i,t}$. The test statistic Z_τ is based on the ratio of the variances $\sigma^2_u / \sigma^2_\varepsilon$. The null hypothesis of the test assumes that this ratio is zero, which implies that there is no random-walk component. Rejection of the null hypothesis indicates the presence of unit-root behaviour of the variable under investigation. Both panel series test statistics are asymptotically normal.

Cointegration tests

In a second preliminary step, we test for cointegration using panel cointegration tests by Pedroni (1999, 2004), which are based on the following regression models:

[10] For a survey of panel unit-root tests, see Banerjee (1999). For a more detailed description and application to a similar set of data, see also Kok Sørensen and Werner (2006).

$$y_{i,t} = \alpha_i + \sum_{j=1}^{K} \beta_{j,i} x_{j,i,t} + \varepsilon_{i,t} \tag{7.4}$$

The long-run coefficients $\beta_{i,j}$ may be different across the euro-area countries and α_i is a country-fixed effects parameter. We use the group mean panel version of the Pedroni test. The null hypothesis of this test assumes a unit root in the residuals of the cointegration regression, which implies absence of cointegration. The alternative hypothesis assumes a root less than one, but allows for different roots in different countries.[11] We use three different types of test statistics: an ADF type (which is similar to the ADF statistic used in univariate unit-root tests), a nonparametric Phillips-Perron (PP) version, and a version that is based directly on the autoregressive coefficient (ρ-test).

7.4 The Data

7.4.1 The Boone indicator

This analysis uses the Bankscope database of banks from eight euro-area countries during 1992-2004, namely Austria, Belgium, France, Germany, Italy, the Netherlands, Portugal and Spain. Our choice of countries was limited by the availability of (usable) data. For countries such as Finland, Greece and Ireland, not enough data are available. Luxembourg is excluded from our sample because its figures do not reflect local market conditions due to the high international profile of its banks. We focus on commercial banks, savings banks, cooperative banks and mortgage banks, ignoring the 25% more specialized institutions such as investment banks, securities firms, long-term credit banks and specialized governmental credit institutions. An exception is made for Germany in order to achieve a more adequate coverage of the national banking systems: specialized German governmental credit institutions, comprising mainly the major Landesbanken, are included. In addition to certain public finance duties, the Landesbanken also offer banking activities in competition with private sector banks, and thus should be included to ensure adequate coverage of the competitive environment in the German banking system (see Hackethal, 2004). The appendix provides a detailed description of the data; see also Chapter 6. Table 7.1 presents summary statistics of the estimated Boone indicator. Over the 1994-2004 period we observe that, on average, banking competition is heaviest in Spain, Germany and Italy. Competition appears to be less strong in Belgium, the Netherlands and Austria, and is

[11] In the panel versions of the tests, the alternative hypothesis assumes a root that is less than one but is identical between the countries. Hence, the group mean versions allow for stronger heterogeneity. As a result, we focus on the test's group mean version.

found to be weakest in France and Portugal. At the same time, the BIs for many countries vary considerably over time.[12]

Table 7.1 Summary statistics of the Boone indicator (1994-2004)

	AT	BE	DE	ES	FR	IT	NL	PT
Average	-1.5	-2.6	-4.0	-4.8	-0.6	-4.0	-2.5	-0.9
Standard deviation	2.3	0.7	1.5	1.8	0.5	1.8	1.5	1.2
Maximum	4.3	-1.5	-2.5	-2.7	0.3	-1.6	1.0	1.6
Minimum	-4.0	-3.4	-7.1	-9.6	-1.3	-7.3	-4.4	-2.4

7.4.2 Bank interest rates and market rates

Our bank loan interest rates are from the ECB's MFI Interest Rate (MIR) statistics, which have been compiled on a harmonised basis across all euro-area countries since January 2003. For the period prior to January 2003, the series were extended backwards to January 1994 using the non-harmonised national retail interest-rate (NRIR) statistics compiled by the national central banks of the (later) Eurosystem.[13] The MIR statistics consist of more detailed breakdowns than the NRIR statistics, particularly with respect to the size of loans and the rate fixation periods. In order to link the two sets of statistics, the MIR series have been aggregated (using new business volumes as weights) to the broader product categories of the NRIR statistics, which include rates on mortgage loans, rates on consumer loans, rates on short-term loans to non-financial corporations (≤1 year) and rates on long-term loans to non-financial corporations (>1 year). The data period covers 147 monthly observations ranging from January 1994 to March 2006.

We select market rates that correspond closest to these bank interest rates in terms of the rate fixation period. Hence, a three-month money-market rate is selected to correspond with bank rates that are either floating or fixed for short periods (under one year), while longer-term government bond yields are selected for long-term fixed bank rates.[14] Table 7.2 presents the data availability of bank interest rates in each country together with the corresponding market rates for each product category. Note that there is strong variation in interest-rate fixation periods across both products and countries. For instance, in many countries the predominant fixation period for mortgages is rather

[12] For more details, see Van Leuvensteijn *et al.* (2007).

[13] For some bank products in some countries, it is not possible (due to insufficient data being available) to extend interest-rate series all the way back to 1994. Hence, we use unbalanced samples for some bank products.

[14] The market rates were chosen to best match bank interest rates on the basis of information from the Methodological Notes for the NRIR statistics and from the volume weights of the MIR statistics.

short, proxied by three months. For Germany and France, however, the typical fixation period on consumer loans is quite long, approximated here by five years.

Table 7.2 Availability of bank interest rates and corresponding market rates

	Mortgage loans	Consumer loans	Short-term enterprise loans	Long-term enterprise loans
AT	April 1995 3M MR	April 1995 3M MR	April 1995 3M MR	
BE	Jan. 1994 3M MR	Jan. 1994 5Y MR	Jan. 1994 3M MR	Jan. 1994 5Y MR
DE	Jan. 1994 10Y MR	Jan. 1994 5Y MR	Jan. 1994 3M MR	Nov. 1996 5Y MR
ES	Jan. 1994 3M MR	Jan. 1994 3M MR	Jan. 1994 3M MR	Jan. 1994 3M MR
FR	Jan. 1994 10Y MR	Jan. 1994 5Y MR	Jan. 1994 3M MR	Jan. 1994 5Y MR
IT	Jan. 1995 3M MR		Jan. 1994 3M MR	Jan. 1995 3M MR
NL	Jan. 1994 10Y MR		Jan. 1994 3M MR	
PT	Jan. 1994 3M MR	Jan. 1994 3M MR	Jan. 1994 3M MR	

Sources: ECB and Bloomberg.
Note: Date indicates 'available since'; '3M MR' is the 3-month money-market rate (MR). '5Y MR' is the 5-year government bond yield. '10Y MR' is the 10-year government bond yield, all in the respective country.

Table 7.3 shows summary statistics of the bank interest-rate data. Bank interest rates differ substantially across countries, across products, and, of course, over time. On average mortgage rates and consumer lending rates, over the 1994-2004 period, were highest (lowest) in Portugal (Austria). Regarding short-term loans to enterprises, rates were on average highest (lowest) in Portugal (Germany), whereas regarding long-term loans to enterprises rates were highest (lowest) in Italy (Belgium).

Table 7.3 Summary statistics of the various bank interest rates in % (1994-2004)

	AT	BE	DE	ES	FR	IT	NL	PT
Mortgage rates								
Average	5.6	5.9	6.4	6.6	6.1	7.0	5.7	7.6
Standard deviation	1.0	1.2	1.1	2.7	1.5	3.2	1.0	3.5
Maximum	7.9	8.8	9.1	11.5	8.9	13.0	8.0	14.5
Minimum	3.8	3.8	4.5	3.1	3.9	3.7	3.8	3.4
Consumer lending rates								
Average	6.6	8.1	7.5	10.4	8.8			13.1
Standard deviation	1.1	0.5	1.0	2.8	1.7			3.6
Maximum	9.5	9.1	10.2	16.2	12.1			19.6
Minimum	5.0	7.3	6.3	7.1	6.2			8.6
Rates on short-term loans to enterprises								
Average	4.8	4.6	4.0	5.9	4.5	6.7	4.2	8.8
Standard deviation	1.0	1.1	0.7	2.2	1.5	2.8	1.0	3.8
Maximum	7.2	7.6	5.8	10.5	7.8	11.7	6.5	16.8
Minimum	2.9	2.9	3.1	3.2	2.6	3.3	2.8	4.4
Rates on long-term loans to enterprises								
Average		5.1	5.2	5.7	5.9	6.3		
Standard deviation		1.1	0.5	2.4	1.4	2.7		
Maximum		8.2	6.1	10.4	8.8	11.8		
Minimum		3.4	4.2	3.0	4.0	3.1		

Table 7.4 details the market interest rates for the considered countries. We find that Italy has, on average, the highest 3-month money-market rate and the Netherlands the lowest. The same picture arises for the 5-year government bond yield. The minima for the 3-month money-market rates and the two government bond yields with, respectively, a 5- and 10-year fixation period are very similar across all countries: these minima were reached after the introduction of the euro in 1999.

Table 7.5 presents the spreads between the various bank and market rates. On average, the spreads are narrow, ranging from 0.5% to 2.0%, with the notable exception of consumer loans, where bank interest rates often include very high risk premiums.

Table 7.4 Summary statistics of the various market rates in % (1994-2004)

	AT	BE	DE	ES	FR	IT	NL	PT
3-month money market rate								
Average	3.6	3.6	3.6	4.9	3.9	5.4	3.5	5.3
Standard deviation	0.9	1.1	1.0	2.3	1.4	2.8	1.0	2.9
Maximum	5.5	7.0	5.9	9.7	8.1	11.0	5.4	12.7
Minimum	2.0	2.0	2.0	2.0	2.0	2.0	2.0	2.0
5-year government bond yield								
Average	4.7	4.8	4.5	5.7	4.8	6.1	4.6	5.9
Standard deviation	1.1	1.2	1.0	2.6	1.3	2.9	1.1	2.7
Maximum	7.3	8.0	7.1	12.2	7.9	13.4	7.3	12.2
Minimum	2.8	2.9	2.8	2.7	2.7	2.9	2.8	2.7
10-year government bond yield								
Average			5.2		5.4		5.3	
Standard deviation			1.0		1.2		1.0	
Maximum			7.6		8.2		7.7	
Minimum			3.6		3.6		3.6	

Table 7.5 Summary statistics of the various bank rate spreads in % (1994-2004)

	AT	BE	DE	ES	FR	IT	NL	PT
Mortgage rates								
Average	2.1	2.2	1.8	1.6	1.3	1.9	1.1	2.2
Standard deviation	0.6	0.6	0.3	0.5	0.7	0.7	0.2	1.0
Maximum	3.6	3.5	2.4	2.9	3.8	3.7	1.7	4.5
Minimum	0.8	0.3	1.0	0.8	0.1	0.7	0.6	0.5
Consumer lending rates								
Average	3.2	4.2	3.1	5.5	4.0			7.7
Standard deviation	0.7	0.9	0.8	0.6	0.9			1.3
Maximum	5.1	6.5	5.2	7.2	7.0			10.2
Minimum	2.1	2.6	1.4	4.2	2.3			4.4
Rates on short-term loans to enterprises								
Average	1.3	1.0	0.5	1.0	0.6	1.3	0.7	3.4
Standard deviation	0.6	0.2	0.6	0.2	0.8	0.5	0.3	1.1
Maximum	2.9	1.5	1.6	2.0	2.8	2.5	1.3	6.7
Minimum	0.4	0.4	-0.4	0.5	-1.8	-0.4	-0.1	1.9
Rates on long-term loans to enterprises								
Average		0.4	1.1	0.9	1.1	1.3		
Standard deviation		0.4	0.2	0.4	0.7	0.4		
Maximum		1.2	1.8	1.8	2.2	3.3		
Minimum		-0.3	0.5	0.1	-0.4	-0.5		

7.5 Empirical evidence

Estimates of the Boone indicator for the loan markets in the euro area countries are presented in the Appendix. This approach is similar to the procedure applied in Chapter 6. We obtain annual BI estimates. As the regressions in this section are based on monthly data, we calculate 'smoothed' BI values using moving averages.

7.5.1 Unit roots and cointegration

Table 7.6 reports the panel unit-root tests for the bank- and market interest-rate series of the considered eight euro-area countries simultaneously. The outcomes indicate non-stationarity at the 5% significance level for all of the bank- and market interest-rate series used. The IPS test on the null hypothesis of a unit root cannot be rejected at the 5% significance level for either the bank rates or the market rates, suggesting non-stationary interest rates. This is confirmed by the Hadri test results.

Table 7.6. Panel unit-root tests on model variables applied to all countries

	Im, Pesaran and Shin test		**Hadri test**	
	Z_{t_bar} [a]	**P-value**	**Z_τ**	**P-value**
Boone indicator				
Boone indicator	-2.16	0.02	10.67	0.00
Bank interest rates				
Mortgage loans	0.98	0.84	18.78	0.00
Consumer loans	-0.89	0.19	16.59	0.00
Short-term loans to enterprises	-0.68	0.25	18.83	0.00
Long-term loans to enterprises	0.40	0.66	13.10	0.00
Market interest rates [b]				
Mortgage loans	0.04	0.52	17.08	0.00
Consumer loans	0.34	0.64	15.21	0.00
Short-term loans to enterprises	-0.68	0.25	17.23	0.00
Long-term loans to enterprises	0.94	0.83	13.39	0.00
Boone indicator times market interest rates [a]				
Mortgage loans	-2.16	0.01	15.76	0.00
Consumer loans	-1.88	0.03	12.64	0.00
Short-term loans to enterprises	-1.44	0.08	17.46	0.00
Long-term loans to enterprises	-1.38	0.08	13.74	0.00

[a] The test statistics are explained in Section 7.3.2.
[b] Market rates are approximated according to Table 7.2.

For the Boone indicator and the interaction variables between BI and market interest rates, the evidence is mixed. The IPS tests indicates stationarity (though sometimes at the 10%-level only), the Hadri test consistently rejects stationarity. Furthermore, we apply the panel unit-root tests to the first differences in interest rates. The results reject nonstationarity and, hence, support the conclusion that the interest-rate series are integrated of order 1. Given these findings, we proceed to test on cointegration between bank interest rates and the corresponding market rates.

Table 7.7 shows the results for Pedroni's three panel cointegration tests as applied to the long-run models of the four bank rates.[15] For bank interest rates on consumer loans, the null hypothesis of no cointegration cannot be rejected. Apparently, therefore, the adjustment of interest rates on consumer loans to changes in market rates is so sluggish that even a long-run relationship cannot be detected in our sample.[16] Consequently, the results of the error-correction model on consumer loans, presented in Section 7.5.2 below, have to be interpreted with caution. For the other three long-run bank-rate models, the null hypothesis of no cointegration has been rejected (for two of the three tests), indicating a long-run equilibrium relationship between bank rates, market rates and the Boone indicator.

Table 7.7 Pedroni cointegration tests on the four long-run bank interest rates models

Bank interest rates	**Group mean panel cointegration tests** [a]		
	ρ-statistic	**PP-statistic**	**ADF-statistic**
Mortgage loans	-3.19 (0.00)	-3.56 (0.00)	-0.07 (0.53)
Consumers loans	0.73 (0.77)	0.19 (0.57)	0.05 (0.52)
Short-term loans to enter-	-5.79 (0.00)	-4.75 (0.00)	-1.50 (0.07)
Long-term loans to enterprises	-2.68 (0.00)	-2.91 (0.00)	-0.75 (0.22)

[a] P-values in parentheses.

7.5.2 Competition and the bank interest-rate pass-through

As a preliminary investigation into the impact of competition on the bank interest-rate pass-through, we analyse the effect of competition on the various bank interest-rate spreads. Using equation 7.1.a, we test the hypothesis that the interest-rate spreads of banks are lower in more competitive markets. We test if true coefficient κ is significantly negative. The results in Table 7.8 show that competition significantly diminishes the bank rate spread for three out of four loan products (namely, for mortgages, consumer loans and short-term loans to enterprises). No significant effect is

[15] P-values of the various test statistics were derived using the standard normal distribution, which is a valid assumption for cointegration tests; see Pedroni (1999).

[16] We should also mention that data on consumer loans prior to January 2003 are available for only six countries, which somewhat limits the analysis of these rates.

found for long-term loans to enterprises. The parameters of the Boone indicator indicate that a one-point change in the BI affects the interest rates of mortgage loans the least, while short-term loans to enterprises are influenced most strongly. This result shows that competition tends to keep bank loan rates more closely in line with the corresponding market rates (implying that they are lower).

Table 7.8. Effect of competition on the spreads between bank- and market lending rates

	Mortgage loans		Consumer loans		Short-term loans to enterprises		Long-term loans to enterprises	
	parameter	z-value[a]	parameter	z-value	parameter	z-value	parameter	z-value
Boone indicator (κ)	-0.030	**-2.12	-0.075	***-3.03	-0.128	***-6.72	0.003	0.15
Constant	1.357	***5.54	5.818	***16.91	.736	***3.02	1.114	***4.26
Country dummies[b]	$\chi^2(7)=498$		$\chi^2(5)=3095$		$\chi^2(7)=911$		$\chi^2(4)=240$	
Monthly dummies[b]	$\chi^2(119)=693$		$\chi^2(119)=766$		$\chi^2(119)=223$		$\chi^2(119)=1084$	
R-squared, centred	0.687		0.907		0.793		0.670	
Number of observations	957		717		957		578	

Two and three asterisks indicate a level of confidence of 95% and 99%, respectively.

[a] The z-value indicates whether the parameter significantly differs from zero under the normal distribution with mean zero and standard deviation one.

[b] Chi-squared distributed Wald tests on H_0 'all country dummy coefficients are zero' and 'all monthly time dummy coefficients are zero', respectively. The null hypotheses are rejected for all loan types.

Table 7.9 presents the estimated long-run relationship of the error-correction model (ECM) described in Section 7.3.1, in order to test the last three hypotheses mentioned in that section. This model explains bank interest rates from the Boone indicator and the market interest rates; see equation (7.1.b). We use Newey-West's kernel-based heteroskedastic and autocorrelation-consistent (HAC) variance estimations to correct for heteroskedasticity and autocorrelation, where the bandwidth has been set on two periods. It should be noted that the impact of market rates on bank interest rates is highly significant for all of the four interest rates considered and in all eight euro-area countries. Moreover, in line with the existing literature, we find that the country-specific long-run pass-through coefficients (β_i) differ considerably across product categories (and across countries) with the final adjustment of bank interest rates to changes in market rates being highest for mortgage loans and loans to enterprises.[17]

[17] See also Mojon (2001), De Bondt (2005) and Kok Sørensen and Werner (2006).

Table 7.9 Estimates of the long-run models for the four bank interest rates

	Mortgage loans		Consumer loans		Short-term loans to enterprises		Long-term loans to enterprises	
	parameter	**z-value**	**parameter**	**z-value**	**parameter**	**z-value**	**parameter**	**z-value**
Boone indicator (α)	-0.198	***-3.32	-0.196	**-2.39	-0.153	**-3.39	-0.181	***-3.59
Market interest rate_AT	0.843	***8.02	0.824	***6.15	0.937	***8.76		
Market interest rate_BE	0.913	***12.26	1.000	***5.98	0.892	***23.05	0.808	***16.79
Market interest rate_DE	0.923	***14.88	0.312	**2.41	0.325	***6.22	0.615	***11.48
Market interest rate_ES	0.777	***10.89	0.785	***7.63	0.725	***10.90	0.691	***10.89
Market interest rate_FR	0.989	***12.85	1.093	***13.38	0.877	***13.04	0.982	***14.42
Market interest rate_IT	0.870	***16.07			0.807	***16.90	0.745	***18.84
Market interest rate_NL	0.784	***18.11			0.879	***20.11		
Market interest rate_PT	1.274	***24.63	1.336	***23.06	1.344	***37.41		
Market interest rate*Boone ind. (γ)	0.053	***4.29	0.057	***3.21	0.039	***3.47	0.046	***4.48
Constant	1.951	***9.74	5.679	***11.21	2.813	***13.62	2.591	***11.58
R-squared, centred	0.940		0.927		0.952		0.956	
Number of observations	957		717		957		578	
$\alpha + \gamma MR_{i,t}$	0.034		0.055		0.002		0.028	
χ^2 H_0: $\alpha + \gamma MR_{i,t} = 0$ [a)]	2.92, P-value = 0.09		2.39, P-value=0.12		0.01, P-value=0.92		2.26, P-value=0.13	

Note: One, two and three asterisks indicate levels of confidence of 90%, 95% and 99%, respectively. Country dummies are included but not shown.

[a] Chi-squared distributed Wald tests on H0 '$\alpha + \gamma$ MRi,t = 0'. The null hypothesis is not rejected for any of the loan categories.

The first hypothesis to be tested with the ECM model is as follows: loan interest rates are lower in more competitive loan markets than in less competitive loan markets. The ECM long-run equation does not assume full pass-through of market rates within one month. Table 7.9 shows that the effect of the combined terms with the BI of

competition is (slightly) positive for all of the four loan products considered.[18] But the Chi-squared distributed Wald tests on H_0: $\alpha+\gamma MR_{i,t}=0$ also show that the combined effects $\alpha+\gamma MR_{i,t}$ are not significant at the 1%-level. Note that the level of the bank rates is significantly lower under competition (that is, $\alpha<0$), but that this effect is reduced by the cross-term of market rates and indicator ($\gamma MR_{i,t} BI_{i,t}$). This outcome does not confirm our earlier finding of significantly lower loan market spreads under competition.[19]

The second hypothesis applied to the ECM model is the following: bank interest rates in more competitive markets show stronger long-run responses to the corresponding market rates compared to less competitive markets. Our results suggest that all of the four bank loan rates do indeed respond significantly more strongly to market rates when competition is high (see the significance of the coefficient γ of the product terms of indicator and market rates in Table 7.9).[20] All in all, we observe that, generally, competition does make for stronger long-run bank rate responses to corresponding market rates, thereby contributing to a more rapid pass-through.

The third hypothesis related to the ECM model is the following: banks in more competitive markets adjust faster in the short run to changes in market interest rates than banks in less competitive markets. To test this hypothesis, we estimate equation (7.1.c). The results in Table 7.10 indicate that the immediate responses of banks' interest rates on loans to changes in market rates tend indeed to be higher in more competitive markets. The coefficient φ of the product terms of Δ market rates and the Boone indicator is positive in Table 7.10.[21] However, the effect is statistically significant only for short-term loans to enterprises.

[18] When tested, one single EU-wide parameter for market interest rates was rejected in favour of separate country-specific parameters for market interest rates.

[19] We tested on a single EU-wide parameter for market interest rates in the long-run ECM model. This null hypothesis was rejected for all loan categories in favour of separate country-specific parameters for market interest rates.

[20] As mentioned in Section 7.4.3, the estimated long-run relationship between interest rates on consumer loans and corresponding market rates may be spurious, owing to the lack of a statistically significant cointegration relationship.

[21] We tested on one single EU-wide parameter for market interest rates and for one single EU-wide parameter for residuals in the short-run ECM model. The null hypotheses of a single EU-wide parameter were rejected for most loan categories in favour of separate country-specific parameters.

Table 7.10 The short-term ECM model of bank interest rates

	Mortgage loans		Consumer loans		Short-term loans to enterprises		Long-term loans to enterprises	
	parameter	z-value	parameter	z-value	parameter	z-value	parameter	z-value
ΔMarket interest rate_AT	0.2272	***3.15	0.203	*1.84	0.275	***3.41		
ΔMarket interest rate_BE	0.207	*1.73	0.358	1.32	0.408	***2.49	0.987	***6.97
ΔMarket interest rate_DE	0.511	***4.33	-0.267	-1.30	0.159	1.20	0.657	***3.56
ΔMarket interest rate_ES	0.217	*1.75	0.041	0.10	0.573	***3.36	0.994	***3.67
ΔMarket interest rate_FR	-0.025	-0.58	-0.005	-0.09	0.079	0.73	0.162	1.47
ΔMarket interest rate_IT	0.156	1.11			0.066	0.42	0.744	***3.34
ΔMarket interest rate_NL	0.262	***2.79			0.464	***3.01		
ΔMarket interest rate_PT	0.173	*1.88	0.001	0.00	0.159	0.87		
ΔMarket interest rate* Boone-ind. (φ)	0.020	0.86	0.071	1.52	0.050	*1.66	0.070	1.41
Residual_AT(-1) [a]	-0.005	***-3.10	-0.004	***-2.89	-0.005	-3.00		
Residual_BE(-1)	-0.007	**-2.20	-0.003	-1.09	-0.005	-1.52	0.001	0.31
Residual_DE(-1)	-0.003	-1.56	-0.003	**-2.07	-0.001	-0.23	-0.001	-0.80
Residual_ES(-1)	-0.006	***-2.80	-0.003	-0.86	-0.000	-0.03	-0.005	-1.51
Residual_FR(-1)	-0.006	***-3.45	-0.004	***-3.25	-0.003	-0.44	-0.004	-1.36
Residual_IT(-1)	-0.006	**-1.96			-0.004	*-1.64	-0.004	-1.33
Residual_NL(-1)	-0.004	-1.63			-0.000	-0.10		
Residual_PT(-1)	-0.009	***-3.89	-0.006	-1.50	-0.011	**-2.28		
R-sq centred	0.19		0.03		0.19		0.27	
Number of observations	949		711		949		573	

Note: One, two and three asterisks indicate a level of confidence of, respectively, 90%, 95% and 99%.

[a] See equation (7.1c).

7.6 Conclusion

This chapter analyses the effects of loan market competition on bank interest rates on loans, measuring competition by a new approach: the Boone indicator. Our results show that, in the euro-area countries, bank interest-rate spreads on mortgage loans, consumer

loans and short-term loans to enterprises are significantly lower in more competitive markets. This result implies that bank loan rates are lower under heavier competition, thus improving social welfare. Furthermore, evidence is found for all of the four loan categories that, in the long run, bank loan rates are aligned more closely with market rates where competition is higher. Finally, we observe that competition in loan markets tends to reinforce the immediate response of bank interest rates to changes in corresponding market rates. These results show that stronger loan market competition reduces bank loan rates, while changes in market rates are transmitted more rapidly to bank rates. These findings underscore the fact that bank competition has a substantial impact on the monetary policy transmission mechanism. More loan market competition enhances the strength and transmission speed of monetary policy.

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Appendix The estimation of the Boone indicator model

Description of the data used

The Boone indicator model uses Bankscope data of banks from eight euro-area countries during 1992-2004.[22] This model is based on marginal costs that are derived from a TCF with output components and input prices. In order to exclude irrelevant and unreliable observations, banks are incorporated in our sample only if they fulfilled the following conditions: total assets, loans, deposits, equity and other non-interest income should be positive; the deposits-to-assets ratio and loans-to-assets ratio should be less than, respectively, 0.98 and 1; the income-to-assets ratio should be below 0.20; the personnel expenses-to-assets ratio and other expenses-to-assets ratios should be between 0.05% and 5%; and, finally, the equity-to-assets ratio should be between 0.01 and 0.50. As a result, our final dataset totals 520 commercial banks, 1506 cooperative banks, 699 savings banks, 28 special governmental credit institutions (Landesbanken) and 62 real estate banks (see Table A.1).

Table A.1 Number of banks by country and by type

Country	Commercial banks	Cooperative banks	Real estate banks	Savings banks	Specialized governmental credit institutions	Total
AT	52	54	10	65	0	181
BE	24	6	0	5	0	35
DE	130	867	44	501	28	1570
ES	61	17	0	43	0	121
FR	115	83	2	30	0	230
IT	105	476	1	52	0	634
NL	24	1	4	1	0	30
PT	9	2	1	2	0	14
Total	520	1506	62	699	28	2815

Table A.2 briefly describes the model variables. To grasp the relative magnitude of the key variables, such as costs, loans, security investment and other services, we present them as shares of corresponding balance sheet items. Total costs are defined as total expenses, which vary between 6.3% and 8.6% of total assets— whereas market shares in the loan market vary between 0.06% and 5.8%. Loans and securities are in the range of, respectively, 35%-60% and 4%-37% of total assets. One of the output components

[22] See also Van Leuvensteijn *et al.* (2007), which uses a similar approach.

we distinguish is *other services*. For lack of direct observations, this variable is proxied by non-interest income. Non-interest income ranges from 12%-20% of total income. Wage rates are proxied as the ratio of personnel expenses and total assets, since for many banks the number of staff is not available. Wages vary across countries between 0.9% and 1.7% of total assets. The input price of capital is proxied by the ratio of other expenses and fixed assets. Finally, interest rates are proxied by dividing interest expenses by total funding and range from 3.2% to 5.9%.

Table A.2 Mean values of key variables for various countries (in %)

Country Code	Boone model	Translog cost function						
	Average loans market-shares in %	Total costs as % of total assets	Loans as % of total assets	Securities as % of total assets	Other services as % of total income	Other expenses as % of fixed assets	Wages as % of total assets	Interest expenses as % of total funding
AT	0.87	6.34	56	22	20	229	1.4	3.2
BE	2.27	6.49	35	37	16	594	1.0	4.5
DE	0.06	6.44	60	22	12	227	1.5	3.7
ES	0.98	6.63	58	14	16	167	1.5	4.1
FR	0.41	7.42	54	4	20	537	1.5	4.8
IT	0.22	6.67	53	26	16	261	1.7	3.5
NL	3.02	6.59	54	15	13	340	0.9	5.4
PT	5.83	8.62	52	8	18	191	1.3	5.9

Estimation results for marginal costs

We estimate a TCF for each separate country and take the first derivative of loans to derive the marginal costs of lending (see equations (6.5) and (6.8) in Chapter 6, respectively).[23] Table A.3 shows the marginal costs of loans across countries and over time. Marginal costs decline over time, reflecting the significant decreases in funding rates during 1992-2004 and possibly also technological improvements. Germany, France and Spain have relatively high marginal costs compared to the Netherlands and Belgium. Apart from differences in funding rates, this may be explained also by lower efficiency in the former countries.[24]

[23] See also Chapter 6, Section 6.2 and Section 3.1 in Van Leuvensteijn *et al.* (2007)

[24] Another explanation is lower population density in the former countries. Low population density may raise operating costs, as it makes retail distribution of banking services more costly.

Table A.3 Marginal costs of loans across countries and over time (in %)

	AT	BE	DE	ES	FR	IT	NL	PT
1992	10.3	7.1	10.2	15.9	13.8	13.2	9.2	21.3
1993	9.4	6.9	9.4	17.2	13.4	12.0	8.1	18.8
1994	7.1	6.4	9.2	14.3	11.9	12.2	7.4	16.6
1995	7.3	5.8	8.9	15.4	11.7	11.8	7.1	15.4
1996	7.1	5.2	8.5	14.3	10.9	11.3	6.3	13.4
1997	6.1	4.6	7.4	11.7	10.9	9.7	6.4	12.3
1998	6.0	3.6	7.1	11.1	11.2	7.5	7.4	9.4
1999	5.5	3.2	6.4	8.8	10.0	6.7	6.4	6.1
2000	6.1	3.3	7.1	9.9	11.2	6.7	6.5	6.3
2001	6.1	3.1	7.3	9.6	11.7	6.6	6.4	5.9
2002	5.7	3.1	7.1	7.8	10.7	6.1	5.7	5.2
2003	5.5	2.7	6.4	5.9	8.9	5.3	4.9	5.3
2004	5.2	2.5	6.0	4.8	7.9	4.9	4.6	5.5

Estimation results for the Boone indicator

Table A.4 shows the estimates of the Boone indicator across countries and over time (usually 1994-2004, depending on the respective country). The results are based on the following model:

$$\ln ms_{i,t} = \alpha + \sum_{t=1,..,T} \beta_t \ln mc_{i,t} + \sum_{t=1,..,(T-1)} \gamma_t d_t + u_{i,t} \,, \qquad \text{(A.1)}$$

explaining loans market shares of bank i in year t ($ms_{i,t}$) by marginal costs ($mc_{i,t}$) and country dummies (d_t). Note that the Boone indicator, β_t, is time dependent. The estimations are carried out using the Generalized Moment Method (GMM) with as instrument variables the one-, two- or three-year lagged values of the explanatory variable, marginal costs, or average costs. See Chapter 6 for an explanation of the test on overidentification of the instruments, the Hansen J-test, and the Anderson canonical correlation likelihood ratio, which test for the relevance of excluded instrument variables. We use kernel-based heteroskedastic and autocorrelation-consistent (HAC) variance estimations. The bandwidth in the estimation is set at two periods, and the Newey-West kernel is applied. Where the instruments are overidentified, 2SLS is used instead of GMM. For this 2SLS estimator, Sargan's statistic is used instead of the Hansen J-test.

Over the sample period, the BIs for Belgium, Germany, and Italy are highly significant, except for one or two years, suggesting stronger loan-market competition

than elsewhere in the euro area.[25] The Dutch and Spanish loan markets take up an intermediate position, with significant Boone indicators for at least a number of years. For France, the degree of competition declined over the years, where the reverse development is observed for Austria and Portugal. If, for each country, we had estimated only one beta for the full-sample period instead of annual ones (that is, $\beta_t = \beta$ for all t), we would have obtained significant values for all countries (except Portugal), reflecting a certain degree of competition in the whole area (see Van Leuvensteijn *et al.* 2007).

[25] Most likely, the favourable result for Germany hinges in part on the special structure of its banking system, being built on three pillars (*i.e.* the commercial banks, the publicly-owned savings banks and the cooperative banks; see Hackethal 2004).

Table A.4 The Boone indicator over time and across various countries[b]

	Germany[a]		France		Italy[a]		Spain[a]	
	β_t	z-value	β_t	z-value	β_t	z-value	β_t	z-value
1993					-5.90	-1.18	-4.21	*-2.49
1994					-7.25	**-3.24	-4.80	*-2.28
1995	-4.47	-1.40	-1.28	**-3.36	-4.51	**-3.53	-5.20	-1.92
1996	-7.09	**-2.92	-1.28	**-3.56	-5.58	**-3.98	-9.61	-0.67
1997	-4.64	**-3.41	-1.11	**-3.55	-5.89	**-4.08	-4.36	-1.78
1998	-5.10	**-3.97	-0.79	*-1.99	-4.60	**-6.08	-5.40	-0.86
1999	-2.60	**-4.04	-0.70	*-2.30	-4.05	**-4.39	-5.46	*-2.21
2000	-2.50	**-4.60	-0.46	-1.34	-3.32	**-4.39	-3.44	-1.93
2001	-3.31	**-7.02	-0.68	-1.67	-2.66	**-3.62	-4.38	**-2.55
2002	-4.53	**-4.71	-0.40	-0.78	-1.59	-1.82	-3.88	*-2.09
2003	-2.73	**-5.62	0.27	0.39	-2.42	**-3.69	-3.42	-1.20
2004	-2.66	**-4.15	0.10	0.12	-1.81	**-2.79	-2.69	**-5.62
F-test	10.70		5.01		13.23		3.33	
Anderson canon corr.	185.20		1023.66		300.34		38.78	
LR-test								
Hansen J-test(P-value)	0.00		19.69 (0.48)		0.00		0.00	
N	14 534		918		4918		1015	

	the Netherlands		Belgium		Austria		Portugal	
	β_t	z-value	β_t	z-value	β_t	z-value	β_t	z-value
1994	-1.92	-1.42			11.2	1.01	0.05	0.05
1995	-4.42	*-2.42	-1.48	-1.59	-4.03	-0.94	1.57	0.91
1996	-2.09	**-2.58	-1.74	**-2.93	-2.31	*-1.93	0.09	0.16
1997	-3.57	-1.70	-2.02	**-3.78	4.25	0.93	-0.04	-0.08
1998	1.04	0.38	-1.98	**-3.19	-0.91	-0.52	-0.55	-0.76
1999	-1.44	-0.85	-2.62	**-4.65	-2.98	-0.73	-1.51	-1.40
2000	-3.26	**-3.00	-3.41	**-6.10	-2.31	-0.50	-2.43	**-4.03
2001	-3.91	**-4.71	-3.00	**-4.51	-0.96	-1.30	-1.92	**-3.77
2002	-2.45	*-2.44	-3.42	**-4.34	-1.49	*-1.97	-2.16	**-7.33
2003	-2.22	-1.80	-2.79	**-3.18	-1.26	**-3.52	-1.74	*-2.05
2004	-3.09	**-2.85	-3.12	**-4.02	-2.99	**-2.23	-1.53	-1.69
F-test	3.33		3.90		2.21		3.94	
Anderson canon corr.	31.71		178.10		28.89		77.92	
LR-test								
Hansen J-test (P-value)	0.00		20.5 (0.039)		9.308 (0.59)		11.71(0.38)	
N	1015		241		988		134	

Notes: Asterisks indicate 95% (*) and 99% (**) levels of confidence. Coefficients of time dummies are not shown.

[a] 2SLS is used and the equation is exactly identified, so that the Hansen J-test is 0.00.

[b] Equation (A.1) is estimated with the GMM.

8 Competition and efficiency in the Dutch life insurance industry

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8.1 Introduction

This chapter investigates efficiency and competitive behaviour on the Dutch life insurance market. In the Netherlands, the life insurance sector is important— with in 2003 a volume of business in terms of annual premiums paid of € 24 billion, invested assets of € 238 billion and insured capital of € 900 billion.[1] This market provides important financial products, such as endowment insurance, annuities, term insurance and burial funds, of often-sizeable value for consumers. Financial planning of many households depends on proper functioning of this market. However, the complexity of the products and dependency on future investment returns make many life insurance products rather opaque. Competition and efficiency in this sector are therefore important issues, from the point of view of both consumers and supervisors whose task it is to monitor the competitiveness of markets.

Most life insurance policies have a long lifespan, which makes consumers sensitive to the reliability of the respective firms. Life insurance firms need to remain in a financially sound condition over decades in order to be able to pay out the promised benefits. The sector has a safety-net arrangement in case a life insurer fails, but that does not cover all risks and excludes policies of the largest ten firms. Without sufficient profitability it is questionable whether life insurers would be able to face unfavourable developments such as a long-lasting decline of long-term interest rates. Obviously, there may be a complex trade-off. Increased competition may yield a short-run advantage to consumers of low premiums, but possibly along with the drawback of higher long-run risk with respect to the insurance benefits. In practice, the likelihood that an insurer in the Netherlands fails appears to be rather limited under normal

[1] In terms of premiums as a percentage of GDP, the Dutch market is around 40% above the European weighted average.

circumstances. Before the subprime crisis of 2008, only one bankruptcy appeared in twenty years— although this likelihood increased dramatically in 2008. Obviously, improvement of efficiency due to competition would benefit all stakeholders, in both the short- and the long run.

Life insurance firms sell different products using various distribution channels, thereby creating several submarkets. The degree of competition may vary across these submarkets. For instance, submarkets in which parties bargain on collective contracts (mainly pension schemes provided by the employer) and submarkets for direct writers are expected to be more competitive than submarkets where insurance agents sell products to uninformed but trusting customers. Lack of sufficient data on the prices of life insurance products, on the market shares of products and on the array of distribution channels makes distinctions with regard to competition on submarkets impossible.

Lack of data also prohibits our ability to measure competition among life insurers *directly* (for instance, by a price-cost margin), even for the total life insurance market. One qualitative way to investigate this market is to work out what its structural features are, particularly those related to its competitive nature. On the supply side, we find that market power of insurance firms is limited due to their plurality and because ample entry possibilities exist— all of which contribute to sound competitive conditions. But on the demand side, we observe that consumer power is limited, particularly due to the opaque nature of many life insurance products, and that there are few substitution possibilities for life insurance policies. This could hamper increased competition. Combining these various insights, we have reason to analyse the competitive nature of this market further. In the analysis, we use four different empirical aggregate indicators of competition: scale efficiency, X-efficiency, profit margins and the Boone indicator (BI).

An often-used quantitative indirect measure of competition is efficiency. Increased competition is assumed to compel firms to operate more efficiently, so that high efficiency might indicate the existence of competition and *vice versa*. We distinguish between various types of efficiency, particularly scale efficiency and X-efficiency. Scale economies are related to output volumes, whereas cost X-efficiency reflects managerial ability to drive down production costs, controlled for output volumes and input price levels. There are various methods to measure scale economies and X-efficiency.[2] We use a translog cost function (TCF) to reveal the existence of scale economies, and a stochastic cost frontier model to measure X-efficiency. Further, large unemployed scale economies may raise questions about the competitive pressure in the market. Note that the existence of scale efficiency is also important for the potential entry of new firms, an important determinant of competition. Strong scale effects would put new firms at a disadvantage.

[2] For an overview, see Bikker (2004) or Bikker and Bos (2005).

A straightforward measure of competition is the profit margin. Above-normal profits would indicate insufficient competition. We observe profits of Dutch life insurers over time and compare them with profits of foreign peers.

Another indirect measure of competition is the Boone indicator. This approach is based on the notion that competition rewards efficiency and punishes inefficiency. In competitive markets, efficient firms perform better— in terms of market shares and hence profit— than inefficient firms. The BI measures the extent to which efficiency differences between firms are translated into performance differences. The more competitive the market is, the stronger is the relationship between efficiency differences and performance differences. The BI is usually measured over time, giving a picture of the development of competition. Further, the BI level in life insurance can be compared with levels in other parts of the service sector, to assess the relative competitiveness of the life insurance market.

This chapter has been part of a larger research project on competition in the life insurance industry; see CPB (2005). Other parts of the project explore in more detail the barriers of competition, product choice and the role of financial advice. This chapter aims to measure competitive behaviour and performance of the Dutch life insurance market as a whole. The study here presented is complementary to other detailed studies in the following sense: whatever goes on in the oft-discussed financial advice part of the business, this chapter verifies what can be said about competition in the market on an aggregate level. Any problems (or lack of problems) should ultimately show up in aggregate indicators of competition. Since we use four different empirical aggregate indicators (average profit margins, scale economies, X-inefficiencies and the Boone indicator), we expect to get a clear picture of competition in this market.

The chapter proceeds as follows. Section 8.2 provides a brief and general explanation of the production of life insurance firms. Section 8.3 investigates the competitive structure of demand- and supply sides of the Dutch life insurance market. Section 8.4 measures scale economies based on the TCF, while section 8.5 introduces the measurement of X-efficiency. Section 8.6 discusses the Boone indicator. Section 8.7 describes the data used and Section 8.8 presents the empirical results of the various indirect measures of competition. The last section sums up and draws conclusions.

8.2 The production of life insurance

The core business of insurance firms is the sale of protection against risks.[3] There are two quite different types of insurance products: life insurance and non-life or property & casualty (P&C) insurance.[4] Life insurance covers deviations in the timing and size of

[3] For life insurance, a second motive is the accumulation of assets. Some countries see many buyers of annuities eventually cashing out their contracts rather than annuitizing.

[4] In the Netherlands, health insurance is part of non-life insurance, whereas in Anglo-Saxon countries, health insurance is seen as part of life insurance.

predetermined cash flows due to (non-)accidental death or disability. While some life insurance products pay out only in the incident of death (term insurance and burial funds), others do so at the end of a term or a number of terms (endowment insurance).[5] A typical annuity policy pays an annual amount starting on a given date (if a specific person is still alive) and continues until that person passes away. The benefits of insurance can be guaranteed beforehand— so that the insurance firm bears the risk that invested premiums may not cover the promised payments. Such guaranteed benefits may be accompanied by some kind of profit sharing (*e.g.* depending on indices of bonds or shares). The benefits of insurance can also be linked to capital market investments (*e.g.* a basket of shares), so that the insurance firm bears no investment risk at all. Such policies are usually referred to as unit-linked funds. We also observe mixed products (*e.g.* unit linked funds with guaranteed minimum investment returns).

A major feature of life insurance is its long-term character, often continuing for decades. Therefore, policyholders need to trust their life insurance company, making insurers very sensitive to their reputation. Life insurers need large reserves to cover their calculated insurance liabilities. These reserves are financed by— annual or single— insurance premiums and invested mainly on the capital market. The major risk of life insurers concerns mismatches between liabilities and assets. Idiosyncratic life risk is negligible, as it can be well diversified. Systematic life risk, however, such as increasing life expectancy, can also pose a threat to life insurers. Yet their major risk will always be investment risk. The main services that life insurance firms provide to their customers are life (and disability) risk pooling and financial intermediation. Significant expenditures include sales expenses, whether in the form of direct sales costs or of fees paid to insurance agencies, administrative costs, investment management and product development.

In the Netherlands, the insurance product market is heavily influenced by fiscal privileges. In the past, endowment-insurance allowances, including any related investment income, used to be tax-exempt, up to certain limits, provided that certain none-too-restrictive conditions were met. Annuity premiums were tax deductible, but annuity allowances were taxed. Consumers could often also benefit from lower marginal tax rates after retirement. In 2001, a major tax revision reduced the tax benefits for all new policies, while the rights of existing policies were respected.[6] The planned reduction in fiscal benefits was announced in advance in earlier years, so that consumers could bring forward their spending on annuities and insurers were eager to sell. Endowment insurance policies became subject to wealth tax, and income tax exemption limits were reduced. Simultaneously, both the standard deduction for annuity premiums and the permission for individuals to deduct annuity premiums to

[5] A typical endowment insurance policy pays an agreed amount on a certain date if a given person is still alive, or earlier when he or she passes away. Of course, there are many variants to these archetypes.

[6] The fiscal regime change might cause a structural break. However, re-estimation of our model for two sub-periods, before and after the change, did not yield different results.

repair pension shortfalls were also reduced. The reduced subsidy on annuities had a particularly great impact on volumes. Finally, in 2003, the standard deduction for annuity premiums was abolished entirely, whereas the permission to do so on an individual basis was limited even further.

8.3 The competitive structure of the Dutch life insurance market

This section briefly discusses structural characteristics of the market for life insurance that may affect competition.[7] The diagnostic framework developed in CPB (2003) enables an assessment of whether a market structure constitutes a *tight oligopoly*, which is defined as an oligopoly that facilitates the realization of supernormal profits for a substantial period of time. Here 'facilitate' refers to the fact that the probability that these profits that are observed are higher than in a more competitive market. These 'supernormal' profits exceed a market-based rate of risk-adjusted return on capital, and 'substantial period of time' implies that oligopolies will be stable for a number of years.

8.3.1 Supply-side factors

The diagnostic framework mentioned above contains a list of coordinated and unilateral factors that increase the probability of a tight oligopoly (see Table 8.1). *Coordinated factors* refer to explicit and tacit collusion, while *unilateral factors* denote actions undertaken by individual firms without any form of coordination with other firms. Economic theory indicates that a high concentration and high entry barriers are conducive to the realization of supernormal profits. Frequent interaction, intra-firm transparency and symmetry (in terms of equal cost structures) are beneficial to a tight oligopoly, since they make it easier for firms to coordinate their actions and to detect and punish deviations from the (explicitly or tacitly) agreed upon behaviour. Heterogeneous products make it easier for firms to raise prices independently of competitors, as consumers are less likely to switch to another firm in response to price differences. Structural links between firms (such as cross-ownerships) would give firms a stake in each other's performance, thus softening competition.[8] Information about risks plays a crucial role in markets for financial products. In the case of life insurance, adverse selection may play a role when consumers have more information regarding their life expectancy than insurance companies. Adverse selection may lead to higher price-cost margins.

[7] See CPB (2005) for a fuller discussion.
[8] For a detailed analysis of the various effects we refer to CPB (2003).

Table 8.1 Determinants of low competition

	Coordinated factors	Unilateral factors
Supply-side factors		
Essential	Few firms	Few firms
	High entry barriers	High entry barriers
	Frequent interaction	Heterogeneous products
Important	Transparency	Structural links
	Symmetry	Adverse selection
Demand-side factors		
	Low firm-level elasticity of demand	
	Stable demand	Imperfection in financial advice

Source: CPB (2003), p. 34 (except adverse selection).

An indicator of market concentration or the number of firms, the first determinant of competition, is the Herfindahl-Hirschman Index (HHI).[9] Over 1995-2003 we calculate an average HHI value of 780 for the Dutch life insurance industry, which is far below any commonly accepted critical value. This low figure reflects also the large number of Dutch life insurance firms, which, over the respective years, ranged from over one hundred to above eighty. An alternative indicator is the so-called *k*-firm concentration ratio, which sums the market shares of the *k* largest firms in the market. In 1999, the five largest firms together controlled 66% of the market (see Table 8.2), where the largest firm had a market share of 26%. These figures are not unusual for large countries such as Australia, Canada and Japan— although Germany, the UK and the US have considerably lower ratios. However, one should keep in mind that, by definition, such ratios typically are substantially higher in smaller markets or countries. We conclude that insurance market concentration in the Netherlands is moderate, although in market segments, such as collective contracts, concentration may be substantial (CPB 2005).

The second determining factor of competition is the set of barriers to entry. Table 8.2 shows that the number of entrants as a percentage of the total sample of Dutch insurance firms varied from 2% in 1991 to 8% in 1997. These numbers are relatively high compared to countries such as Canada, Germany and the UK, where the degree of entry varied between 1% and 4%. This suggests that entry opportunities in the Dutch life insurance market seem to be quite large compared to other countries.

[9] Concentration ratios are discussed in Bikker and Haaf (2002). $HHI = \sum_{i=1}^{n} s_i^2$ where s_i represents the market share of firm *i*.

Table 8.2 Concentration indices, numbers of firms and numbers of entrants as %

	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999
5-firm concentration ratio										
France	48.2	48.9	51.3	49.2	48.5	49.6	53.9	53.2	58.4	56.0
Germany	29.9	29.1	29.4	29.6	29.5	29.5	29.1	28.9	29.9	29.4
Netherlands	65.7	63.3	63.6	63.3	63.1	61.4	60.5	59.0	57.7	65.7
UK	36.3	35.3	34.2	38.1	35.9	34.7	35.6	34.8	38.6	
Australia	73.5	70.9	65.8	64.1	61.5	60.0	58.3	61.6	60.0	
US			28.2	27.5	26	25.3	25.7	25.5	25.2	
Canada						65.6	68.4	70.6	73.1	73.3
Japan	63.9	63.6	63.8	63.8	64.1	64.2	63.7	65.1	53.8	
Number of firms and new entries										
Germany, nr. of firms	338	342	326	327	319	323	320	319	318	314
Germany, entrants (%)				0.9	0.9	2.2	1.6	1.3	1.3	1.6
Netherlands, nr. of firms	96	96	97	98	95	96	99	107	108	109
Netherlands, entrants (%)	0.0	4.2	2.1	5.1	5.3	3.1	6.1	8.4	2.8	3.7
UK, nr. of firms	205	202	196	194	191	174	177	177	176	
UK, entrants (%)	4.4	2.0	1.5	2.1	1.0	3.4	1.1	1.1		
Canada, nr. of firms							146	151	150	146
Canada, entrants (%)							2.1	3.3	0.7	0.7
Japan, nr. of firms[10]	30	30	30	30	31	31	44	45	46	47
Japan, entrants (%)	0.0	0.0	0.0	0.0	3.2	0.0	29.5	2.2	2.2	4.3

Source: Group of Ten (2001).

8.3.2 Demand-side factors

Coordinated and unilateral demand-side factors also affect the intensity of competition (see Table 8.1). The elasticity of residual demand determines how attractive it is for a firm to unilaterally change its prices. High search and switching costs contribute to low firm-level demand elasticity. Stable, predictable demand makes it easier for firms to collude in order to keep prices high— as in that case cheating by one or more firms will be easier to detect than with fluctuating demand.

In practice, the elasticity of residual demand for life insurance policies is limited, due to the absence of perfect substitutes. Investment funds or bank savings could in principle be an alternative for old-age savings (such as annuities), but these lack the risk-pooling element, which is essential for life insurance policies. Moreover, annuities generally enjoy a more favourable fiscal status related to the tax deductibility of premiums (particularly in the Netherlands, although less so since 2001), which is another reason why alternatives are less attractive. A significant portion of the

[10] In 1996, Japanese entrance increased sharply due to a structural change.

endowment insurance policies is used in combination with mortgage loans. Here, the importance of risk pooling is less dominant and may diverge across policyholders, but fiscal treatment with respect to income and wealth taxation is still linked to the life-policy status.

High switching costs are typical for life insurance policies, since contracts are often of a long-term nature and early termination of contracts is costly. It involves disinvestments and a reimbursement of the company's client of not-yet-paid acquisition costs, which have a front-loading nature.[11]

Search costs for life insurance products are high, as these products are complicated and the market is opaque. These costs could be alleviated if search could be entrusted to insurance agents, which would help consumers to avoid errors in their product choice. Moreover, it would make the market more competitive by raising the elasticity of demand. However, the Dutch market for financial advice may not function properly (CPB 2005).[12] In particular, due to the incentive structure in this market (notably commissions) coupled with inexperienced consumers, insurance agents may give advice that is not in the best interest of consumers.

Consumer power is weaker, as the market is less transparent. Strong brand names are indicators of non-transparency, as confidence in a well-known brand may replace price comparisons or personal judgment. Another indicator is the degree to which buyers organize themselves— for instance, by collecting information and thereby reduce the opaque nature of the market. The major consumer organization in the Netherlands, a number of Internet sites[13] and other sources such as the magazine *Money View*, compare prices and inform consumers continuously with regard to life insurance policy conditions and prices in order to help them make comparisons and have well-founded choices. For a minority of the consumers the magazine's information equips them sufficiently to take out a life insurance policy as direct writer or at bank or post offices. However, as products remain complicated and come in a great variety of properties (type, age, and so on), the majority of consumers are not able (or are unwilling) to take out policies themselves, and call upon the services of insurance agents.

A third indicator is the degree to which consumers can take out life insurance policies collectively. Collective contracts are usually based on thorough comparisons of conditions and prices by experts, are often negotiated via the employer and contribute substantially to consumer power but many people, of course, are unable to take advantage of this consumer power-enhancing instrument.

Finally, the number of suppliers, which is also an important factor, is sufficiently large, as appears from Table 8.2.

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[11] Acquisition costs are marketing costs and sales costs, which include commissions to insurance agents.

[12] Incidentally, a new Dutch Financial Services Act (Wet Financiële Dienstverlening) came into force at the beginning of 2006, stipulating greater transparency in this market, which may also work to improve competition in this submarket.

[13] See Consumentenbond, 2004, *Consumentengeldgids* (Personal finance guide), September, 34–37.

8.3.3 Conclusions

The supply-side characteristics of the market for life insurance suggest limited supplier power: the number of firms is quite large, the level of concentration is not particularly high and entry opportunities are relatively high. However, at the demand side we find factors such as high search costs and high switching costs, few substitution possibilities, limited consumer power due to the opaque nature of life insurance products and substantial product differentiation. The demand-side conditions may impair the competitive nature of the life insurance market and call for further analysis.

8.4 Measuring scale economies

In the present market, we expect that scale economies would be reduced under increased competition.[14] The existence of non-exhausted scale economies is an indication that the potential to reduce costs has not been employed fully and, therefore, can be seen as an indirect indicator of (lack of) competition. This is the first reason why we investigate scale economies. A second reason is that we will correct for (potential) distortion by possible scale economies in a subsequent analysis based on the Boone indicator by using the estimation results presented below.

We measure scale economies using a translog cost function (TCF). Measurement and analysis of differences in life insurance cost levels are based on the assumption that the technology of an individual life insurer can be described by a production function that links the various types of life insurer output to input factor prices, such as wages (management), acquisition fees and so on. Under proper conditions, a dual cost function can be derived, using output levels and factor prices as arguments. In line with most of the literature, we use the translog cost function to describe costs. Christensen *et al.* (1973) proposed the TCF as a second-order Taylor expansion, usually around the mean, of a generic function with all variables appearing as logarithms. This TCF is a flexible functional form that has proven to be an effective tool for the empirical assessment of efficiency. For a theoretical underpinning and an overview of applications in the literature, see Bikker *et al.* (2006). The TCF reads as follows:

$$ln\ c_{it} = \alpha + \sum_j \beta_j\ ln\ x_{ijt} + \sum_j \sum_k \gamma_{jk}\ ln\ x_{ijt}\ ln\ x_{ikt} + v_{it}, \tag{8.1}$$

where the dependent variable c_{it} is the cost of production of the ith firm ($i = 1, ..., N$) in year t ($t = 1, \ldots, T$). The explanatory variables x_{ijt} represent output or output components ($j, k = 1, ..., m$) and input prices ($j, k = m + 1, \ldots, M$). The two sum terms constitute the

[14] This interpretation would be different in a market with only few firms, so that further consolidation would be impossible. Further, this interpretation would also change when new entrees incur unfavourable scale effects during the initial phase of their growth path.

multiproduct TCF: the linear terms, on the one hand, and the squares and cross-terms, on the other— each accompanied by the unknown parameters β_j and γ_{jk}, respectively. v_{it} is the error term.

We need the number of additional calculations to interpret the coefficients of the TCF in equation (8.1) and to draw conclusions from them. For these calculations, the insurance firm-year observations are divided into a number of size classes, based on the related value of premium income. The marginal costs of output category j (for $j = 1, ..., m$) for size class q in units of the currency, $mc_{j,q}$, is defined as:

$$mc_{j,q} = \partial c / \partial x_j = (c_q / x_{j,q})\, \partial \ln c / \partial \ln x_j \quad , \tag{8.2}$$

where $x_{j,q}$ and c_q are averages for size class q of the variables. It is important to check whether marginal resource costs are positive at all average output levels in each size class. Otherwise, from the point of view of economic theory, the estimates would not make sense.

Scale economies indicate the percentage by which operating costs go up when all output levels increase proportionately. We define scale economies as:[15]

$$SE = \Sigma_{j=1, \ ,m}\, \partial \ln c / \partial \ln x_j \ , \tag{8.3}$$

where $SE < 1$ corresponds to economies of scale (that is, a less than proportionate increase in cost when output levels are raised), whereas $SE > 1$ indicates diseconomies of scale.

The literature provides various examples of (dis)economies of scale. Fecher *et al.* (1991) applied TCFs to estimate scale economies in the French insurance industry. They found increasing returns to scale. However, it is unclear whether this effect is significant. An increase of production by one percent increases costs by only 0.85 percent in France's life insurance industry. Grace and Timme (1992) examine cost economies in the US life insurance industry. They found strong and significant scale economies for the US life insurance industry. Depending on the type of firm and the size of the firm, an increase of production by one percent would increase costs by 0.73% to 0.96%.

This chapter applies two versions of the TCF. The first is used to estimate the scale effects and marginal cost, which will also be taken as input for the Boone indicator (BI) model. In this version, production is proxied by *one* variable, namely premium income. This makes it possible to calculate the optimal size of the firm. Particularly for marginal costs, it is necessary to use a single measure of production— even if that would be

[15] Note that scale economies are sometimes defined by the reciprocal of Equation (8.3); see, for instance, Baumol *et al.* (1982, p. 21) and Resti (1997).

somewhat less accurate (see Section 8.8.1). The second is the stochastic cost approach model, discussed in the next section, which is used to estimate X-inefficiencies. Since it is essential that the multi-product character of life insurance be recognized, a set of five variables has been used to approximate production (see Sections 8.5, 8.8.2 and 8.8.3).

8.5 Measuring X-inefficiency

It is expected that increased competition forces insurance firms to drive down their X-inefficiency, Therefore, X-efficiency is often used as an indirect measure of competition. X-efficiency reflects managerial ability to drive down production costs, controlled for output volumes and input price levels. X-efficiency of firm *i* is defined as the difference in costs between that firm and the best-practice firms of similar size and input prices (Leibenstein 1966). Errors, lags between the adoption of the production plan and its implementation, human inertia, distorted communications and uncertainty cause deviations between firms' performance and the efficient frontier formed by the best-practice life insurers with the lowest costs, controlled for output volumes and input price levels.

Various approaches are available to estimate X-inefficiency (see, for example, Lozano-Vivas 1998). All methods involve determining an efficient frontier on the basis of observed (sets of) minimal values rather than presupposing certain technologically determined minima. Each method, however, uses different assumptions and may result in diverging estimates of inefficiency. In the case of banks, Berger and Humphrey (1997) report a roughly equal split between studies applying non-parametric and parametric techniques. The number of efficiency studies for life insurers is small compared to that for banks. For a survey, see Cummins and Weiss (2000) and Bikker *et al.* (2006). *Non-parametric* approaches, such as data envelopment analysis (DEA) and free disposable hull (FDH) analysis, have the practical advantage that no functional form needs to be specified. At the same time, however, they do not allow for random error terms, so that specification errors, missing variables and so on, if they do exist, may be wrongly measured as inefficiency, raising the estimated level of inefficiency. The results of the DEA method are also sensitive to the number of constraints specified. An even greater disadvantage of these techniques is that they generally ignore prices and can, therefore, account only for technical, not for economic inefficiency.

One of the *parametric* methods is the stochastic frontier approach, which assumes that the random error term is the sum of a random error term and an inefficiency term. These two components can be distinguished by making one or more assumptions about the asymmetry of the distribution of the inefficiency term. Although such assumptions are not very restrictive, they are nevertheless criticized for being somewhat arbitrary. A flexible alternative for panel data is the distribution-free approach, which avoids any assumption regarding the distribution of the inefficiency term, but supposes that the error term for each life insurance company over time is zero. Hence, the average

predicted error of a firm is its estimated inefficiency. The assumption under this approach of (on average) zero random error terms for each company is a very strong one and, hence, a drawback. Moreover, shifts in time remain unidentified. Finally, the thick frontier method does not compare single life insurers with the best-practice life insurers on the frontier, but produces an inefficiency measure for the entire sample. The 25*th* percentile of the life insurer cost distribution is taken as the 'thick' frontier and the range between the 25th and 75th percentile as inefficiency. This approach avoids the influence of outliers, but at the same time assumes that all errors of the 25th percentile reflect only random error terms, not inefficiency.

All approaches have their pros and cons. All in all, the stochastic frontier approach, which has been applied widely, is selected as being— in principle— the least biased. This chapter also uses this approach. Berger and Mester (1997) found that the efficiency estimates are fairly robust to differences in methodology, which fortunately makes the choice of efficiency measurement approach less critical.

The stochastic cost frontier (SCF) function[16] elaborates on the TCF, splitting the error term into two components, one to account for random effects due to the model specification and another to account for cost X-inefficiencies:

$$ln\ c_{it} = \alpha + \sum_j \beta_j\ ln\ x_{ijt} + \sum_j \sum_k \gamma_{jk}\ ln\ x_{ijt}\ ln\ x_{ikt} + v_{it} + u_{it} \tag{8.4}$$

The subindices refer to firms i and time t. The v_{it} terms represent the random error terms of the TCF, which are assumed to be identically and independently $N(0,\sigma_v^2)$ distributed and the u_{it} terms are *non-negative* random variables that describe cost inefficiency and are assumed to be identically and independently half-normally ($|N(0,\sigma_u^2)|$) distributed and to be independent from the v_{it}. In other words, the density function of u_{it} is (twice) the positive half of the normal density function.

Cost efficiency of a life insurer relative to the cost frontier estimated by equation (8.4) is calculated as follows. X is the matrix containing the explanatory variables. Cost efficiency is defined as:[17]

$$EFF_{it} = E(c_{it} \mid u_{it} = 0, X) / E(c_{it} \mid u_{it}, X) = 1/\exp(u_{it})\ . \tag{8.5}$$

In other words, efficiency is the ratio of expected costs on the frontier (where production would be completely efficient, or $u_{it} = 0$) and expected costs, conditional

[16] The first stochastic frontier function for production was independently proposed by Aigner, Lovell and Schmidt (1977) and Meeusen and Van den Broeck (1977). Schmidt and Lovell (1979) presented its dual function as a stochastic cost frontier function.

[17] This expression relies upon the predicted value of the unobservable, u_{it}, which can be calculated from expectations of u_{it}, conditional upon the observed values of v_{it} and u_{it}, (see Battese and Coelli 1992, 1993, 1995).

upon the observed degree of inefficiency.[18] Numerator and denominator are both conditional upon X, the given level of output components and input prices. Values of EFF_{it} range from 0 to 1. We define inefficiency as $INEFF = 1 - EFF$.[19]

The SCF model encompasses the TCF in cases where the inefficiencies u_{it} can be ignored. A test on the restriction that reduces the former to the latter is available after reparameterisation of the model of equation (8.4) by replacing σ_v^2 and σ_u^2 by, respectively, $\sigma^2 = \sigma_v^2 + \sigma_u^2$ and $\lambda = \sigma_u^2/(\sigma_v^2 + \sigma_u^2)$; see Battese and Corra (1977). The λ parameter can be employed to test whether a SCF model is necessary at all. Acceptance of the null hypothesis $\lambda = 0$ would imply that $\sigma_u = 0$ and hence that the term u_{it} could be removed from the model, so that equation (8.4) narrows down to the TCF of equation (8.1).

An extensive body of literature is devoted to the measurement of X-efficiency in life insurance markets; see Bikker *et al.* (2006) for an overview. Most studies estimate efficiency on a single-country base, using different methods to measure scale economies and the X-efficiency of the life insurance industry. Furthermore, the studies employ diverging definitions for output, input factors and input factor prices. Key results of the insurance economies studies are that scale economies exist, that scope economies are small, rare or even negative and that average X-inefficiencies vary from low levels around 10% to high levels, even up to above 50%, generally with large dispersion of inefficiency for individual firms. The studies present mixed results with respect to the relationship between size and inefficiency. The stochastic cost frontier approach is generally seen as more reliable than the non-parametric methods, which appear to provide diverging levels and rankings of inefficiencies.

8.6 The Boone indicator of competition

Recently, Boone presented a novel approach to measuring competition.[20] His approach is based on the idea that competition rewards efficiency. In general, an efficient firm will realise higher market shares and hence higher profits than a less efficient one. Crucial for the Boone indicator (BI) approach is that this effect will be stronger, the more competitive the market is. This leads to the following empirical model:

$$\pi_{it}/\pi_{jt} = \alpha + \beta_t\,(mc_{it}/mc_{jt}) + \gamma\,\tau_t + \varepsilon_{it}\,, \tag{8.6}$$

where α, β_t and γ are parameters and π_{it} denotes the profit of firm i in year t. Relative profits π_{it}/π_{jt} are defined for any pair of firms and depend, among other things, on the

[18] Note that the $E(c_{it} \mid u_{it}, X)$ differs from actual costs, c_{it}, due to v_{it}.

[19] An alternative definition would be the inverse of EFF_{it}, $INEFF_{it} = \exp(u_{it})$, which is bounded between 1 and ∞.

[20] See Boone and Weigand in CPB (2000) and Boone (2001, 2004).

relative marginal costs of the respective firms, mc_{it}/mc_{jt}. The variable τ_t is a time trend and ε_{it} an error term. The parameter of interest is β_t. It is expected to have a negative sign, because relatively efficient firms make higher profits. In what follows we refer to β_t as the Boone indicator. Boone shows that when profit differences are increasingly determined by marginal-cost differences, this indicates increased competition. The BI can be used to answer two types of questions. The first type focuses on the time dimension of β_t 'how does competition evolve over time?' and the second type looks at the potential cross-section nature of equation (8.6) 'how does competition in the life insurance market compare to competition in other service sectors?' Since measurement errors are less likely to vary over time than over industries, the former interpretation is more robust than the latter. For that reason, Boone focuses on the *change* in β_t, over time within a given sector. Comparisons of β_t, across sectors are possible, but unobserved sector-specific factors may affect β_t. An advantage of the BI is that it is more directly linked to competition than measures such as scale economies and X-inefficiency, or frequently used (both theoretically and empirically) but often misleading measures such as the concentration index.[21] The Boone indicator requires data of fairly homogeneous products. Although some heterogeneity in life insurance products exists, its degree of homogeneity is high compared to similar studies using the BI (e.g. Creusen *et al*. 2006).

We are not aware of any empirical application of the Boone model to the life insurance industry. Boone and Weigand in CPB (2000) and Boone (2004) applied their model to data from different manufacturing industries. Both papers approximate a firm's marginal costs by the ratio of variable costs and revenues, as marginal costs cannot be observed directly. CPB (2000) uses the *relative* values of profits and the ratio of variable cost and revenues, whereas Boone *et al.* (2004) consider *absolute* values. To obtain a comparable scale for the dependent variable (relative profits) and the independent variable (relative marginal costs) and to keep outliers from exerting too much effect on the estimated slope, these variables are both expressed in logarithms. Consequently, all observations of companies with losses— instead of profits— have been deleted, introducing a bias in the sample towards profitable firms. Boone realized that this introduces a bias towards profitable firms, but stated that the competitive effect of firms with losses is still present in the behaviour and results of the other firms in the sample.[22]

We improve Boone's model also by replacing often-used proxies for marginal costs, such as average variable cost, by a model-based estimate of marginal cost itself. We do so using the TCF from Section 8.4. Moreover, this enables us to correct the marginal cost for the effects of scale economies. The correction is based on an auxiliary

[21] More competition can compel firms to consolidate (see our scale economies discussion). Claessens and Laeven (2004) found in a worldwide study on banking that concentration was positively instead of negatively related to competition.

[22] Suppose that the negative-profit firms are price fighters. In a market that functions well, the price fighters will influence the profitability of the other firms.

regression wherein marginal costs are explained by a quadratic function of production. The residuals of this auxiliary regression are used as adjusted marginal costs.

8.7 Description of the data

This chapter uses data of the former Pensions and Insurance Supervisory Authority of the Netherlands, which recently merged with the Nederlandsche Bank. The data were reported by Dutch life insurance companies over 1995-2003 in the context of supervision and consist of 867 firm-year observations. In our dataset, the number of active companies in the Netherlands was 84 in 2003 and 105 in 1998. In 2003, 40 insurers were independent and 46 were owned by 16 different holding companies. Most of the latter 46 subsidiary companies operated entirely or highly independently, and competed with each other. In a few cases, the subsidiary companies were more integrated and less independent of their holding companies. However, they focussed on different product types, used different distribution channels or operated in different regions, so that the question of whether they were competing with one another is less relevant. We conclude that the aggregation of insurers to the holding company level would be less appropriate.

The average size of a life insurance company in terms of total assets on its balance sheets is around € 2.5 billion (see Table 8.3). This imaginary average firm has around half a million policies in its portfolio, insures a total endowment capital of 7 billion euro and has current and future annual rents of almost 400 million euro. Profits are defined as technical results, so that profits arising from investments are included, and are taken before tax. Profits of an average firm amount to 5.5% of their premium income. An average firm uses five percent of its gross premiums for reinsurance. Roughly 63% of premiums are from individual contracts; the remainder is of a collective nature. More than half of the insurance firms have no collective contracts at all. Two-thirds of the contracts are based on periodic payments (periodic premium). Annual premiums reflect both old and new contracts. Because on average 48% of the premiums paid are of the lump-sum type (whereas, on average, 15% of the periodic premiums refer also to new policies), most of the annual premiums stem from new business.

Table 8.3 Description of the data on Dutch insurance firms (1995–2003)

	Median	Mean		Standard deviation
		Weighted [a]	Unweighted	
Total assets (in million €)	521.5	.	2,472.5	6,991.6
Annual premiums (in million €)	66.0	.	247.7	588.8
Annual costs, total (in million €)	18.2	.	32.8	63.2
Annual profits (in million €)	2.6	.	15.7	47.6
Total endowment capital (in million €)	2,229	.	7,376	13,483
Amount of annuity rent [b] (in million €)	9	.	387	1,397
Total unit-linked capital (in million €)	67	.	246	589
Number of policies (in 1000 €)	168.7	.	522.4	973.6
Profit/premium	0.047	0.078	0.055	0.25
Reinsurance premiums/premium	0.013	0.034	0.050	0.11
Individual contracts/premium	1.00	0.63	0.90	0.21
Periodic payments/premium	0.72	0.52	0.67	0.27
Unit-linked funds/premium	0.25	0.44	0.33	0.32
Endowment premium/premium	0.93	0.57	0.82	0.26
Acquisition costs/premium	0.09	0.06	0.16	0.29
Management costs/premium	0.18	0.13	0.23	0.22
Number of observations per year				
1995	94			
1996 [c]	103			
1997	104			
1998	105			
1999	101			
2000	94			
2001	93			
2002	89			
2003	84			
Total	867			

[a] Weighted with the size of insurance firms, in terms of the respective denominator; thus, weighted average of 'profit/premiums' is total profits divided by total premiums;
[b] Annual payment;
[c] Ten new entrants to the market in 1996 and one termination.

Note that cost and profit figures are also based on a mixture of new and old business. Balance sheet and profit and loss data for new policies only is not available. So-called unit-linked fund policies, where policyholders bear the investment risk on their own deposits (that is, premiums minus costs), have become more popular: 44% of premiums are related to this kind of policies. Endowment insurance is the major product category, as 57% of all premiums are collected for this type of insurance.[23] This type of insurance

[23] For an explanation of the terms *endowment* and *unit-linked*, see Section 8.2.

policy is often combined with a mortgage loan. The total costs are around 13% of the total premium income, half of which consists of acquisition (or sales) costs, such as costs for the marketing of products and payments to intermediaries. Management costs consist mainly of salary payments. The medians and the differences between weighted and unweighted averages reflect skewness in the (size) distributions. There are many small firms and a few large firms. The latter tend to have higher profit margins and relatively lower acquisition costs, lower management costs, fewer individual contracts, fewer periodic payments, more unit-linked fund policies and fewer endowment policies.

8.8 Empirical results

8.8.1 Scale economies

This section estimates scale economies using the translog cost function (TCF). In a later section of this chapter, the TCF is used also to calculate marginal costs (see sections 8.4 and 8.8.4). For these two purposes, the TCF explains the insurance company's cost by (only) one measure of production: namely, premiums. As both scale effects and marginal costs are obtained from the first derivatives of the TCF to production, we disregard other production measures here to enable us to derive the optimal size. Generally, inclusion of more measures of components of production or proxies is common practice in the case of multi-product firms, and has indeed been applied in the X-efficiency models in section 8.8.2.

In the literature, measuring output in the life insurance industry is greatly debated. Whereas in many other industries, output is equal to the value added, we cannot calculate this figure for insurers, due to conceptual problems.[24] Most studies on the life insurance industry use premium income as the output measure. Hirschhorn and Geehan (1977) view the production of contracts as the main activity of a life insurance company. Premiums collected directly concern the technical activity of an insurance company. The ability of an insurance company to market products, to select clients and to accept risks is reflected by premiums. However, premiums do not reflect financial activities properly— as e.g. asset management, represented by the returns on investment, is ignored.[25] Despite its shortcomings, premium income is used in this section as the relevant output measure.

As our model reads in logarithms, we cannot use observations where one or more of the variables have a zero or negative value. Insurance firms may employ various sales channels: own sales organizations, tiered and multiple insurance agencies, and other

[24] Some insurance firms can approximate their value added by comparing their embedded value over time. These data are not publicly available.

[25] The definition of production of life insurance firms is discussed further in Section 8.8.2.

channels, such as banks, post offices, etc. We have to drop observations of firms that do not use insurance agencies and report zero acquisition costs[26]. In this sense, we clearly are left with a subsample of firms.

Table 8.4 presents the TCF estimates. We assume that costs are explained by production (in terms of total premiums), reinsurance and acquisition costs partitioned by premiums (proxies of input prices for reinsurance and acquisition fees[27]), so that these variables also emerge as squares and in cross-terms. These are the prices of the main inputs, except of personnel costs. These costs, expressed by the ratio of management costs to premium, are not used as an input price, because the insurance companies are subject to a collective labour agreement (in Dutch: Collectieve Arbeidsovereenkomst (CAO)), so that differences in personnel costs reflect differences mainly in the age structure of employees and in management inefficiencies, and not so much in input prices. To test this basic model for robustness, we also add four control variables in an extended version of the model. Periodic premium policies go with additional administration costs, whereas unit-linked fund policies save costs. The bottom lines of Table 8.4 show that life insurance companies, on average, have scale economies of 14%. Correcting for differences in the product mix or the share of unit-linked funds and so on does not qualitatively change the results. We also calculated average scale economies for various size classes, with size measured as the companies' premium income. Scale economies appear to be larger for the smaller size classes. According to the extended model, small firms— in the lowest 25-percentile class— may realize average scale economies of 34%, whereas large firms— in the highest 25-percentile class— enjoy just 8% economies of scale.

Decreasing scale economies with firm size were found by Fecher *et al.* (1993) for the French life insurance industry. Comparison between the basic model and the extended model shows that the average scale economies per size class depend (only) slightly on the model specification. Although the average economies of scale for both models are rather similar, the dependency of the scale economies on size classes in the basic model is less than that in the extended model.

The optimal production volume in terms of gross premium is defined as the volume at which point an additional increase would no longer diminish marginal costs, so that the derivative of marginal costs is zero. According to the basic model, the optimal size can be calculated as far above the size of all actual life insurance firms.[28] This implies that (almost) all firms are in the (upper) left-hand part of the well-known U-shaped average cost curve. The scale economies suggest that consolidation in the Dutch

[26] Costs for these firms were not zero.

[27] The price of management (or wages) was excluded by applying the two standard properties of cost functions: linear homogeneity in the input prices and cost-exhaustion (Jorgenson 1986).

[28] Of course, the accuracy of this optimal size is limited, as its calculated location lies far outside of our sample range.

insurance markets is still far from its optimal level. Of course, diseconomies of conglomeration and mistakes in post-merger integration can outweigh scale economies.

The TCF estimates clearly show that average scale economies of around 15 to 20% are an important feature of the Dutch life insurance industry. While these scale economies are generally higher than those found for Dutch banks (*e.g.* Bos and Kolari 2005), they are not uncommon in other sectors. Similar figures were found in other countries. Fecher *et al.* (1991) found 15% for France, and Grace and Timme (1992) observed 4% to 27% for the US, depending on type and size of firm. The existence of substantial scale economies might indicate a moderate degree of competition, as firms have so far not been forced to employ all possible scale economies.

Table 8.4 Estimation results of the TCF[a]

Dependent variable: total costs	**Basic model**		**Extended model**	
Explanatory variables:	**Coefficient**	**t-value** [b]	**Coefficient**	**t-value** [b]
Premium income (production)	0.50	**7.9	0.39	**4.1
Reinsurance ratio	0.05	0.6	-0.12	1.2
Acquisition costs/ premium	0.17	1.7	0.25	1.7
Premium income^2	0.02	**4.9	0.03	**5.5
Reinsurance ratio^2	-0.01	*-2.0	-0.003	0.7
(Acquisition costs/premium)^2	0.17	-1.7	0.04	**3.30
Premium income * reinsurance ratio	-0.02	*-2.6	0.01	**0.6
Premium income * (acquisition	0.03	**2.9	0.04	**2.9
Reinsurance ratio * (acquisition	-0.001	-0.2	0.02	1.4
Individual premiums ratio			-0.11	-0.7
Periodic premium ratio			0.18	**6.7
Unit-linked fund ratio			-0.04	**-3.8
Endowment insurance ratio			0.06	1.1
Intercept	2.21	**6.4	2.88	**5.7
Adjusted R^2	0.93		0.93	
Number of observations	607		456	
Economies of scale	0.86		0.82	
Idem, small firms (25%)	0.75		0.66	
Idem, small- to medium-sized firms (50%)	0.81		0.74	
Idem, medium-sized to larger firms (75%)	0.84		0.78	
Idem, large firms (100%)	0.93		0.92	

[a] All terms are expressed in logarithms.
[b] One and two asterisks indicate a level of confidence of 95% and 99%, respectively.

8.8.2 Cost X-inefficiency

This section applies the stochastic cost frontier model (8.4) to data of Dutch insurance firms. Costs are defined as total operating expenses, which consist of two components: acquisition cost and other costs. The latter includes management costs, salaries, depreciation on capital equipment, and so on. A further split of 'other cost' in its constituent components would be highly welcome, but is regrettably unavailable. As the input price for personnel is heavily regulated in the collective labour agreement (in Dutch: CAO) and does not differ between insurance companies, we will not use this variable as an input price; rather, it will be seen as a control variable for the other costs, such as capital equipment. The price of the input factor, acquisition costs, was estimated as the costs per unit of premium. Such a proxy is fairly common in the efficiency model literature, in the absence of a better alternative.

As stated above, the definition of *production* of life insurance firms is a complicated issue. Insurance firms produce a bundle of services for their policyholders. Particularly with regard to life insurance, services may be provided over a long period. Given the available data, we selected the following five proxies of services to policyholders, constituting together the multiple products of insurance firms: (1) annual premium income. This variable serves as a proxy for production that is related to new and current policies. A drawback of this variable might be that premiums are made up of the pure cost price plus a profit margin. But it is the only available measure of new policies; (2) the total number of outstanding policies. This variable approximates the services provided under all existing policies (hence, the stock instead of the flow). In particular, it reflects services supplied in respect of all policies, irrespective of their size; (3) the sum total of insured capital; (4) the sum total of insured annuities. Endowment insurance and annuity policies are different products. The two variables reflect the different services that are provided to the respective groups of policyholders; and (5) unit-linked fund policies. There are two types of policies regarding the risk on the investments concerned. These risks may be borne by the insurance firms or by the policyholders. The latter type of policies is also known as 'unit-linked'. As the insurance firm provides different services with respect to these two types of policy, we include the variable 'unit-linked fund policies'. Note that these five production factors do not describe the production of separate services, but aspects of the production. For example, a unit-linked policy may be of either an endowment insurance type or an annuity type, so that two variables describe four different types of services.

The five production measures and the input price and control variable also appear as squares and cross-terms in the translog cost function, making for a total of 35 explanatory variables. Such models have been proven to provide a close approximation to the complex multiproduct output of financial institutions, resulting in an adequate

explanation of cost, conditional on production volume and input factor prices. In our sample, this model explains 94.0% of the variation in the (logarithm of) cost.[29]

The set of suitable (non-zero) data consists of 105 licensed life insurance firms in the Netherlands over the 1995-2003 period, providing a total of 689 firm-year observations. This unbalanced panel dataset includes new entries, taken-over firms and merged companies.

Table A.1 in Appendix I provides the full set of estimation results. Due to the non-linear nature of the TCF, it is difficult to interpret the coefficients of the individual explanatory variables. As indicated by γ, 91% of the variation in the stochastic terms (σ^2) of the cost model can be attributed to the inefficiency term. A test on the hypothesis that inefficiency can be ignored ($\gamma = 0$) is rejected strongly. The essential results are the cost-efficiency values calculated according to equation (8.5). Table 8.5 provides average values of cost X-efficiency per year and for the total sample .

Table 8.5 Average cost X-efficiency in 1995-2003

Year	Cost X-efficiency
1995	0.716
1996	0.727
1997	0.741
1998	0.724
1999	0.725
2000	0.710
2001	0.729
2002	0.728
2003	0.718
Total	0.724

The average cost X-*efficiency* is 72%, which implies that the *inefficiency* is, on average, 28%. Costs are thus, on average, 28% higher than for the best-practice firms, conditional on production composition, production scale and input prices. The average cost X-efficiencies fluctuate irregularly over time, without a clear time trend. Inefficiencies are assumed to reflect managerial shortcomings in making optimal decisions in the composition of output factors and the use of input factors.

A possible reduction of cost by at least one-fourth does not seem plausible in a competitive market. However, it should be remembered that these inefficiency figures set an upper bound to the measured inefficiencies, as they may partly be the result of imperfect measurements of production and input factor prices. Particularly in services, such as in the financial sector, production is difficult to measure, while our dataset also

[29] This figure is based on the OLS estimates, which provide the starting values of the numerical optimisation procedure. As OLS minimizes the error terms and maximises the degree of fit, the latter will be lower in the SCF model.

suffers from none-too-exact information on input prices. Instead of drawing very strong conclusions regarding competition, it is better to compare these results with benchmarks.

Any comparison should be handled with caution, as estimation results are generally based on varying estimation techniques, different insurance production models and diverging empirical specifications. In the literature, the insurance inefficiency figures in other countries range from 10% to 65%. This implies that our inefficiencies are quite common and even relatively low. They are similar to the inefficiencies that have generally been found in the banking literature, which are spread – widely – around 20% of the costs (Berger and Humphrey 1997; Altunbas *et al.* 2000). Bikker (2004, p. 218) reports an average X-inefficiency for Dutch banks in 1997 of 26%, remarkably similar to the figure for insurance firms.

Table 8.6 Average cost X-efficiency over size classes

Size class	Cost efficiency	Average size (× € 1000)
1	0.747	13,261
2	0.763	94,904
3	0.731	277,937
4	0.693	548,474
5	0.696	936,795
6	0.701	2,107,749
7	0.724	14,479,608
Total average		2,447,891
Median		519,970

Table 8.6 shows average cost X-efficiency for seven size classes. Here we observe a significant U-curve for cost efficiency: higher efficiency for small insurance firms, lower efficiency for medium-sized companies and, again, increasing efficiency for larger firms. A possible explanation could be that smaller firms generally profit from their orderly structure and neatly arranged composition of products, so that differences in managerial inability across smaller firms are limited (as has also been found for banks; see Bikker 2004, p. 209). The largest firms operate more on competitive submarkets such as pensions, and on the more competitive international markets, which have forced them to become more efficient.

8.8.3 Profitability

A straightforward measure of competition is the profit margin. Supernormal profits could indicate insufficient competition. A traditional measure of profitability is the

price-cost margin.[30] We cannot calculate the price-cost margin for life insurance companies, as we do not know the output prices and market shares of all insurance products per firm. However, we are able to calculate the average profit margin, defined as the ratio of profits before taxes and gross premium written. Using figures on consolidated life insurance firms from the ISIS dataset, we compare the Netherlands with some major European economies (see Table 8.7).[31] We are aware that profits could be influenced by differences in accounting rules, products, distribution channels, maturity or other characteristics of the markets.[32] However, we draw some conclusions from the remarkable profit margins in the Netherlands (around 9%) compared to those in other EU countries such as France, Germany, Italy and the UK, with respective profit margins of around 7%, 2%, 5% and 4%. The higher profits in the Netherlands suggest less competition than in the other countries.[33] The Dutch profit margins may be exaggerated, because the ISIS dataset does include fewer small life insurance companies— but this phenomenon also holds for the other countries.

Table 8.7 Average profit margins of life insurance firms in various countries in %[a]

			ISIS [b]			DNB
	Germany	**France**	**UK**	**Italy**	**the Netherlands**	**the Netherlands**
1995	2.2	-	5.0	-	-	8.1
1996	2.3	12.9	4.2	-	10.2	8.1
1997	2.6	6.3	4.9	7.2	8.1	7.3
1998	2.9	5.6	5.1	5.3	10.0	6.6
1999	3.0	5.8	3.9	4.2	12.6	7.1
2000	2.0	6.9	3.1	6.1	12.0	7.3
2001	1.3	6.2	2.4	4.7	10.9	6.8
2002	1.6	2.1	1.0	2.8	2.2	3.2
2003	-	-	-	-	-	8.9

[a] Weighted averages.
[b] Sources: Own calculations based on ISIS (first columns) and DNB (last column).

We also have data published by De Nederlandsche Bank (DNB, the Dutch supervisory authority on insurance companies), which includes all licensed firms and refers to domestic activities only. These figures also point to high Dutch profit margins of around 7%.

[30] This measure can be defined as $PCM = \sum_{i=1}^{n} s_i (p_i - mc_i)/p_i$, where p_i denotes the firm's equilibrium output price and mc_i its marginal cost.

[31] ISIS data concern both domestic and foreign activities. Pure domestic figures would be more precise but are not available.

[32] For instance, firms in the Netherlands use more agents as selling channels than those in other countries (CEDA, 2004, p. 144).

[33] A similar picture emerges from figures of CEDA (2004), p. 198.

Of course, these figures largely reflect profit margins on past production, as profit stems from the existing portfolio of policies and not only from new business.[34] Sources at hand of specialized on-site supervisors indicate that profit margins of domestic production have declined strongly in recent years. Whereas Table 8.7 concludes that in the past competition in the Dutch market has been weak, this may have changed in recent years.

8.8.4 The Boone indicator

Table 8.8 presents estimates of the Boone indicator (BI), based on an extended version of equation (8.6) with profits and marginal costs in logarithms. Marginal costs are measured in three ways: average variable cost (defined as management costs as a share of the total premium, as in the traditional Boone model; see e.g. Boone 2004; Creusen *et al.* 2004), marginal cost (derived from the TCF of Section 8.8.1), and adjusted marginal costs (*i.e.* marginal costs adjusted for scale economies; see Appendix II).[35] Average variable costs have the advantage of being less complex than marginal cost estimates, since they are not model based— but they are less accurate because we cannot distinguish between variable and fixed costs. In practice, average variable costs are commonly proxied by average costs. Adjusted marginal costs allow one to distinguish between the effects of two components of marginal cost, namely scale economies and X-efficiency.

Following Boone (2004) and Creusen *et al.* (2004), we also introduce so-called fixed effects: that is, a dummy variable for each insurance firm (coefficients of these dummies are not reported here).[36] The advantage is that these fixed effects pick up all company-specific characteristics, including scale, that are not captured by the other variables, so that some of the disturbances are eliminated. Around 10% of the variance in the error term of the model without fixed effects (unexplained variance: σ_u^2) can be explained by these fixed effects (explained variance: σ_e^2) when they are introduced, where ρ is equal to $\sigma_u^2/(\sigma_u^2 + \sigma_e^2)$. R^2 reflects the overall explanatory power of the model. With respect to the control variables, we find a systematic, significantly positive contribution of individual policyholders to profits. The other control variables,

[34] This lagging adjustment of profitability does not disturb the international comparison, as this limitation holds also for the foreign data.

[35] Note that the variable cost may change over the size classes due to scale efficiency (just as the marginal cost may do), so that the *average* variable cost may differ from the marginal cost. Apart from this theoretical dissimilarity, these variables are also measured differently in practice.

[36] We have also estimated random-effect models for profits (Table 8.8) and markets shares (Table 8.9). Their coefficients were quite similar to those of the fixed-effect models, with even slightly higher values and higher levels of significance. This suggests that the estimates presented in Tables 8.8 and 8.9 are quite robust. We tested for random effect using the Hausman test, but this test appeared to be undefined, suffering from the 'small sample problem'. All models include year dummies, also not reported in the tables.

policyholders with periodic payments, unit-linked fund policies and endowment insurances, do not affect profits.

Table 8.8 Fixed-effect estimates of the Boone model for profits[a]

	Average variable costs		Marginal cost		Adjusted marginal costs	
	Coefficient(β)	t-value[c]	Coefficient(β)	t-value[c]	Coefficient(β)	t-value[c]
Boone indicator 1995	-0.52	**-2.7	-0.51	*-2.4	-0.32	-1.4
Idem, 1996	-0.42	*-2.2	-0.37	*-1.7	-0.20	-0.9
Idem, 1997	-0.43	*-2.0	-0.30	-1.3	-0.05	-0.2
Idem, 1998	-0.69	**-3.2	-0.68	**-2.9	-0.23	-0.9
Idem, 1999	-0.34	*-1.7	-0.33	-1.4	-0.08	-0.3
Idem, 2000	-0.43	*-2.1	-0.36	-1.5	-0.10	-0.4
Idem, 2001	-0.55	**-2.7	-0.40	*-1.7	-0.15	-0.6
Idem, 2002	-0.17	-0.9	0.15	0.5	0.39	1.3
Idem, 2003	-0.37	*-1.7	-0.16	-0.6	0.34	1.2
Individual premiums ratio	1.71	**3.0	1.46	**2.4	1.43	*2.4
Periodic payments ratio	0.34	0.9	0.25	0.6	0.15	0.4
Unit-linked funds ratio	0.22	0.6	0.34	0.8	0.34	0.8
Endowment insurance ratio	-0.27	-0.4	-0.26	-0.3	-0.52	-0.7
Intercept	6.76	**8.1	7.54	**7.6	8.14	**11.5
σ_u	2.01		1.97		1.98	
σ_e	0.66		0.68		0.68	
ρ	0.90		0.90		0.89	
Overall R^2	0.01		0.01		0.00	
Within/between R^2	0.26	0.04	0.28	0.05	0.26	0.08
Number of observations	500	(89)	444	(85)	444	(85)

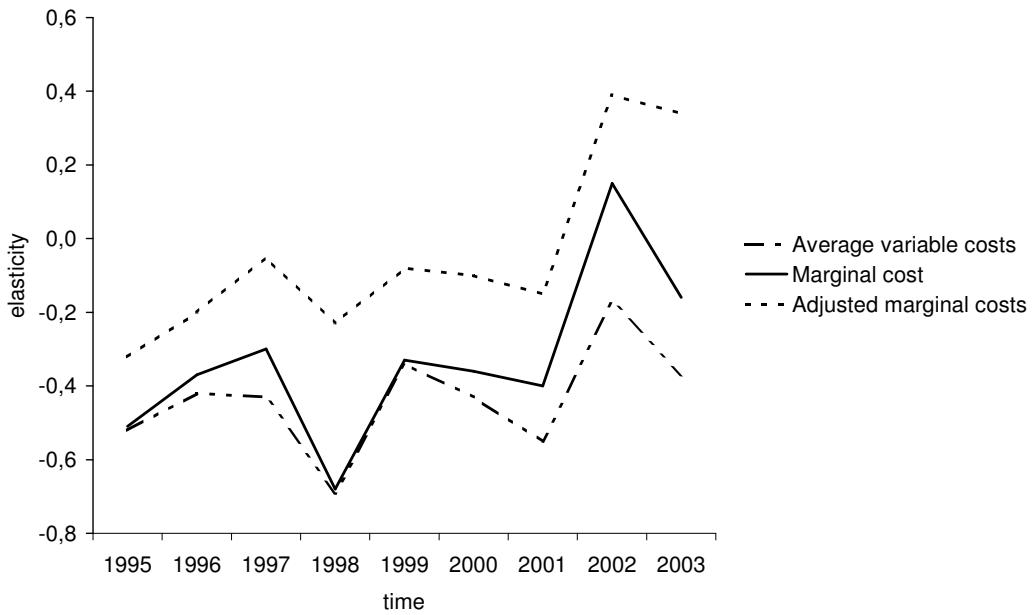
[a] Profits and marginal costs are in logarithms.
[b] Adjusted for scale economies.
[c] One and two asterisks indicate a level of confidence of 95% and 99%, respectively. Within R^2 reflects the explanatory power of the model through time, between R^2 shows the explanatory power between firms.

As indicators of competition, the annual estimates of beta are, of course, pivotal in the analysis. The first two columns of Table 8.8 present estimates of beta that are based on average variable costs, which range from -0.2 to -0.7 and are significant in all years but one. The model-based marginal cost estimates are slightly less negative and only significant in four out of nine years. Although the level of the indicator is difficult to interpret, its low degree of significance suggests moderate competition. When marginal costs are adjusted for scale economies, none of the betas are significant. This indicates that scale economies are an important component of the observed Boone indicator. Figure 8.1 shows that the coefficient β fluctuates somewhat over time in all three model versions. We observe an upward trend, indicating a (slight) decline in competition over the respective years. Average variable costs and model-based marginal costs result in similar estimates. The third measure of marginal cost renders a comparable pattern over

time, but — due to the eliminated scale economies — at a higher level. This correction for scale economies yields in the end the best method of investigating the relationship between performance and efficiency.

In order to assess whether our estimates for the BI are high or low, we compare them with estimates for other Dutch industries. Creusen *et al.* (2006) estimated the traditional Boone model for the manufacturing and service industries and found elasticities between average variable costs and profits of around, respectively, -5.7 and -2.5, for the years 1993-2001. The BI of the life insurance industry is around -0.45. As noted in section 8.6, BI comparisons across sectors are problematic due to measurement error — for example, due to differences in accounting practises of profits and losses. However, the absolute value of the BI of insurance companies appears to be much closer to zero than in other service industries. Moreover, estimations using exactly the same definition for profit as in Creusen *et al.* (2006) render the same conclusion.[37] All in all, this suggests that the life insurance industry is less competitive than the manufacturing and service industries.

Figure 8.1 Boone indicator (profit-based)



Due to the logarithmic specification of the Boone model, all loss-making firms, including new entrants, have been ignored. This creates a potential bias because 20% of our observations concerned loss-making companies. Estimation of the BI in a model

[37] The value of the BI in these estimations is around -0.85. Results can be obtained from the authors.

with ratios instead of logarithms using the full sample results in a significantly more negative relationship between efficiency and profits. However, solving this bias would at most add -0.5 to the Boone indicator. The conclusion remains that the BI is substantially smaller in the life insurance industry than in other service industries. Furthermore, the BI is subject to the same deficiencies as the profit margin in Section 8.8.4, as it is based on profitability of past business instead of only new production. The next section solves these issues by analysing another performance indicator: market shares. Market shares are based on annual premiums, and a significant part (55% of these premiums) is due to new policies. Market shares therefore reflect largely the current business. Furthermore, using market shares, we can utilize information of the full sample — loss-making firms included.

8.8.5 Sensitivity analysis: the Boone indicator based on markets shares

Although the indicator as originally formulated by Boone is based on relative profits, the idea behind it — namely, that competition rewards efficiency — implies that we could also use the intermediate variable, *relative market share*, as our outcome variable. As a check on the findings in the previous section, this section therefore presents estimation results based on market shares. Results are shown in Table 8.6. We find that average variable costs appear to have a significantly negative effect on market shares; see the first two columns. An increase of this marginal cost measure by one percent results in a market share loss of around 0.45%. Note that this value is similar to the Boone indicator based on profits in Section 8.8.5.

If we consider changes in β_t over time, we observe larger negative values in the years just before the major fiscal policy changeover of 2001 with respect to annuities, as described in Section 8.2 (see also Figure 8.2). This indicates that competition has intensified somewhat in these years, probably with respect to annuities, which is in line with the observed increase in advertising and sales. In the subsequent years, we see that the effect of marginal costs on market shares decreases, pointing to weakening competition.

Considering the other estimation results in Table 8.9, the unit-linked funds appear to have been a major innovation in gaining market shares.[38] Collective contracts were also favourable for gaining larger market shares. The year dummies are (almost) insignificant and, therefore, were not shown in the table. When the four control variables are dropped (as a second test on robustness), we find similar results for β_t (not reported here). The most important conclusion is that the central results — significant negative values for the β_ts and a (negative) peak in the β_t just before the fiscal reform of 2001 — appear to be robust for specification choices.

[38] The elasticity of this variable is the coefficient (0.45) times the average of the unit-linked fund ratio (0.33; see Table 7.1), so 0.15.

Table 8.9 Fixed-effect estimates of the model for market shares[a]

Year	Average variable costs Coefficient(β_t)	t-value[c]	Marginal costs Coefficient(β_t)	t-value[c]	Adjusted marginal costs[b] Coefficient(β_t)	t-value[c]
1995	-0.36	**-5.4	-0.35	**-4.9	-0.18	*-2.2
1996	-0.45	**-7.3	-0.42	**-6.5	-0.25	**-3.5
1997	-0.50	**-7.8	-0.46	**-6.6	-0.24	**-3.0
1998	-0.47	**-6.8	-0.42	**-5.5	-0.18	*-2.1
1999	-0.57	**-7.9	-0.53	**-6.4	-0.11	-1.1
2000	-0.59	**-8.3	-0.57	**-7.0	-0.38	**-4.2
2001	-0.48	**-6.6	-0.40	**-4.7	-0.22	*-2.3
2002	-0.34	**-5.2	-0.32	*-3.6	-0.10	-0.9
2003	-0.33	**-4.4	-0.26	**-2.9	0.02	0.2
Individual premiums ratio	0.62	**2.9	0.74	**3.4	0.66	**2.9
Periodic payments ratio	-0.71	**-5.3	-0.70	**-5.1	-0.82	**-5.7
Unit-linked funds ratio	0.45	**3.3	0.56	**4.0	0.59	**4.0
Endowment insurance ratio	0.63	**2.9	0.39	1.6	0.25	1.0
Intercept	-7.13	**-25.7	-6.74	**-21.3	-6.03	**-24.5
σ_u	2.11		1.86		1.95	
σ_e	0.30		0.29		0.31	
ρ	0.98		0.98		0.98	
Overall R^2	0.19		0.10		0.02	
Within/between R^2	0.30	0.17	0.28	0.10	0.19	0.01
Number of observations (groups)	651	(101)	581	(96)	581	(96)

[a] Market shares and marginal costs in logarithms
[b] Adjusted for scale economies
[c] One and two asterisks indicate a level of confidence of 95% and 99%, respectively.

The two middle columns of Table 8.9 repeat the results for marginal cost instead of average variable cost. The values of β_t are similar in level and development over time and are only slightly less significant.[39] Apparently, average (variable) costs do well as a proxy for marginal costs. The control variables have effects that are in line with earlier results.

Although the results presented above uniformly indicate that efficiency gains lead to larger market shares, this could also fully or partly be due to scale economies, as observed in Section 8.1. Large firms enjoy these scale economies, which reduce

[39] In the basic model, the β_t values for mc are lower than for average variable costs (namely around -1) and for one year are even not significant; see Table A.2 in the appendix.

marginal costs and serve to increase market share. To avoid possible distortion due to this kind of endogeneity, we correct the marginal costs (*mc*) for scale economies as set out in Appendix II. This correction for scale economies yields the purest method of investigating the present relationship. The right-hand columns of Table 8.9 present the estimates for the market-share model based on marginal cost adjusted for scale economies. As in the earlier versions of the model, we find that higher marginal costs tend to diminish a firm's market share and *vice versa*. However, the value of β_t and its level of significance are much lower now (namely around -0.2), apparently due to the fact that the positive contribution of scale economies has been eliminated (see also Figure 8.2). Note that this coefficient may also be affected by measurement errors. Nevertheless, if we estimate one single β_t for the whole period, this coefficient is significant (value: -0.21, t-value: 4.0). The control variable coefficients are similar to earlier results. The conclusion is that even after correcting for scale economies, efficiency gains still tend to increase market shares, although their contribution is smaller.

Figure 8.2 Boone indicator (market-share based)

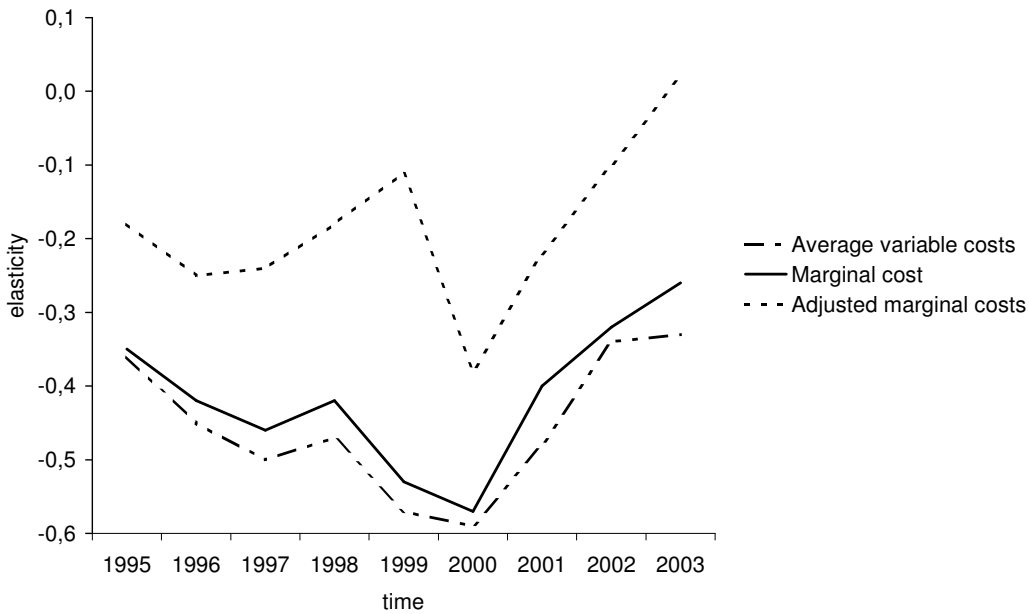


Figure 8.2 shows that the annual estimates of beta in each of the three versions of the model indicate no upward or downward trend. More negative values of β_t are found in the years just before the major fiscal policy changeover of 2001 with respect to annuities, as described in Section 8.2. This indicates that competition intensified somewhat in these years with respect to annuities, which concern around 30% of the market. In the subsequent years, we see that the effect of marginal costs on market

shares decreased, pointing to weaker competition. In these years, profit margins on annuities recovered (according to sector experts). Apparently, the level of competition did not change much over time.

8.9 Conclusions

This chapter analyses competition and efficiency in the Dutch life insurance market. As competition cannot be observed directly, we use five indicators to estimate competition in an indirect manner.

The *first* indicator is of a qualitative nature. We investigate the structure of the insurance market using what is called the tight oligopoly analysis, yielding diverging results. For the supply-side factors we find that supplier power is limited, due to the large number of insurance firms, and that ample entry possibilities exist, which in principle enable sound competition. However, on the demand side we observe that consumer power is limited, particularly due to the opaque nature of many life insurance products, and that few substitution possibilities exist for life insurance policies, which may hinder competition. In short, the resulting overall picture from these considerations is mixed.

The *second* indicator is the scale efficiency level. A TCF was applied to measure scale economies in the Dutch life insurance industry. Estimates indicate that scale economies exist and amount to 18% on average, ranging from 8% for large firms to 34% for small firms. Such scale economies are substantial compared to what was found in other countries and to what is usually found for other financial institutions (such as banks). All existing insurance companies are far below the estimated (theoretical) optimal size, so that further consolidation in the Dutch life insurance market might be beneficial. Apparently, competitive pressure in the insurance market has thus far been insufficient to force insurance firms to exploit these existing scale economies. Of course, consolidation could interfere with entry of new competitors.

The *third* indicator is the X-efficiency level. We find cost X-inefficiency estimates of around 25%, on average, a magnitude that would not be expected in a market with increased competition. Incidentally, such inefficiencies are not uncommon for life insurance in other countries or other financial institutions.

The *fourth* indicator is the profit margin. We observe that profit margins of the Dutch life insurance firms have been high compared to those of their peers in other European countries. Although this might indicate relatively low competitive pressure in the Netherlands, this result mainly reflects the competitive state of affairs in the past rather than the situation of recent years.

The *fifth* indicator is the Boone indicator. Estimates of this indicator point to weak competition in the Dutch life insurance industry in comparison to indicator values in other service industries. All of our empirical analyses are based on balance sheet and profit and loss data from both new and old business. Although the majority of annual

premiums stems from new policies, the portfolio of policies is built up over the years. Hence, eventual improvement of competition shows up in these figures only with some delay, depending on the approach. However, annual estimates of the Boone indicator for the most recent years find a weakening rather than a strengthening of competition.

The evidence in this chapter indicates that there is a lack of competition in the life insurance markets, as is shown in Table 8.7, where all five indicators point in this direction. However, this does not exclude the possibility that some corners of the life insurance market are still competitive. Our analysis is on an aggregate level and disregards potentially relevant details with respect to *e.g.* product markets, distributional channels and fiscal treatment, due to lack of data.

It seems obvious that reduction of X-inefficiency would be advantageous for all parties involved. Developments in information technology make further improvements in efficiency possible. Our empirical research suggests that consolidation might carry substantial cost savings. A comparison with other countries reveals that foreign markets are much more consolidated, so that scaling-up in the Dutch market is apparently lagging. From that perspective, and given the observed potential savings, further consolidation would be sensible.

Table 8.10 Conclusion for competitiveness of the life insurance market

Indicators of competition	Indication of more (+) or less (-) competition
1. Structure of the market	Supply (+) , but Demand (-)
2. Unexploited scale economies	(-)
3. X-efficiency	(-)
4. Profit Margin	(-)
5. Boone indicator	(-)

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Appendix I Estimation results

Table A.1 Estimation results of the cost X-efficiency models for insurance firms

Variables	Coefficients	t-values [a]
Intercept	4.020	**5.1
Premiums (1)	0.149	0.9
Unit-linked funds (2)	0.317	**4.5
Numbers of policies (3)	-0.178	-1.3
Endowment insurance (4)	0.305	**3.4
Amount of annual annuities (5)	0.267	**4.0
Price of acquisition (6)	0.181	1.5
Price of management cost (7)	1.630	**8.0
Squares (1)	-0.054	**-2.6
Squares (2)	0.000	0.0
Squares (3)	-0.005	-0.4
Squares (4)	0.013	**2.5
Squares (5)	0.004	1.5
Squares (6)	0.038	**5.3
Squares (7)	-0.058	**-4.0
Cross-terms (1, 2)	0.039	**4.4
Cross-terms (1, 3)	0.084	**3.4
Cross-terms (1, 4)	-0.018	-1.3
Cross-terms (1, 5)	0.014	1.0
Cross-terms (1, 6)	0.025	1.2
Cross-terms (1, 7)	-0.103	**-3.4
Cross-terms (2, 3)	-0.028	**-3.9
Cross-terms (2, 4)	-0.006	*-2.3
Cross-terms (2, 5)	-0.008	**-3.0
Cross-terms (2, 6)	0.020	**3.7
Cross-terms (2, 7)	0.032	**3.9
Cross-terms (3, 4)	-0.035	-1.6
Cross-terms (3, 5)	-0.021	**-2.6
Cross-terms (3, 6)	-0.019	-1.2
Cross-terms (3, 7)	-0.105	**-4.6
Cross-terms (4, 5)	0.009	1.1
Cross-terms (4, 6)	0.020	**2.5
Cross-terms (4, 7)	-0.022	-1.1
Cross-terms (5, 6)	-0.009	-1.5
Cross-terms (5, 7)	0.052	**6.1
Cross-terms (6, 7)	0.004	0.3
σ^2	0.952	8.0
γ	0.914	52.6
μ	-1.865	-7.1

[a] One and two asterisks indicate a level of confidence of 95% and 99%, respectively.

Appendix II Marginal costs adjusted for scale economies

Section 8.8.1 has confirmed the existence of substantial scale economies in the Dutch life insurance industry. To avoid possible distortion due to endogeneity, we correct the marginal costs (*mc*) for scale economies, based on a simple regression of *mc* on production, where *mc* occurs both in linear terms and squared, either as logarithms or in their natural form (the former for the market-share model, the latter for the profit-margin model). Table A.2 shows that a one percent increase in production reduces marginal costs by, on average, 0.15% according to the log-based model and 0.17% in the second model.[40] These figures are in line with the scale economies of Section 8.8.1. The residuals of these auxiliary equations are interpreted as marginal costs corrected for scale economies.

Table A.2 Auxiliary regressions for marginal cost and scale economies corrections

	Model in logarithms	
	Coefficient	**t-value** [a]
Production	-0.39	**-4.6
Production^2	0.01	**2.9
Intercept	0.96	*2.2
Adjusted R^2	0.18	
Number of observations	607	

[a] One and two asterisks indicate a level of confidence of 95% and 99%, respectively.

[40] The elasticity, the first derivative of the auxiliary equation in logs, is -0.39+0.01*2*average production in logarithms. For the auxiliary model in natural values it is equal to ∂ *mc*/∂ *prod*uction * (average *production* / average *mc*) = (-0.134e-7 + (0.249e-14* 247707.4*2) * 247707 / 0.18.

Samenvatting (Summary in Dutch)

Achtergrond en motivatie

Dit proefschrift bevat een aantal empirische studies over het meten van concurrentie in financiële markten. De belangrijkste motivatie om dit proefschrift te richten op de financiële sector is het grote belang dat deze sector heeft in de economie. Zij levert het werkkapitaal aan bedrijven om diensten en goederen te produceren. In het eurogebied zijn vooral banken de belangrijkste aanbieders van kapitaal aan bedrijven. Zij zijn belangrijker dan obligatiemarkten of aandelenbeurzen. Voor consumenten zijn vooral hypotheekmarkten van belang. Het huizenbezit is voor de gemiddelde consument hun belangrijkste bezit. Banken bieden de mogelijkheid aan consumenten om uitgaven te verdelen over een lange reeks van jaren over hun gehele levensloop, waardoor het mogelijk is om nu grote uitgaven te doen, bijvoorbeeld voor de woning, die men later terugbetaald als de capaciteit om terug te betalen groter is.

Het meten van concurrentie in financiële markten is belangrijk, omdat sterke concurrentie kan leiden tot een meer efficiënt productieproces van financiële producten en uiteindelijk hierdoor de welvaart in de economie kan worden verhoogd. Tegelijkertijd zou hevige concurrentie tot meer risicovol gedrag van banken kunnen leiden, welke de stabiliteit van het financiële systeem kan bedreigen. Er is enig bewijs dat een dergelijke relatie bestaat tussen stabiliteit en concurrentie, maar er zijn ook indicaties dat concurrentie juist zal leiden tot meer stabiliteit omdat slecht functionerende banken met grote operationele risico's hun beleid moeten aanpassen, overgenomen worden door hun beter functionerende concurrenten of gedwongen worden de markt te verlaten.[1] Om inzicht in deze complexe materie te krijgen, moet men allereerst over een betrouwbare methode beschikken om concurrentie te meten.

Ten slotte, het functioneren van financiële markten is belangrijk vanuit het perspectief van het monetair beleid. De Europese Centrale Bank heeft de doelstelling van prijsstabiliteit en stelt haar beleidsrente vast om deze doelstelling te bereiken. De effectiviteit van haar instrumentarium in het bereiken van deze doelstelling wordt mede bepaald door de mate waarin veranderingen in beleidsrente worden doorgegeven in de

[1] Zie Martinez-Miera en Repullo (2008) voor een overzicht van de literatuur.

rentes voor bedrijven en consumenten. Eén van de elementen die dit bepaalt, is de mate van concurrentie in de kredietmarkt.

Al deze overwegingen hebben er voor gezorgd dat ik dit proefschrift richt op het functioneren van de financiële sector. De doelstelling van het proefschrift is het meten van concurrentie in de volgende markten: kredietmarkten, meer specifiek hypotheekmarkten, en markten voor levensverzekeringen.

De plaats in de literatuur

Hoe het niveau van concurrentie het beste kan worden gemeten is een open vraag. Er zijn hiervoor een groot aantal manieren. Het meest gebruikt zijn de Lerner-index en de Hirschman-Herfindahl index (HHI). Bij de Lerner-index staat de prijs-kostenmarge (PCM) centraal. De PCM wordt vervolgens gecorrigeerd voor de prijsgevoeligheid van de vraag naar het product. HHI kijkt naar de structuur van de markt, met name naar de concentratie van aanbieders in de markt. Deze twee maatstaven hebben echter een aantal grote theoretische beperkingen zoals Boone(2008) heeft aangetoond.

Er bestaat een vrij brede literatuur over het meten van competitie in de financiële sector, waarbij gebruik wordt gemaakt van concepten zoals marktmacht en efficiëntie. Een bekende benadering van het meten van marktmacht in de banksector is gesuggereerd door Bresnahan (1982) en Lau (1982) en is recent gebruikt door Bikker (2003) en door Uchida en Tsutsui (2005). Zij analyseren gedrag van banken op een geaggregeerd niveau en bepalen in hoeverre de banken hun strategieën met elkaar in overeenstemming brengen. Een hoge mate waarin deze variatie overeenkomt betekent dat banken in hoge mate bewust zijn van de onderlinge afhankelijkheid met andere banken in termen van productie en prijzen.

Panzar en Rosse (1987) stellen een benadering voor gebaseerd op de zogenaamde H-statistiek, welke gebaseerd is op de som van de elasticiteiten van de inputprijzen op de inkomsten. Deze H-statistiek kan waarden aannemen tussen $-\infty$ en 1. Als de H-waarde tussen 0 en $-\infty$ ligt, indiceert dit monopolie of perfecte collusie, terwijl een waarde tussen 0 en 1 een indicatie oplevert van een reeks aan oligopolistische en monopolistische typen van concurrentie. Een waarde van 1 wijst op perfecte concurrentie.

Een derde indicator van marktmacht is de eerder genoemde Hirschman-Herfindahl (HHI), die de mate van marktconcentratie meet. Deze indicator wordt vaak gebruikt in de context van het 'Structuur-Gedrag-Prestatie' (SGP) model (zie bijvoorbeeld Berger cs (2004) en Bos (2002), welke veronderstelt dat marktstructuur het gedrag van banken beïnvloedt, die op zijn beurt het resultaat van de onderneming bepaalt.[2] Het idee is dat banken met grote marktaandelen meer marktmacht kunnen hebben en dat ook benutten. Bovendien geldt dat het bestaan van een klein aantal banken vergemakkelijkt dat er

[2] Bikker en Bos(2005), blz. 22 en 23.

onderlinge afspraken worden gemaakt (collusie). De SGP-hypothese kan worden getest door het resultaat van de bank (de winst) te relateren aan het marktaandeel. Er zijn veel artikelen die het SGP-model gezamenlijk testen met een alternatieve verklaring: de efficiëntie-hypothese, waarbij verschillen in winst worden verklaard door verschillen in efficiëntie. (bijvoorbeeld Goldberg en Rai (1996) en Smirlock (1995)).

Marktmacht kan ook gerelateerd zijn aan winsten of zelfs overwinsten. Een traditionele manier om winstgevendheid te meten is de prijs –kostenmarge (PCM), eerder genoemd als onderdeel van de Lerner-index.[3] Deze marge wordt vaak gemeten als het verschil tussen outputprijs en marginale kosten, gedeeld door de outputprijs. De PCM is frequent gebruikt in de empirische literatuur van de industriële organisatie als een empirische benadering van de theoretische Lerner-index.

Ten slotte is er een stroming in de literatuur die zich gericht heeft op X-efficiëntie. Dit begrip reflecteert de mogelijkheden die managers hebben om hun productiekosten te verlagen, hun productievolumes en inputprijzen te beheersen. X-efficiëntie wordt gemeten als het verschil in kosten tussen de onderzochte onderneming en de onderneming van gelijke omvang en inputprijzen die de beste resultaten behaald (Leibenstein 1966). Zware concurrentie zal de X-inefficiëntie van bedrijven moeten verlagen. En daarom kan X-inefficiëntie als een indirecte meting van concurrentie worden gezien.

Dit proefschrift gebruikt vele van de bovengenoemde concepten om concurrentie in de financiële sector te analyseren. Ik geef speciale aandacht aan een relatief nieuwe indicator van competitie, de Boone-indicator. De Boone-indicator heeft theoretisch een betere basis dan PCM of HHI. Bijvoorbeeld, in het geval dat een inefficiënt bedrijf wordt overgenomen door een efficiënt bedrijf, zal de HHI wijzen op minder concurrentie door de toename in concentratie, terwijl in werkelijkheid de concurrentie toeneemt. De Boone-indicator zal juist wijzen op meer concurrentie omdat de relatie tussen resultaat en efficiëntie wordt versterkt. Verder als door toegenomen concurrentie bedrijven meer efficiënt zijn geworden, dan kan dit leiden tot hogere prijs-kostenmarges. Deze hogere prijs-kostenmarges zouden juist wijzen op minder concurrentie, terwijl in werkelijkheid de concurrentie is toegenomen. Omdat in dit voorbeeld de relatie tussen resultaat en efficiëntie is versterkt, zal de Boone-indicator juist wijzen op meer concurrentie. Dit proefschrift introduceert de Boone-indicator in de literatuur van de financiële sector.

[3] De Lerner-index leidt een verschil af tussen prijs en marginale kosten gedeeld door de prijs op basis van de winstmaximalisatie voorwaarden van een monopolist. De monopolist maximeert de winst als de Lerner-index gelijk is aan de inverse van de prijselasticiteit van de marktvraag. Onder perfecte concurrentie is de Lerner-index gelijk aan nul (marktvraag is oneindig elastisch). Onder monopolie benadert zij de waarde één voor positieve marginale kosten. De Lerner-index kan ook worden afgeleid voor tussenliggende situaties. Voor een discussie verwijs ik naar Church en War (2000).

Opzet van het proefschrift

De structuur van het proefschrift is als volgt. De hoofdstukken 2 tot en met 4 richten zich op de Nederlandse hypotheekmarkt en beargumenteren waarom concurrentie voor deze markt van belang is. In hoofdstuk 4 ga ik in op twee aspecten van concurrentie als prelude op het meten van concurrentie: de transparantie van de markt en de macht om de prijs te bepalen op de markt. De hoofdstukken 5 tot en met 8 gaan op deze lijn voort en richten zich op het meten van concurrentie met een nieuwe maatstaf voor concurrentie: de Boone-indicator. In deze hoofdstukken gaat de aandacht uit naar het meten van concurrentie in de financiële sector in brede zin, in bijzonder banken en levensverzekeringsmaatschappijen. Hoofdstuk 5 introduceert de Boone-indicator. In Hoofdstuk 6 en 7, meet ik de hoogte van concurrentie met een licht aangepaste versie voor deze maatstaf voor de kredietmarkt en bereid ik het bereik van het onderzoek naar het eurogebied, de Verenigde Staten en Japan uit. Verder analyseer ik hier het effect van concurrentie tussen banken op de mate waarin de rente op kredieten zich aanpast aan de veranderingen in de beleidsrentes van de Europese Centrale Bank. Ten slotte kijk ik in Hoofdstuk 8 naar het niveau van concurrentie in de Nederlandse levensverzekeringmarkt.

Hoofdstuk 2 onderzoekt het belang van eigenwoningbezit voor de arbeidsmarkt, en dus ook het belang voor de hypotheekmarkt. Om een eigen woning te kunnen kopen, moet normaal gesproken een huishouden een hypotheek afsluiten bij een financiële instelling. Uit een groot aantal macro-economische studies blijkt dat eigenwoningbezit baanmobiliteit beperkt en werkloosheid vergroot. In dit hoofdstuk wordt één van de hypotheses van Oswald getest: eigenwoningbezit beperkt baanmobiliteit door verhoogde transactiekosten. Hierdoor wordt de kans op werkloosheid vergroot voor eigenwoningbezitters ten opzichte van huurders, omdat eigenwoningbezitters minder bereid zijn banen buiten hun eigen regio te accepteren vanwege de hoge kosten van verhuizing. Mijn onderzoek is verricht met Nederlandse microdata. Voor Nederland vind ik echter dat eigenwoningbezitters niet minder vaak van baan wisselen dan huurders en juist een kleinere kans hebben om werkloos te worden dan huurders. Het eerste resultaat kan worden verklaard door de hoge bevolkingsdichtheid in Nederland, de sterke huisprijsstijgingen die de hoge verhuiskosten kunnen hebben gecompenseerd en de sterke regulering van de sociale huursector, welke weer tot hoge verhuiskosten van huurders kan hebben geleid. Dit laatste resultaat wordt verklaard door de hoge mate waarin werknemers aan hun baan zijn gecommitteerd in vergelijking tot huurders. Dit aspect lijkt ten voordele te zijn van eigenwoningbezitters.

In Hoofdstuk 3 wordt geanalyseerd hoe banken de kans dat huishoudens verhuizen waarderen. Hier onderzoek ik empirisch in welke mate het niveau van de rente op spaarhypotheken kan worden verklaard door verschillen in het risico dat huishoudens voor de contractueel afgesproken datum hun hypotheek terugbetalen. Ik laat zien dat voor dit type hypotheek huishoudens eerder de hypotheek terugbetalen vanwege verhuizingen. Vervolgens heb ik onderzocht hoe belangrijk veranderingen in inkomen

of in vermogen zijn voor verhuisbeslissingen volgens banken. Ik vind dat veranderingen in inkomen de belangrijkste reden zijn om te verhuizen volgens banken, in ieder geval belangrijker dan fluctuaties in de waarde van de woning. De verhouding tussen de waarde van de lening en het inkomen is veel belangrijker dan de verhouding tussen de waarde van de woning en de lening. In andere woorden de liquiditeitspositie heeft in de perceptie van banken veel meer invloed op de verhuisbeslissingen dan de solvabiliteitspositie, die vooral relevant wordt bij faillissement.

Hoofdstuk 4 gaat over de transparantie van de Nederlandse hypotheekmarkt. Een empirische studie naar het beprijzen van hypotheken in deze hypotheekmarkt wordt in dit hoofdstuk gepresenteerd. Transparantie wordt gemeten als het prijsverschil tussen de beste aanbieding en de slechtste. Het prijsverschil kan de indicatie geven dat er sprake is van imperfecte concurrentie, veroorzaakt door zoekkosten van leners of hoge kosten van onder andere monitoring bij uitleners. In het algemeen kan worden gesteld dat grote prijsverschillen duiden op intransparantie van de markt, wat weer de mate van concurrentie kan beperken op de hypotheekmarkt. Er zijn grote verschillen tussen het gedeelte van de markt waar banken zelf actief zijn en daar waar tussenpersonen een rol spelen. Deze verschillen zitten in de spreiding van rentes tussen banken en niet-banken, zoals verzekeraars en pensioenfondsen, die vooral gebruik maken van tussenpersonen. Het onderzoek wijst uit dat de hypotheekmarkt waar tussenpersonen actief zijn, meer intranparant is dan die waar banken actief zijn. Een verdere test of niet-banken meer prijsmacht hebben dan banken levert gemengde resultaten op. Daarom hebben we maar beperkt bewijs voor de stelling dat meer intransparantie leidt tot meer prijsmacht bij verstrekkers van hypotheken.

In hoofdstuk 5 lever ik een empirische onderbouwing voor een nieuwe manier om concurrentie te meten: de Boone-indicator. Deze indicator is geïntroduceerd door Boone (2008). De indicator is gebaseerd op de relatie tussen resultaat en efficiëntie. Of deze indicator correct de verschillende regimes van concurrentie kan onderscheiden is een tot nu toe onbeantwoorde vraag. Om te demonstreren dat de Boone-indicator weldegelijk deze mogelijkheid heeft, gebruik ik data van Genesove en Mullin (1998) voor de Amerikaanse suikerindustrie voor de periode 1890 -1914. Uit mijn analyse volgt dat de Boone-indicator inderdaad de mogelijkheid heeft deze regimes te onderscheiden, en wel net zo goed als de voor elasticiteiten gecorrigeerde Lerner-index.

Na een empirisch onderbouwing te hebben gegeven in hoofdstuk 5, pas ik in hoofdstuk 6 de Boone-indicator toe op de kredietmarkten in het eurogebied en schenk ik aandacht aan de Verenigde Staten en Japan. In tegenstelling tot veel bekende maatstaven van concurrentie, zoals de Panzar-Rosse methode, meet de Boone-indicator concurrentie in een markt en niet (alleen) van een bedrijfstak of bedrijf. We hebben de mogelijkheid om op segmenten het niveau van concurrentie te meten. Mijn uitkomsten suggereren dat de Verenigde Staten de meest competitieve markt heeft. De markten in Duitsland en Spanje zijn binnen het eurogebied de meest competitieve markten. Nederland neemt hierbinnen een tussenpositie in. Italië heeft te maken met een daling

in concurrentie. Frankrijk en het Verenigd Koninkrijk zijn de minst competitieve markten. Japan heeft een sterke stijging van concurrentie laten zien op de kredietmarkt.

In hoofdstuk 7, ga ik in de analyse nog één stap verder en bestudeer of concurrentie een effect heeft op het monetaire transmissie mechanisme van de ECB in het eurogebied. Ik vind dat sterke concurrentie leidt tot een kleiner verschil tussen bankrentes en marktrentes, maar ook tot een snellere overname van veranderingen in marktrentes door bankrentes. De belangrijkste implicatie voor monetair beleid is dat concurrentie in de kredietmarkten de effectiviteit van het monetaire instrumentarium in de Europese bankensector verbetert.

Hoofdstuk 8 richt de aandacht op de markt voor levensverzekeringen. Ook hier pas ik de Boone-indicator toe naast een aantal andere maatstaven die concurrentie meer indirect meten. De Boone-indicator is één van de weinige directe concurrentiemaatstaven die geen gebruik maakt van prijsinformatie en daarom goed kan worden toegepast op de markt voor levensverzekeringen. Ik vind dat het concurrentieniveau is deze sector laag is, wat ook wordt bevestigd door de andere maatstaven zoals grote niet-gebruikte schaalvoordelen, hoge winstmarges en sterke X-inefficiënties, dat wil zeggen inefficiënties veroorzaakt door beslissingen van het management.

Algemene conclusies

Uit de eerste drie hoofdstukken van dit proefschrift kan de les worden getrokken dat kapitaalmarktimperfecties in de hypotheekmarkt de voordelige effecten van eigenwoningbezit te niet kunnen doen. Deze voordelige effecten bestaan uit de investeringen in de baan door eigenwoningbezitters. Verder concludeer ik dat negatieve inkomensschokken verhuizingen kan beperken, volgens de verwachtingen van banken. Dit ondersteunt een Oswald hypothese: werkloze eigenwoningbezitters zijn minder geneigd om een baan buiten hun eigen regio te accepteren dan huurders. Tegelijkertijd lijken dalingen in de waarde van de woning weinig invloed te hebben op de beslissing om te verhuizen.

Hoofdstuk 4 richt zich op de transparantie van de Nederlandse hypotheekmarkt. Uit de analyse blijkt dat banken meer prijsmacht hebben dan pensioenfondsen en levensverzekeraars en dat het niveau van concurrentie verhoogd kan worden. Banken domineren deze markt in termen van marktaandeel en zij zijn de prijsleiders in deze markt, de Rabobank met name. Tegelijkertijd blijkt dat de intransparantie in deze markt het grootst is in het segment van tussenpersonen, maar in het licht van de prijsmacht lijkt dit minder belangrijk. De prijsmacht ligt bij de banken en niet bij de pensioenfondsen, levensverzekeraars en hun tussenpersonen.

Concurrentie is het belangrijkste onderwerp in de rest van het proefschrift. De mate van concurrentie in de financiële sector en in de bankensector in het bijzonder is van het grootste belang, gegeven de cruciale rol die het financiële systeem speelt in de

economische ontwikkeling. Dit belang wordt nog eens vergroot als men zich bewust is van het feit dat banken in het eurogebied de belangrijkste aanbieders zijn van financieel kapitaal. Concurrentie zorgt voor het beter functioneren van kapitaalmarkten, leidt tot lagere rentes en vergroot op deze manier de welvaart van huishoudens en ondernemingen, zoals aangetoond in hoofdstuk 7. Langs deze weg heeft concurrentie in de financiële sector een belangrijke invloed op de macro economische resultaten en welvaart van een land. De empirische resultaten van hoofdstuk 6 indiceren dat er belangrijke verschillen in concurrentie bestaan tussen de belangrijkste industriële machten en de belangrijkste industriële landen in het eurogebied. Dit resultaat is belangrijk voor beleidsmakers die streven naar een optimaal resultaat van een beleid, voor banken in hun rol van aanbieders van kredieten en voor niet-financiële bedrijven die proberen hun projecten te financieren. De resultaten in dit proefschrift suggereren dat een aantal landen zoals Frankrijk en het Verenigd Koninkrijk in potentie voordeel zouden kunnen hebben van verbeterde competitieve omstandigheden op hun kredietmarkten. De resultaten, gemeten door de tijd heen, geven indicaties dat competitieve omstandigheden inderdaad kunnen verbeteren, zoals de resultaten voor Japan laten zien, waar concurrentie in de kredietmarkt in meer recente jaren sterk is toegenomen.

Het belang van bankconcurrentie voor beleidsmedewerkers is duidelijk, in het bijzonder voor centrale banken en toezichthouders die monetair beleid en prudentieel toezicht uitvoeren. Ten eerste door hun centrale positie in het financiële systeem speelt de bankensector een vooraanstaande rol in de transmissie van impulsen van monetair beleid. In een meer competitieve markt wordt verwacht dat impulsen van monetair beleid sterker en sneller door worden gegeven aan bancaire rentes. De resultaten van hoofdstuk 7 duiden hier ook op. Dus beleid op het gebied van concurrentie leidt niet alleen tot lagere kosten voor consumenten en bedrijven, maar ook tot een effectiever monetair beleid zoals dat geïmplementeerd wordt door de Europese Centrale Bank. Ten tweede, de gezondheid en stabiliteit van het bancaire systeem kan op verschillende manieren beïnvloed worden door de competitieve omstandigheden. Omdat een gezond bancair systeem van cruciaal belang is voor de economische ontwikkeling, zoals pijnlijk is gebleken door de financiële crisis die het fundament van het wereldwijde financiële systeem in 2008 heeft doen wankelen, blijft het onderwerp van bankconcurrentie grote aandacht vragen.

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