"Competition, transmission and bank pricing policies: Evidence from Belgian loan and deposit markets"

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Abstract:

This paper analyses the pass-through of money market rates to retail interest rates in the Belgian banking market using disaggregate data and allowing for heterogeneous price setting behavior. We find that 1) corporate loans are priced more competitively than consumer loans, 2) pass-through is higher for products with longer maturities, 3) EMU did not increase price competition, 4) bank behavior is consistent with the presence of menu costs, and 5) existing empirical evidence may underestimate adjustment speed. Furthermore, heterogeneous price setting among banks is driven by market power as well as the bank lending channel.

JEL: C23, E43, E52, G21, L11

Keywords: pass-through, retail bank interest rates, heterogeneous panel cointegration, bank lending channel, asymmetry

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1 Introduction

Recent years have been characterized by an increasing interest in the mechanics of the transmission of monetary policy to the banking sector. Even in the U.S., where bank finance is much less predominant than in the Euro area, the issue has attracted considerable attention (see e.g. Bernanke and Gertler, 1995; Kashyap and Stein, 2000). The present paper elaborates on the issue by studying the pass-through of market interest rates to retail bank interest rates in Belgium. Our analysis focuses on the measurement of the pass-through as well as determinants of differences in pass-through among different types of banks. Both from a monetary policy and a banking perspective a thorough understanding of the pass-through is crucial. Measurement of the pass-through provides insight into the extent and timing of agents' reaction to monetary policy, and market conditions more generally. Such analysis aids in the comprehension of lags in the transmission of monetary policy, which is a major concern for central banks. Moreover, the pass-through also sheds light on the compositional response of the economy to monetary policy, which is of direct relevance to the financing decisions of both firms and consumers. We also investigate determinants of heterogeneity in pass-through across banks. We thus characterize the exact mechanisms at work in the banking sector. Identification of the channels through which monetary policy operates is a topic of interest for central bankers and academics alike. Finally, this type of pass-through research is complementary to the analysis of bank interest rate spreads. As such, it is also of significance to competition and bank supervision authorities.

Cross-country evidence suggests that interest rate behavior in Belgium is representative for EMU as a whole (see e.g. the overview in de Bondt, 2002). In the last decade, the Belgian bank industry witnessed a pronounced shift in terms of market structure due to a series of mergers and acquisitions, which included all the major bank groups. Most large banks opted for the bancassurance model, causing the banking system to become more consolidated and more diversified. Both aspects may have an impact on the pricing of retail bank products. Moreover, the Belgian banking market is characterized by a relatively large degree of foreign penetration. Although the number of foreign banks is proportionately larger than their market share in various retail markets, it gives a rough indication of the market's contestability.

The present analysis contributes to the existing pass-through literature in a number of ways. A first contribution is related to the uniqueness of the data we use. Contrary to aggregate, country-level studies (e.g. Cottarelli and Kourelis, 1994; Borio and Fritz, 1995; Mojon, 2000), we have retail interest rates of individual banks at our disposal (see e.g. Cottarelli et al., 1995; Weth, 2002; Gambacorta, 2004b). This enables us to measure the extent of pass-through at the micro level and investigate its bank-specific determinants. We find that there is considerable heterogeneity in price-setting among banks. On the aggregate level, our results confirm the rigidity of prices, especially in the short run. Second, the analysis also comprises the liability side of retail banking. In contrast to the US (Hannan and Berger, 1991; Neumark and Sharpe, 1992), there hardly exists evidence on the pass-through for bank deposits in EMU. Using data on Belgian banks, we account for some of this shortage. Third, we analyse a total of thirteen loan and deposit products, covering about the whole spectrum of retail banking activities. In contrast to existing studies, which typically consider only a limited number of products, this leaves scope for identifying pass-through characteristics over distinct product categories. Indeed, we find that corporate loans are priced more competitively than consumer loans. We also uncover a positive relationship between the product's maturity and the extent of pass-through that calls for a re-interpretation of some previous findings. Fourth, we also address the issue of asymmetry. The evidence implies that most deposit rates respond faster when market rates fall than when market rates rise. This confirms the evidence e.g. Neumark and Sharpe (1992) provide for the US. By contrast, there are no clear asymmetric dynamics in the loan rate adjustment process. Furthermore, for both loan and deposit rates, adjustment is fastest when deviations from banks' equilibrium margins are relatively large. This type of adjustment is consistent with both menu and switching cost theories. Finally, incorporation of bank balance sheet data allows investigation of factors driving differences in pass-through (Cottarelli et al., 1995; Bruggeman and Wouters, 2001; Weth, 2002; Gambacorta, 2004b). We examine a more comprehensive set of determinants and find, among other things, that interest rates of well-capitalized banks are particularly sluggish in their adjustment to changing market conditions. We relate these findings to the debate on monetary policy transmission. In particular, the evidence is consistent with the existence of a bank lending channel rather than a financial accelerator or a bank capital channel. Furthermore, our results also bear on the bank pricing literature. More specifically, they offer support for the structure-conduct-performance, rather than the efficiency hypothesis.

The paper also incorporates a number of methodological contributions in the setup of the empirical analysis. We argue that when dealing with retail bank interest rates, one should allow for heterogeneity. Not only fixed (as in Gambacorta, 2004b), but also random variation over banks should be taken into account. Our results confirm the presence of both sources of heterogeneity. Another contribution of our analysis lies in the way we test for and infer from cointegration relations. We incorporate lessons learned from the "large *n*, large *T*"-panel data literature in testing for (Pedroni, 1999; McCoskey and Kao, 1999) and estimating (Phillips and Moon, 1999) cointegrating relations. On the one hand, we obtain a complete distribution of the long-run pass-through estimates. As a result, we shed light on the (in)completeness of the pass-through, an issue that has received little or no attention in the literature. On the other hand, applications of these techniques are not widespread and almost exclusively cover macro data. In this respect, the paper provides an illustrative (micro) example of some of the advances made in the "large *n*, large *T*" domain. Finally, we stress that existing pass-through estimates potentially suffer from several biases. In particular, pass-through estimates might be contaminated by biases due to lagged dependent variables (e.g. Kiviet and Phillips, 1994), nonlinearity (e.g. Pesaran and Zhao, 1999), aggregation (e.g. Granger, 1980) or heterogeneity (e.g. Barker and Pesaran, 1990). Whereas previous studies often only mention these biases, we provide an indication of the importance of each of them. Our results indicate that heterogeneity in retail interest rate data is substantial, and that failing to account for this feature will give rise to misleading conclusions. By contrast, we find no evidence to suspect that either lagged dependent variable bias or nonlinearity bias contaminates pass-through estimation.

The remainder of the paper is organized as follows. Section 2 describes the structure of the dataset. In Section 3 we measure the pass-through. The specificity of the data has implications for the econometric approach used in the paper. After elaborating on the methodology, we present and discuss our results. The remainder of the section provides an answer to three specific questions regarding the pass-through: 1) Did the introduction of the Euro affect the pass-through? 2) Is the pass-through asymmetric? 3) Is accounting for heterogeneity in measuring the pass-through necessary? In Section 4 we investigate which bank characteristics can account for heterogeneity in interest rate pass-through. A final section concludes.

2 The data

The dataset comprises bank-specific interest rates of the majority of Belgian banks for a series of loan and deposit products over the period January 1993 – December 2002. While aggregated bank retail rates are publicly available (see e.g. ECB, IFS), bank-specific rates are not. In Belgium, the central bank (National Bank of Belgium, NBB) conducts a monthly inquiry, asking banks what rate they offer or would offer on a range of thirteen standardized products. The products are standardized in the sense that maturity, amount and debtor quality are stipulated. The loan rates in the sample are those charged to the most creditworthy borrowers. Similarly, studies analyzing US loan markets focus on the “prime” rate (see e.g. Levine and Loeb, 1989; Berlin and Mester, 1995) thus enabling some comparability with our results. The use of standardized products in the analysis has the advantage of eliminating to a large extent the effect of non-price competition. Data are collected for six loan products and seven types of deposits, with both short and long maturities, and oriented both to consumers and firms. The reporting banks account for more than 90% of total assets of Belgian banks[1]. The dataset contains 31 banks and a total of 250 retail interest rate series[2]. A second part of the dataset consists of money market interest rates of different maturities, which are publicly available. A third part covers data from bank balance sheets and profit and loss accounts, all provided by the NBB[3]. The frequency of the entire analysis is monthly.

We present our summary statistics in the form of a series of charts (see Figure 1). Over most of the sample period from January 1993 to December 2002, interest rates have been declining, a characteristic that can largely be explained by the EMU-related convergence of interest rates, inflation and the stance of the business cycle and of monetary policy. The general picture that emerges from the loan and deposit panels of Figure 1 is that bank retail rates generally follow changes in market rates (of comparable maturity), but there are clear differences across products in terms of speed and magnitude of the adjustment. For short-term trade credit and bank advances, the interest rates offered by banks change only slowly and remain constant over various time intervals. For long-term investment loans the association between market and bank rates appears to be more pronounced and the difference between the highest and lowest bank rate is also smaller. Next to the loan products offered to corporations, we also provide information on two typical customer retail lending products, mortgages and consumer credit. For 36-month consumer credit, the bank rates appear to only loosely follow the corresponding market rate and the differences across banks are relatively high. In the case of mortgages the correlation between bank rates and the relevant market rate (5-year government bonds) is much more pronounced. Overall, there are considerable

[1] Publicly available aggregate bank retail rates are constructed on the basis of these inquiries.

[2] Regarding the bank retail rates, two adjustments are made. First, in January 1996, the definition for consumer credit in the NBB's inquiry changed, which we accommodate by restricting the analysis (for this product only) to the post-1995 period. Second, for mortgages, a (significant) dummy enters each regression to account for the level effect of an annual housing fair ("batibouw") affecting the interest rates reported in March.

[3] We treat banks that were involved in a merger or acquisition as different units before the merger, and as one thereafter.

differences between the maximum and minimum bank rates, leaving scope to investigate bank-specific determinants of the pass-through. In the case of deposits, shown in the lower three rows of Figure 1, the association between market and retail rates is weakest for the savings and demand deposits. From the corresponding charts, it is clear that the compensation for savings deposits is only broadly related to changes in market rates, often with considerable lags. In the case of savings bonds and time deposits, the evolution of bank retail rates is much more in line with changes in market rates. The differences between the maximum and minimum retail rates offered by banks are also much smaller than in the case of savings and demand deposits.

3 Measurement of the pass-through

In this section we analyse the extent of pass-through from market to retail bank interest rates. We start by indicating the importance of heterogeneity in the analysis. This will result in an estimation strategy that will be used in this and subsequent sections. Next, we present our results, compare them with the literature, and check the robustness of our conclusions. Then, we verify whether the introduction of the euro affected price setting behavior. Subsequently, we assess the scope for nonlinearities in the adjustment dynamics. Finally, we examine the effect of ignoring heterogeneity in price setting on pass-through estimates.

3.1 Methodology

For each of the thirteen products, we consider a separate panel[4]. There are several characteristics of the data, of the hypotheses we wish to test, and of the underlying theoretical framework, that have implications for the way one should address estimation. We now turn to each of these.

[4] Examining cross-product relationships is beyond the scope of this paper.

As our study focuses on both the short and the long-term relation between bank retail rates and the market rate, we are interested in the time series characteristics of our dataset. Having a cross-section of banks per product allows pooling the data and estimating the model more efficiently[5]. One should, however, be careful in pooling, as there may be considerable heterogeneity in the data. This heterogeneity seems especially relevant in our dataset and may be twofold: fixed (i.e. systematic or bank-specific) or random (i.e. uncorrelated with bank characteristics). First, differences in pass-through may be due to differences in bank characteristics. As this is one of the hypotheses we wish to test, allowing for fixed heterogeneity is crucial. We address issues concerning systematic heterogeneity in Section 4, where determinants are dealt with. Second, the interest rate data are the outcome of an inquiry, which allows for some subjectivity and/or differences in timing of reporting. Furthermore, the inquiry considers standardized products and not every bank may offer all the exact products. Allowing for random heterogeneity in estimation can capture the effect of measurement error in the data. Third, in regressions where bank characteristics are not included it may also mitigate the effect of fixed -but not modelled- heterogeneity. Fourth, another objection to pooling the data (especially in dynamic models like ours) is given by Pesaran and Smith (1995). They show that pooling in heterogeneous dynamic panels gives rise to inconsistent estimates. In view of these considerations, we measure the pass-through using a random coefficient model[6]. Incorporating heterogeneity is feasible in our dataset as the time dimension is large (T ranges from 36 to 120). Hence, unlike the "large n, small T"-panel data literature, we are not forced to impose cross-sectional parameter equality. Moreover, the stationarity assumption present in that literature can be relaxed.

Marginal costs

A first step in measuring the pass-through is determining the relevant marginal cost for each product. For almost all products in our dataset, the inquiry specifies a well-defined maturity. Hence, a natural

[5] Throughout the paper, we refer to pooling or pooled coefficients whenever the estimation imposes common coefficients over cross-sections. Thus, in our terminology, the traditional pooled, fixed effects and random effects estimators all belong to the "pooled" class of estimators. The models we consider have fixed and/or random variation in all coefficients, not just in the constant term.

[6] Appendix A elaborates on this type of model. See Hsiao (2003) for a comprehensive overview.

choice for the marginal cost of the different products emerges: the money market rate with a comparable maturity. As Table 1 shows, this choice is largely confirmed by correlation analysis. We use the maximum correlation to determine marginal costs for those products for which a reference maturity was not specified. From an economic point of view, computing the pass-through relative to a market rate with comparable maturity rather than to the policy rate is important (see also de Bondt, 2002). Doing so, one disentangles the pass-through of marginal costs on the one hand, and term structure effects of policy rates[7] on the other.

Cointegration

The fact that a considerable part of our sample period is characterized by falling interest rates results in nonstationarity for the majority of series in our data set[8]. For modelling purposes, in order to avoid spurious results, a natural question to ask is whether the respective retail and market rates are cointegrated. Overall, we follow the two-step procedure outlined by Engle and Granger (1987). Working in a panel context, however, alters the way one should test and estimate these models.

It is common knowledge that standard unit root and cointegration tests have low power. The basic advantage of "large n, large T" panels[9] in using these tests is that exploiting the cross-sectional information improves their power. By now, the literature has established a wide variety of panel cointegration tests, surveyed in Banerjee (1999). Most of these tests differ in the specification of the null and alternative hypotheses. The arguments stated above indicate that we wish to allow for heterogeneity. Therefore, we apply Pedroni's (1999) cointegration test, i.c. the between dimension

[7] The term structure effect of policy on market rates is typically not considered in pass-through studies, but is an interesting domain on its own. See e.g. Cook and Hahn (1989), Ellingsen and Söderström (2001).
[8] There are several theoretical arguments that imply the nominal interest rate should be stationary. In finite samples, however, the observed behavior could resemble that of an integrated series. Evans and Savin (1981) show that treating such persistent but stationary series as integrated can be preferable.
[9] The cross-sectional dimension in our dataset is not large ($n \leq 31$) relative to the time dimension ($36 \leq T \leq 120$), but comparable to that of, for instance, McCoskey and Kao (1999). Furthermore, much of the theoretical results we rely on (e.g. Phillips and Moon, 1999) hold for moderate n and large T.

ADF-test (see also Kao, 1999; McCoskey and Kao, 1999). This residual-based test is based on individual cointegrating regressions of the form (see Engle and Granger, 1987):

$$b_{i,t} = c_{2i} + \delta_i \cdot m_t + u_{i,t} \qquad (1)$$

This test, under the null hypothesis of no cointegration, allows for both short ($u_{i,t}$) and long-run (δ_i) heterogeneity under the alternative.

When estimating a cointegration relation in the univariate case, OLS provides (super)consistent estimates. Due to the nonstationarity of the regressors, however, these estimators no longer have standard distributions. As a result, most of the pass-through literature avoids statistical inference on long-run coefficients[10]. One notable exception is Hofmann and Mizen (2004), who analyse long-run coefficients using likelihood ratio tests *vis-à-vis* the model with complete long-term pass-through. The present paper follows a different route, resulting in a complete distribution of the long-run coefficient. In a panel context too, one can estimate the cointegration vector by OLS. A crucial difference with the univariate case, however, is that the noise in cointegration relations is attenuated when estimating over various cross-sections. As a result, Phillips and Moon (1999) show that panel estimators of cointegration coefficients converge to a normal distribution. Hence, when taking into account the appropriate distribution of the estimators, standard hypothesis testing becomes possible on long-run coefficients. In order to obtain one average long-run coefficient per product, the cointegrating vector is estimated directly using the pooled estimator suggested by Phillips and Moon (1999). This is a pooled estimator of the cointegration coefficient that can be interpreted as the average long-run coefficient of the heterogeneous individual cointegrating relations[11].

[10] Remark that the distribution of the long-run coefficient affects the distribution of every intermediate, with the exception of the immediate, pass-through.
[11] Note that the variance of the exogenous variable in (*1*) is (almost surely) the same for each cross-sectional unit. As a result, average long-run and long-run average coefficients coincide (see Pesaran and Smith, 1995; Phillips and Moon, 1999).

In case of cointegration (or alternatively, stationary residuals $u_{i,t}$), an error correction representation (ECM) of the retail rate exists:

$$\Delta b_{i,t} = c_{1i} + \sum_{k=1}^{p} \alpha_{ki} \cdot \Delta b_{i,t-k} + \sum_{l=0}^{q} \beta_{li} \cdot \Delta m_{t-l} + \gamma_i \cdot u_{i,t-1} + \varepsilon_{i,t} \qquad (2)$$

where b = bank rate, m = market rate, $t = 1, \ldots, T$ and incorporation of heterogeneity is clear from the "i" subscripts on the parameters ($i = 1, \ldots, N$). The term $\gamma_i \cdot u_{i,t-1}$ captures the adjustment towards equilibrium. A significantly negative γ_i confirms the presence of an equilibrium-restoring relation. The dynamic heterogeneity is captured by estimating *(2)* using Swamy's (1970) random coefficient procedure. The final step in model selection is determining the optimal choice of lag length *(p, q)*. We use the Schwarz Bayesian Information Criterion to choose among models containing up to six lags (in levels). In the spirit of Granger causality tests, we first determine p, and then q. A moving average term is added to each equation to ensure white noise residuals and consistency of estimates.

3.2 Results

The results are summarized in Figure 2 and Tables 2 and 3. Figure 2 plots the pass-through for the different products: the first two rows contain the loan products; the lower three rows present the deposit products. At each date, the pass-through measures the contribution of a 1%-point permanent increase in the market rate to the retail bank interest rate. Table 2 shows the outcome of the cointegration tests, by means of the adjusted t-statistics for each panel. Appendix A provides some overall tests of the model. Table 3 summarizes the estimation results[12]. Within each product panel, we restrict attention to the main coefficients of interest: the immediate pass-through (ST PT), the

[12] Starting the analysis from 1994 onward, excluding the late 1993 market turbulence due to the EMS-crisis, never had a significant impact on the results.

long-run pass-through (LT PT) and the adjustment coefficient (ADJ). We also report the mean adjustment lag as a summary measure.

First, for both loans and deposits, the size and significance of the negative adjustment coefficients confirm the presence of an equilibrium-restoring relationship. This is consistent with the results of the cointegration tests in Table 2. As the t-statistics in Table 2 show, for every product panel, the null hypothesis of no cointegration is rejected. Although the cointegration test indicates the presence of a cointegrating relation in the demand deposit panel, its adjustment coefficient is only marginally significant. Conversely, in the case of trade credit cointegration is confirmed only marginally by the panel ADF test, but its adjustment coefficient is highly significant. All other loan and deposit products are clearly cointegrated with their respective comparable market rates. Second, Figure 2 shows relatively large confidence intervals, for loans in particular. For the most part, this is due to the amount of cross-sectional variation in the pass-through estimates, as the fifth column of Table 3 indicates. We now discuss our results for the measurement of the pass-through in detail.

Consider the long-run pass-through for loans, shown in Figure 2 and Table 3 (LT PT). The evidence reveals that the long-run response is one-for-one only for two of the corporate loans, *viz.* the term and investment loans (their estimated long-term pass-through is 0.92 and 1.01, respectively). The remaining products exhibit an incomplete pass-through[13]. We stress that, in contrast to much of the existing literature, the completeness hypothesis is now truly tested. Regarding the point estimates, the long-run pass-through is relatively low for the two consumer-oriented products (69% for consumer credit and 87% for mortgages). The fact that the pass-through is often incomplete in the long run warrants caution in interpreting results stemming from estimations imposing complete long-term pass-through. At this point, it is not possible to distinguish whether the incomplete transmission

[13] Note that in the presence of a financial accelerator, one can expect to find a loan rate pass-through that exceeds one. In other words, an increase in market rates may well give rise to an increase in the external finance premium (see e.g. Repullo and Suarez, 2000). We find no evidence of such a phenomenon, which need not be surprising. Recall that the loan rates in the analysis are those charged to the most creditworthy borrowers, for which financial accelerator effects play no role.

is due to market power on behalf of the banks or due to an inelastic loan demand. An interesting result is that long-term adjustment is more complete for both firm and consumer loans the longer their maturities. This result has not been identified in previous research due to either a lack of products to compare with, or the use of a short-term market rate, rather than one with comparable maturity. Pass-through estimates that do not distinguish between marginal cost and term structure effects -using the short-term market rate as marginal cost-, typically find the opposite: the pass-through is lower the longer the maturity of the product. Our results show that this finding is only due to the incomplete transmission of short rate movements to the entire yield curve. Conform the bulk of evidence in the literature, we also find considerable short-term stickiness (see ST PT in Column 3 of Table 3), although there are differences across the respective loan products. Just as in the long run, this stickiness is most pronounced for the consumer loans in our sample, while only to a lesser extent for firm loans. Regarding the consumer loans, at most 40% of the long-term pass-through is adjusted on impact, whereas for firm loans at least 75% of the final response is immediately realized. With respect to the speed of adjustment, computation of the mean lag reveals a similar result. Banks are slower in their adjustment to market rates for consumer-oriented products.

Turning to deposits, an inspection of the estimates in Table 3 shows that complete long-run pass-through is almost always rejected statistically, although not for the long-term time deposit and only marginally so for the savings bond with long maturity (point estimates of 0.98 and 0.96, respectively). For time deposits and savings bonds point estimates of the long-run effect are found to be higher for longer maturities. Thus, liabilities seem to exhibit a similar maturity effect as the one found for loans. Although there is some immediate stickiness, adjustment to the long-run level is rapid. Table 3 shows that mean lags for time deposits and savings bonds are typically very low, mostly below 1.5 months. Demand and savings deposits, on the other hand, show a different picture. Adjustment is particularly sluggish for both these products, as indicated by their mean lags (up to 7 months for saving deposits). Moreover, the estimated immediate pass-through is 6% for savings and

14% for demand deposits. Even in the long run, the response is far from complete (63% and 49%, respectively, and these estimates are significantly different from one). Hence, the Belgian bank deposit market seems to consist of two distinct segments. The first is the market for time deposits and savings bonds, where banks seem to follow changes in market conditions quite rapidly in their competition for the deposits of companies and households. The second is the segment of current and savings accounts, where adjustments to market conditions are much slower and competitive pressure seems to be lower.

The observation that consumers are faced with less competitive pricing is consistent with the model of Rosen (2002). The latter argues that the more sophisticated (in terms of search intensity and access to alternative finance) customers are, the more complete the pass-through will be. Rosen (2002) finds evidence for his model using aggregate U.S. deposit data. Interpreting consumers as being less sophisticated than firms, we too find evidence in support of his model, but using disaggregated data on loans. The finding that the interest rate pass-through is faster and more complete for corporate loans than for consumer credit may have implications for the ability of the central bank to influence investment versus consumption decisions. In particular, the relatively weak pass-through of consumer loans may be a key element in understanding why the ECB's policy decisions have a stronger impact on investment relative to private consumption (Angeloni et al., 2004).

The other observation, *viz.* the longer the maturity of the product, the more complete the pass-through, is consistent with several theoretical considerations. Firstly, the longer the maturity of a product is, the larger the scope for moral hazard phenomena to occur. In an attempt to avoid this, banks can follow the market more closely (reflected in a higher pass-through). Secondly, the maturity effect can also be rationalized by more intense bank or non-bank competition in longer term-markets. The higher long-term pass-through for longer term products is not linked to lower (static) measures of concentration (e.g. Herfindahl-index) in those markets. Unfortunately, dynamic measures of competition as well as indicators of non-bank competition are not available at the level of disaggregation our products require. Thirdly, products with longer maturities are typically those with large underlying amounts. The higher the amount of the loan, the more significant interest payments become for the customer. Hence, for these products the search for banks offering competitive conditions is more intense (Stigler, 1961). Increased customer search implies more competitive behavior among banks, and thus a more complete pass-through. Finally, a similar argument could hold from the bank's perspective. Not only for its customers, but also for the bank interest payments are more substantial for longer maturities. Thus, deviating from the competitive pass-through is potentially more costly in terms of expected loss for longer term products. The reverse argument -with the bank as a debtor and the consumer as a creditor- can rationalize the maturity effect for deposits.

3.3 *Robustness*

The main goal of this section is to ascertain whether the conclusions based on the measurement of the pass-through are robust to changes in the empirical specification[14]. First, Appendix A demonstrates that pass-through estimates hardly change when considering an alternative weighting of individual coefficients. Second, Appendix B analyses to what extent our results suffer from a bias due to the presence of the lagged dependent variable in the model or due to nonlinearity of pass-through measures. Overall, the analysis and discussion of these two biases presents some good news for our analysis and possibly for pass-through research in general. Even though there may exist some minor differences in point estimation, broad conclusions about the measurement of the pass-through do not seem to suffer from lagged dependent variable or nonlinearity bias. Third, the maturity effect is confirmed when the average long-run coefficient is estimated using a variable coefficient model, rather than the estimator suggested by Phillips and Moon (1999). Fourth, inflation and the business

[14] Detailed results are available upon request.

cycle do not appear in the pass-through model (1)-(2). The rationale for such a specification is that movements in inflation or output relevant for banks' marginal costs should be reflected in the respective money market rates. There might be a concern that market rates do not capture all relevant information contained in both these macro variables. We therefore add consumer price inflation and a measure for the business cycle to the model. Results are very robust to the inclusion of inflation. Inclusion of the monthly business cycle indicator constructed by the NBB increases the long-term pass-through estimate for consumer credit, while leaving other products' estimates virtually unaffected. Note, however, that the sample for consumer credit is the shortest one in the dataset, explaining some of its variability. As a result, for consumer loans, there is no confirmation of the maturity and the consumer effect in the long run. Both effects remain present in estimates of the short run pass-through. Moreover, the estimated adjustment coefficients affirm the sluggish response of consumer loans. Furthermore, the maturity effect is confirmed for firm loans, saving bonds and term deposits. Fifth, from a general price-setting point of view, the presence of price staggering induces firms to also consider expected future marginal costs in setting today's prices. As these are not incorporated in the model, this might explain the finding of increased stickiness for shorter term products. For these products expected future marginal costs are, in line with the pure expectations theory, contained in long-term interest rates. If the maturity effect would indeed be due to a misspecification of marginal costs, we should not find it when measuring the pass-through relative to a longer term money market rate. Thus, as a robustness check for the maturity effect, we also estimate the pass-through of the five-year market rate to each product's interest rate. While point estimates (obviously) differ, the positive relation between the pass-through and the maturity of the product still stands[15]. Thus, we find that the maturity effect is robust to the specification of

[15] For brevity, we do not report the exact results, but they can for the long-term pass-through largely be inferred from the correlations in Table 3. There it is apparent that considering expected marginal costs (in terms of longer term market rates) does not entail a more similar pass-through for long and short term products.

marginal costs[16]. The same is true for the consumer effect. Finally, in each of the above robustness checks the relative stickiness of demand and savings deposits is confirmed.

3.4 EMU

After the completion of the EU single market in 1993, the introduction of the euro in 1999 was intended to be the final milestone in the creation of a truly integrated banking market in the Eurozone. However, studies on the remaining legal and cultural barriers (see Heinemann and Jopp, 2002) and empirical evidence on the pricing of retail banking products (see Corvoisier and Gropp, 2002) indicate that the degree of integration of Eurozone bank markets differs markedly between the wholesale, corporate and customer retail market segments. Within the context of interest rate pass-through, de Bondt (2002) and Sander and Kleimeier (2004) provide evidence suggesting less competitive behavior after the launch of EMU. Similar to those studies, we re-estimate the pass-through for the EMU period (1999-2002) separately[17]. The results are presented in Figure 3 and tend to confirm the weakening of the pass-through. Moreover, the variety of products in our analysis yields some additional insights.

Concerning the bank assets in our analysis, once again, a distinction should be made between firm and consumer-oriented products. The figure illustrates that the shift to EMU seems to have resulted in less competitive pricing of consumer products. From an economic point of view, the drop in both immediate and long-term pass-through is considerable for mortgages and consumer credit (e.g. the long-term pass-through for consumer credit is 0.58 in the EMU era compared to 0.69 for the full sample). We also observe an increase in the mean lag, altogether implying a slower adjustment to a lower long-run level. For firm loans, no such clear pattern is observed. Adjustments in long and

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[16] There seems to be some negative correlation with the volatility of the market rate, but one would expect such volatility to have its effect on the speed of adjustment and/or margins, rather than on the long term pass-through. Higher volatility poses a signal extraction problem which vanishes (averages out) in the long run.

[17] This section contrasts the EMU subsample estimates with those of the whole sample. Comparing with the pre-EMU estimates does not change any of the conclusions.

short-term responses often go both ways. For the firm loans with very short maturity there seems to be an increase in sluggishness, while the others exhibit a minor drop in their mean adjustment lag. For liabilities, the results indicate a fall in long-term pass-through for all term deposits and savings bonds. This is combined with a rise in the short-term response for these products. Overall, the adjustment becomes quicker, but smaller. A remarkable response is found for the demand and savings deposits. In the EMU era, they no longer show any reaction to the respective market rates. Thus, our pass-through results for the Belgian bank market lend no support to the conjecture that the single currency spurred more cross-border (actual or potential) competition. By contrast, consumer loans, saving deposits and demand deposits all experience a considerable drop in pass-through.

3.5 Nonlinearities

The present section deals with deviations from the symmetric pass-through as modelled in Section 3.1. Knowing the extent to which retail rates react differently to rising compared to falling interest rates can yield insights in the mechanics of the monetary transmission process. An asymmetric pass-through provides a potential explanation for the difference in effectiveness of expansionary and contractionary monetary policy (see e.g. Cover, 1992).

Our analysis differs in a number of respects from the literature. We share the use of micro data with Neumark and Sharpe (1992) and Hofmann and Mizen (2004). While the former adopt a pooled coefficient panel approach and the latter refrain from panel analysis -stressing heterogeneity-, our model allows heterogeneity over banks within the panel approach. In addition to efficiency gains, the panel approach allows observations on a macro scale. Second, while the US has been extensively analysed (Hannan and Berger, 1991; Neumark and Sharpe, 1992), and there is some evidence for the UK (Hofmann and Mizen, 2004), we know of no micro-evidence on asymmetry for the Euro Area. Third, we try to unify much of the existing types of asymmetry into one convenient but comprehensive form. The resulting advantage is that we allow several theories/types of asymmetry to coexist. The focus of much of the existing literature is on the choice of the driving process (see e.g. Frost and Bowden, 1999; Hofmann and Mizen, 2004; Sander and Kleimeier, 2004). Our model puts more emphasis on the exact form of the reaction, rather than the source of the shock[18].

Similar to most of the existing literature, we focus on asymmetries in the speed of adjustment[19]. Consider the following expression for γ_i, the adjustment coefficient of the error correction model (*2*), as our baseline specification:

$$\gamma_{it} = \gamma_{i1} + \gamma_{i1}^{+} \cdot \mathrm{I}(u_{it-1} \geq 0) + \gamma_{i2} \cdot u_{it-1} + \gamma_{i2}^{+} \cdot u_{it-1} \cdot \mathrm{I}(u_{it-1} \geq 0) + \gamma_{i3} \cdot (u_{it-1})^2 + \gamma_{i3}^{+} \cdot (u_{it-1})^2 \cdot \mathrm{I}(u_{it-1} \geq 0) \qquad (3)$$

where *I(.)* is an indicator function equal to one when the condition in brackets is fulfilled and zero otherwise. Equation (*3*) makes the dynamic adjustment regime dependent. The driving force is the deviation from equilibrium. In the lower regime (i.e. below the cointegration relation) the adjustment is characterized by the coefficients[20] γ_1, γ_2 and γ_3. The upper regime measures the adjustment based on $\gamma_1 + \gamma_1^+$, $\gamma_2 + \gamma_2^+$ and $\gamma_3 + \gamma_3^+$. The specification captures several types of adjustment behavior economic theory suggests. First of all, notice that equation (*3*) nests the simplest type of adjustment as described in Section 3.1. $\gamma_1^+ = \gamma_2 = \gamma_2^+ = \gamma_3 = \gamma_3^+ = 0$ implies that adjustment towards equilibrium takes place at a given rate γ_1, regardless of where the bank retail rate is with respect to the money market interest rate. Several theoretical contingencies, however, imply that the speed of adjustment does depend on the value of the retail interest rate, relative to its equilibrium. The following presentation of these contingencies focuses on lending rates, but note that every mechanism could equally apply to deposits.

[18] The difference is a subtle one. While combination of several drivers can result in functional forms similar to the ones we propose, we argue that these functional forms are possibly relevant for every driver in its own. In our view, in order to grasp the micro bank incentives, understanding the functional form is the more promising approach. A combined analysis of both the functional form and the possible driving forces is left for future research.

[19] In principle, one could allow asymmetries in each coefficient of the ECM, but this is typically avoided in order to keep the model tractable (see e.g. Neumark and Sharpe, 1992; Frost and Bowden, 1999; Sander and Kleimeier, 2004). Alternatively, Borenstein et al. (1997) consider an ECM which allows all parameters but the adjustment coefficient to vary.

[20] In the remainder of the section, we drop the "*i*" subscripts.

Banks have little incentive to adjust their retail lending rates when they are above their equilibrium value ($r_t > c_2 + \delta \cdot m_t$ in terms of equation (*1*)). During such a period they earn positive "supermargins"[21]. Whenever banks have some market power, such behavior could be sustained. If, however, the market is characterized by customers with sufficiently high (absolute) demand elasticities, such a policy of prolonged deviations from equilibrium prices would result in a loss of demand, potentially more than offsetting the gain in profits due to the positive supermargin. Similarly, margins temporarily below their equilibrium value erode the bank's profits, and will thus stimulate it to swiftly increase its lending rate. Again, such a reaction could be hampered by fears of customer retaliation. Both these mechanisms could be at work, and perhaps differently so depending on the sign of the deviation from equilibrium. Consumer retaliation, for example, might be especially relevant in instances of negative supermargins, where banks are tempted to increase their lending rates. In case of positive supermargins, rather, the bank may prove to be unwilling to lower its lending rates. γ_1^+ captures the possibility of such asymmetric reactions. For loans (deposits), a significantly positive (negative) estimate of γ_1^+ indicates that banks are slower in adjusting retail rates when their mark-up (mark-down) is above its equilibrium level. An opposite sign would provide an indication of asymmetry consistent with the customer retaliation hypothesis. Asymmetry is modelled in a similar fashion in Levine and Loeb (1989), Neumark and Sharpe (1992), Scholnick (1996), Frost and Bowden (1999), Mojon (2000) and Sander and Kleimeier (2004).

Inclusion of γ_2 takes into account the possibility that the same bank will adjust faster when its retail interest rate is a certain amount below the value consistent with its long-run mark-up, than when it is, e.g., only half that amount below its equilibrium value. In economic terms, we expect γ_2 to be positive (negative), meaning that the bank's incentive to adjust its loan (deposit) rates is a negative function of its supermargin. Again, as the size of the margin could have a different effect depending on its sign, we also estimate γ_2^+. A finding of $\gamma_2 > 0$ and $(\gamma_2 + \gamma_2^+) < 0$, for instance, means adjustment is

[21] We label residuals from equation (*1*) supermargins to indicate temporary deviations from the long run margin c_2.

faster the further prices are from their equilibrium value. Combined with an asymmetric γ_1 this formulation also allows for downward nominal price rigidity (e.g. $\gamma_1^+ \geq 0$, $\gamma_2^+ \geq 0$). Frost and Bowden (1999) and Hofmann and Mizen (2004) also suggest that the adjustment dynamics possibly depend on both the sign and the size of the deviation from equilibrium.

An even more elaborate specification is designed to cope with the possibility of increasingly large rigidities, the closer the retail rate is to its marginal cost. First, the incentives that are captured by γ_2 could become increasingly more important for larger deviations from equilibrium. Second, theories of menu and switching costs imply relatively weak transmission of shocks when the retail interest rate is in the vicinity of its equilibrium, but faster adjustment for larger deviations. Third, the reverse phenomenon, *viz.* little adjustment in case of large (positive) margins, or alternatively, the persistence of large gaps between the market and retail interest rates, is a time-series implication of Rosen's (2002) model. The switching cost prediction implies $\gamma_3 < 0$, while the opposite result would provide support for the conjecture of Rosen (2002). This specification is also related to the Band-TAR* model of Sander and Kleimeier (2004). In their model there is an interval around equilibrium in which the bank rate adjusts differently in comparison with large deviations. While our model does not generate exact bounds, it captures the same idea in a continuous fashion[22]. Moreover, the present model potentially attributes increasingly more adjustment speed to supermargins further away from equilibrium. Again, there may be reasons to suspect that the proportionality differs depending on whether the retail rate is above or below the cointegration relation. We therefore also include γ_3^+ in the baseline specification.

In the above model, asymmetry is considered relative to equilibrium. One could argue, however, that the relevant threshold for the residuals is different from zero. A simple menu cost story could

[22] We also examined models with two thresholds to account for distinct adjustment in the neighbourhood of the equilibrium (as in Sander and Kleimeier, 2004), in addition to the possible dynamics described in (2). These models do not seem to add much relative to the estimates of the two-regime models.

motivate such a bound. It is conceivable, for example, that banks only raise loan rates when the margin is sufficiently low, such that the fall in profits exceeds the menu cost. In the empirical implementation of the above models, we allow for a threshold different from zero in a manner similar to the one in Sander and Kleimeier (2004). More specifically, the optimal threshold is that point in the middle 80% of the domain of the residuals for which the model's likelihood is maximal. Starting from (*3*), we perform a general-to-specific procedure to determine the optimal model.

Figure 4 plots the implied adjustment coefficients for each of the products we consider. Point estimates are shown in Table 4. The implied adjustment coefficients should broadly lie in the [-*1,0*] interval to confirm cointegration[23]. The present models, however, allow for a non-constant speed of adjustment, depending on the size and the magnitude of the deviation from equilibrium[24]. For both loans and deposits, even though there are some differences in the exact form of the asymmetry, we find highly negative adjustment coefficients the further the residuals are from zero (or away from the estimated threshold). All the optimal asymmetric models contain either a positive γ_2 combined with a more negative γ_2^+, or a negative γ_3 (possibly combined with a negative γ_3^+, or a positive one, but smaller in absolute value). Thus, one notable tendency of the retail interest rate adjustment process is that large deviations from equilibrium are swiftly corrected. Regarding the functional form in the case of loans, we find no clearly distinct asymmetric effects over products. Three of the loan products (bank advances, investment loans and mortgages) exhibit a symmetric adjustment process. For the other panels there is a minor difference in slope depending on the sign of the residual. After taking into account non-zero thresholds, we do not find that the slope is uniformly higher in one regime. Note that the general-to-specific procedure we employ forces us to pick one model out of the spectrum of specifications we consider. However, the difference between the competing models is often negligible (in terms of e.g. likelihood). The data show no clear distinction between an

[23] The (implied) adjustment coefficient can take on values outside the [-*1,0*] interval as long as there is a possible return to a stable, equilibrium-restoring value of the adjustment coefficient (i.e. within the interval).
[24] Dynamic coefficients of the ECM other than the adjustment coefficient are remarkably stable. This is reassuring for conclusions about the determinants of pass-through heterogeneity, which are based predominantly on the immediate and long-run pass-through regressions.

asymmetric slope model and a parabolic adjustment coefficient. Given that in the former type of model the difference between $|\gamma_2|$ and $|\gamma_2+\gamma_2^+|$ is often small, we view the evidence for asymmetry as not entirely convincing. Thus, although there may be some asymmetry in the loan rate adjustment process, the size effects are relatively more important. Turning to deposits, the evidence for asymmetric effects is somewhat more pronounced. In six of the seven panels, we find indications of asymmetric adjustment. Moreover, four of these models imply faster adjustment at times where the deposit rate is above its equilibrium value. In particular, the adjustment of the shortest maturity term deposit is characterized by $|\gamma_2| < |\gamma_2+\gamma_2^+|$ and the saving deposit has $|\gamma_3| < |\gamma_3+\gamma_3^+|$. The long maturity term deposit and the short term saving bond have a significantly negative intercept (γ_1^+) in the upper regime. These results suggest that the type of asymmetry Neumark and Sharpe (1992) show to be important in the US is also present in some of the Belgian deposit markets. In general, however, we do not find that adjustment is faster in one of the regimes. As for loans, each deposit (except for the demand deposit) exhibits faster adjustment for larger supermargins (in absolute value).

One type of nonlinearity the data strongly reject, both for loans and deposits, is the one advocated by Rosen (2002). He suggests that large deviations from equilibrium are persistent. By contrast, all the chosen models in our sample have one thing in common: the largest deviations are the ones that are most promptly corrected (indicated by relatively more negative adjustment coefficients on the outer parts of the x-axis). The finding of greater inertia in interest rates when they are close to their equilibrium level is suggestive of menu or switching costs at work. Menu cost theories predict that when the price is close but not equal to its desired level, small costs of changing prices will prevent a full equilibrium correction. Similarly, switching costs predict that small deviations from equilibrium will not be sufficient to make customers consider changing bank, and will thus hamper quick price changes.

3.6 *A comparison with non-heterogeneous evidence*

Since much of the empirical pass-through literature is based on aggregated data (see de Bondt (2002) for an overview), it is of interest to know to what extent aggregate findings relate to those based on the micro data they stem from. Aggregation may bias estimation, especially in dynamic relations (Harvey, 1981; Barker and Pesaran, 1990). To gain some insight in this respect, we also perform the analysis univariately on the aggregate Belgian ECB-retail rates over our sample period[25]. Although some of the estimates are in line using either data, lots of aggregate point estimates lie outside the confidence intervals surrounding the disaggregated estimates (detailed results available upon request). From an economic point of view, too, this is worrisome. Differences in (both long and short-term) pass-through often exceed 5 basis points, reaching a maximum difference of 18 basis points for the immediate pass-through of time deposits. Moreover, we find systematic underestimation of adjustment coefficients when estimation is based on aggregate series. Figure 5 graphically represents this underestimation. Thus, in contrast to the lagged dependent variable and nonlinear bias, aggregation bias may play an important role in pass-through estimations.

Appreciation of the possibility of aggregation bias has spurred pass-through research on disaggregate data (e.g. Cottarelli et al., 1995; Weth, 2002; Gambacorta, 2004b). However, merely changing the level of aggregation of the data does not guarantee to solve the problem. The reason is that banks may well be heterogeneous agents. In this subsection we shed light on the importance of this “heterogeneity bias”. We compare estimates of a pooled coefficient model to those of the random coefficient model. The former imposes parameter equality over all cross-sections and is predominant in the literature. The latter allows heterogeneous behavior between banks and is the preferred model for each panel in our analysis (see Appendix A). Long-term pass-through estimates are rather similar. A few exceptions notwithstanding, this is also the case for immediate pass-through estimates

[25] Since the ECB data do not cover all thirteen products in our dataset, we can only provide estimates for the available comparable products. All conclusions remain when we create mean series from our dataset and reinvestigate aggregation bias. Estimation results are available upon request.

(at least from a statistical point of view). Similar to the aggregate results, however, we find systematic underestimation of adjustment coefficients in estimating the pooled model, also shown in Figure 5. The bias in the adjustment coefficient is an indication of large underlying differences between banks.

Illustrations of and theoretical expressions for heterogeneity bias are provided by Robertson and Symons (1992), Pesaran and Smith (1995) and Pesaran et al. (1996). Intuitively, both the aggregate and the common coefficient approach average the data before estimation, whereas the heterogeneous model averages afterwards. Averaging the data before estimation has the effect of eliminating heterogeneity. Whenever cross-sectional units are indeed heterogeneous, imposing them to behave identically will result in inconsistent estimates. The inconsistency is due to the fact that, as heterogeneity is suppressed, it will show up in the residuals. As a result, there will be a non-zero correlation between regressors and residuals, thus violating the OLS-assumptions. In our sample the inconsistency is most severe in the estimation of adjustment coefficients. Figure 5 visualizes the systematic underestimation in adjustment coefficients, by plotting them over the different models.

What the discussion of aggregation and heterogeneity implies for pass-through research is the following. From an economic point of view our results indicate that banks respond quicker to changing money market rates, and, by implication, to policy rates, than was previously believed. Such information is relevant in that it can help understand (lags in) the monetary transmission mechanism. One should be careful in interpreting point estimates based on aggregate retail interest rate series, as these are potentially misleading. Analysis of disaggregate series eliminates aggregation bias, but may still suffer from a bias due to heterogeneity. The solution to this problem lies in incorporating heterogeneity into the model. This section does so by estimating random coefficients, which also control for measurement error. The following section in addition considers systematic (or bank-specific) heterogeneity.

4 Determinants of heterogeneity in pass-through

In this section we investigate whether bank characteristics, such as the balance sheet structure, the risk profile or the market share of the bank, systematically cause a faster or more complete pass-through of market to retail interest rates. We first address some methodological issues. Next, we give an overview of the factors that might explain cross-bank heterogeneity in adjustment. Subsequently, we estimate the model and interpret the results.

4.1 Methodology

From Section 3.2 we have both bank-specific and average (Swamy or Phillips-Moon) pass-through measures. We use this information to investigate whether bank-specific characteristics explain heterogeneity in pass-through. To this extent, we regress the differences between individual bank and average pass-through coefficients on a number of bank characteristics. Product-specific effects cancel out by considering deviations *vis-à-vis* the average product-specific (Swamy or Phillips-Moon) estimates. Thus, the focus of the analysis is on bank-specific, rather than market driven differences in pass-through. For the latter, we refer to e.g. Neumark and Sharpe (1992) and Mojon (2000). The characteristics we consider are structural in the sense that they capture typical features of banks that do not change very much over time, such as balance sheet structure or market position[26]. In the analysis, we pool along the product dimension, assuming that bank characteristics isomorphically affect the pass-through across products. However, we maintain the distinction between loan and deposit products, because their pricing may be driven by different factors. Thus, for each of the three pass-through measures (the immediate pass-through, the long-run pass-through

[26] One instance in which such characteristics do change significantly over time is the case of mergers. The fact that we treat merged banks as different units before the merger (see Section 2) implies that this effect is taken into account in the analysis.

and the adjustment coefficient), we pool the individual deviations from the average estimator into one dependent variable across the six loan products and across the seven deposit products.

The presence of heteroscedasticity complicates estimation of the model. Within the above setup, heteroscedasticity comes into the equation in at least three ways. First, the dependent variable contains a parameter estimate that is the result of an individually estimated equation. As each of these parameters has a different variance, the homoscedasticity condition will be violated. Second, the left hand term also contains the Swamy-estimate, which is a weighted average of all individually estimated parameters within a product category. Unless all individual coefficient estimates share the same variance, there will be some observation-specific covariance between the individual and Swamy coefficients. This covariance is a second source of heteroscedasticity. Third, all the observations within a product-class have some common variance. By pooling over products, each observation will inherit some product-specific variance, again causing heteroscedasticity. For a large part, the form of the heteroscedasticity is known. Hanushek (1974) shows how to incorporate sampling error of the first kind in the model using Feasible Generalized Least Squares. With some minor modifications, we extend Hanushek's method to also capture the second and third kind of variance. In addition, following Greene (2000), we compute White-heteroscedasticity-consistent standard errors to control for possibly remaining heteroscedasticity of unknown form.

4.2 Bank characteristics and interest rate pass-through

In order to identify the bank characteristics that may influence the pass-through of market to retail interest rates, we review several types of literature and examine their relation with interest rate pass-through. More specifically, we consider studies on the role of banks in monetary transmission and studies on the determinants of bank interest margins and profitability.

The literature concerned with the credit channel of monetary policy transmission has stressed the importance of banks' financial structure, in particular bank capitalization and liquidity, in determining their responsiveness to monetary policy. Poorly capitalized (Kishan and Opiela, 2000) and illiquid (Kashyap and Stein, 2000) banks are hypothesized to be relatively vulnerable to monetary, and by implication, market shocks. Moreover, banks have to maintain regulatory capital against their risk-weighted assets, implying that their capacity to expand lending depends on their capital adequacy. In line with most other research, we measure the capital position of a bank as its capital-to-asset ratio. We expect that the capital position of a bank and both its lending and deposit interest rate pass-through will be negatively related. As a measure of liquidity we include the ratio of cash plus securities over short term deposits in the empirical analysis. Similar to equity, we expect liquidity to act as a buffer against market fluctuations, implying a negative effect on pass-through. Contrary to most analyses in the credit channel literature, we do not consider bank size as a separate characteristic. Both from a theoretical and an empirical perspective, bank size is usually considered to proxy for some (mostly conjectured) size-related characteristics, for which data are not available. We explicitly take into account the effect of these size-related factors, leaving little independent scope for bank size in the analysis.

Since a bank's price-setting behavior is affected by its risk, we include two specific types of risk, i.e. default and interest-rate risk, and one general measure of diversification. The maturity transformation a bank performs, exposes the bank's profits to fluctuations in market interest rates. The extent of interest-rate risk exposure is positively related to the relative importance of interest-sensitive assets and liabilities. Similar to Weth (2002), we approximate interest rate risk by the ratio of long-term assets over liabilities. The conjectured effect of interest rate risk on pass-through is positive. A bank vulnerable to interest rate risk requires lots of hedging activities, whose terms are typically closely tied to the market. Similarly, one might expect a positive effect of default risk on (loan and deposit) interest rates. However, on the lending side, the level of default risk in the loan portfolio will also determine the conditions for future lending and, consequently, the reaction of the bank to changes in market conditions. A bank will only lend to riskier borrowers when it is capable of compensating expected losses by charging higher than competitive loan rates. Overall, the expected effect of default risk is thus ambiguous. In the empirical application we approximate default risk by the ratio of non-performing loans to total credit. Finally, we also include a measure of diversification in the analysis as an overall indicator of the bank's riskiness. A bank that is not only active in traditional intermediation, but also in other financial services such as insurance, investment banking or asset management is assumed to be less vulnerable to shocks in the interest rate environment than specialized retail banks. As a measure of diversification, we construct the ratio of non-interest operating income to total operating income. The expectation is that changing market conditions will have only a limited effect on the loan and deposit prices of diversified banks.

Another obvious determinant of bank pricing behavior is the degree of competition in the loan or deposit market. Since Berger and Hannan (1989), tests discerning between the structure-conduct-performance and efficiency hypotheses in explaining bank margins and bank profitability have attracted considerable interest in empirical banking. Recall that we control for the effect of product-related determinants (such as concentration) by considering deviations from the average pass-through measure. Instead we rely on bank-specific indicators of market power, i.e. the bank's market share in the loan or deposit market. The market share measure is calculated for each of the loan and deposit products separately. This is consistent with the relative market power hypothesis advanced by Berger (1995) which states that banks with large market shares may be able to set interest rates less competitively. A negative effect of the market share variable on the pass-through would thus corroborate the relative market power hypothesis. The alternative hypothesis is that bank pricing decisions are driven by the degree of operational efficiency as opposed to its market power. The rationale is that efficient banks will have the incentive to pass this advantage on to their customers in the form of below-average lending rates or above-average deposit rates, thereby allowing them to increase their market share. We measure the degree of each bank's operational inefficiency with the cost-income ratio (see e.g. Vander Vennet, 2002) and we expect a negative relationship with the estimated pass-through intensity.

Finally, similar to Gambacorta (2004b), we include two variables in the loan regressions to measure possible effects of relationship lending. On the lending side, the percentage of long-term loans in total loans is intended to proxy for long-term contacts between a bank and its customers (see Berger and Udell, 1992). The hypothesis is that relationship banks will tend to smooth market shocks for their customers by smoothing interest rates over the business cycle. We also include the ratio of demand and savings deposits to total deposits to verify the thesis of Berlin and Mester (1999) who suggest that banks with a stable pool of deposits, which leaves them less vulnerable to exogenous interest rate shocks, will provide more loan interest rate smoothing.

Inclusion of the above variables also allows us to investigate the importance of some of the different channels of monetary policy transmission. First and foremost, the bank lending channel posits that in the face of shocks, illiquid banks are unable to insulate their loan supply (Kashyap and Stein, 2000). Liquidity can be interpreted broadly and should capture at least two possible shock-offsetting mechanisms. First, banks with a substantial buffer stock of liquid assets will be more able to sustain lending policies, regardless of monetary or market movements. Second, even when such a buffer does not exist, some banks are able to fund themselves relatively easily in the (uninsured) deposit market[27]. The latter source of funds should be accessible especially for well-capitalized banks (Kishan and Opiela, 2000). The second subchannel of the credit view we discuss is the bank capital channel (e.g. Van den Heuvel, 2001). Via this channel, monetary (and real) shocks affect banks' loan supply by influencing the ability of banks to acquire equity in the face of a capital constraint. Monetary shocks, for instance, affect banks' profitability. A natural channel through which this

[27] This is the point Romer and Romer (1990) make for the banking sector as a whole, but with which credit view (bank lending channel in particular) proponents disagree.

operates is via the maturity mismatch in banks' balance sheets. Thus, the extent to which profits fluctuate with these shocks depends on the amount of interest rate risk a bank is exposed to. Banks are able to raise equity only when profits are sufficiently high. Bank equity, in turn, determines bank lending through the existence of capital requirements.

4.3 Results

The results are summarized in Table 5. This table shows the estimated coefficients per equation horizontally, or per bank characteristic vertically. We also report t-statistics, the range of the bank characteristics and the implied differences in pass-through between the 25th and 75th percentile bank. Recall that 1) the left hand side is specified as deviations from the average and 2) the adjustment coefficient is negative, such that a negative effect on this measure implies a faster pass-through.

The results show that the baseline model is able to capture heterogeneity mostly for the long-run pass-through and least for the adjustment coefficient. This finding is in contrast with Gambacorta (2004b), who finds no heterogeneity in the long run. The rather low goodness-of-fit measures in Table 5 are not only a common finding in cross-sectional regressions, but possibly an indication of random heterogeneity in the adjustment process. Moreover, the results presented are those of the baseline specification, which still contains insignificant variables.

As Table 5 shows, we find no evidence supporting the relationship lending hypothesis. The long-term loans and core deposit indicators are always insignificant. In the adjustment coefficient regression -the coefficient for which the relationship lending hypothesis has the clearest prediction (see Berger and Udell, 1992)- both indicators even have the wrong (negative) sign. This finding contrasts with the evidence of Berlin and Mester (1998) for the US. They find that banks with a stable pool of core deposits exhibit smoother price setting behavior. This does, however, not necessarily preclude the existence of relationship banking in the Belgian market. Relationships can, for instance, manifest themselves in the availability of loans (credit lines), rather than in their conditions.

Turning to competition effects, we find that efficiency never induces banks to price more competitively. If operational efficiency were to strengthen the pass-through, we would expect to find a negative (positive) sign for the cost-income ratio in the regressions with the short-term or long-term pass-through (adjustment) coefficient as the dependent variable. If anything, we find the opposite. But only in the case of the adjustment coefficient for loans (-0.784) is the unexpected sign significant. Hence, inefficient banks are generally found to mimic market conditions more closely than the average bank. For the short-term pass-through on loans, we find that a bank with a high market share exploits its market power by following market movements less closely (the coefficient is -0.005 and significant). For the long-term pass-through the market share variable is significant at the 10% level only. However, other specifications -dropping insignificant variables[28]- confirm the significantly negative effect of market shares on the pass-through. At first sight, the economic significance, measured by the implied difference in pass-through between the 25th and 75th percentile bank, seems rather small (-0.021 for the long-term and -0.033 for the short-term pass-through). Notice, however, that the distribution of market shares is highly skewed, indicating that market power is concentrated in a few banks. The implied difference between the 25th percentile and the bank with the largest market share is as large as 34 basis points in case of the short term pass-through. Market shares never influence the adjustment speed in significant ways. In sum, for loans it seems that market power will give rise to less competitive pricing policies, strengthening the case for the relative market power hypothesis. This may have implications for the application of national competition policy in the banking sector.

[28] Results are available upon request.

Table 5 shows that while credit risk has a positive and significant impact on deposits' long-term pass-through, interest rate risk has a significantly positive effect on the short-term pass-through of loan rates. Both are consistent with Weth's (2002) conjecture: banks with a large (interest-rate or credit) risk exposure require lots of hedging activities, whose terms are market-related. In the adjustment coefficient regression for loans the diversification measure is highly significant. Regarding the sign of the response, Table 5 shows that a high diversification variable increases the adjustment coefficient (relative to the average). Thus, the results indicate that diversified banks are slower in adjusting retail loan rates in response to changing market conditions. Hence, banks that are active in different financial market segments are able to smooth interest rate shocks.

Capital is probably the most discerning characteristic in explaining retail bank interest rate pass-through heterogeneity. The capital variable is negative and very significant in the (long and short-term) pass-through regressions for both loans and deposits. Well-capitalized banks exhibit stickier interest rate setting behavior. In economic terms, the 25^{th} percentile bank has a pass-through that is ten to twenty basis points higher than the 75^{th}. The results also indicate that better capitalized banks are more sluggish in adjusting loan rates to market conditions. Liquidity has a similar effect on pass-through as capital, albeit less economically and statistically significant.

These results allow some observations regarding the respective channels of monetary transmission. The fact that liquidity has a negative effect on loan pass-through (the adjustment coefficient is high relative to the mean, implying slower adjustment) is supportive of bank lending channel effects. Liquid banks react less to market movements. We also find that the pass-through is higher for poorly capitalized banks. This finding is consistent with both the bank lending and bank capital channel, which are not mutually exclusive. For the bank lending channel to cause this, a well-capitalized bank should have less problems in generating liquidity, other than from liquidating its buffer stock. In the US, the typical alternative source of liquidity is certificates of deposits. In EMU, and Belgium in particular, the use of such certificates is not widespread. The response of the liabilities in the analysis may give a more meaningful indication. Indeed, it seems that well-capitalized banks set deposit prices less competitively. To the extent that this is due to depositors perceiving these banks as less risky[29], this is additional evidence in favour of the bank lending channel. Gambacorta (2004a) demonstrates similar cross-sectional effects of capital on deposit quantities in the Italian banking market. In order to test for the bank capital channel we include a dummy variable that equals one for those banks that are both lowly capitalized and have a high interest risk exposure. The channel predicts that poorly capitalized banks with a large exposure to interest rate risk react more to monetary and market shocks. If the bank capital channel is at work, we should find a significantly positive (negative) effect on the pass-through (speed of adjustment). The estimation results (Table 6, panel A) show that whenever the dummy is significant it has the wrong sign. Hence, we find no evidence of a bank capital channel in Belgium. Note that in Table 6 the significance of liquidity is reduced. While this somewhat weakens the evidence in favour of the bank lending channel, the capital variable is still very significant. Especially since the bank capital channel is identified separately, this still supports the bank lending hypothesis, through heterogeneity in the ability of raising deposits.

A final but nonetheless important remark is the following. The evidence presented here is capable of discerning whether there is scope for the different channels. As described above, our results are consistent with the existence of a bank lending channel. However, we do not claim to disentangle loan supply from loan demand effects. As a result, our results are to some extent also consistent with a financial accelerator interpretation, as in e.g. Gertler and Gilchrist (1994) and Oliner and Rudebusch (1996). The possibility that e.g. highly capitalized banks mainly serve those firms whose loan demand is relatively less dependent on market conditions, rather than using their capital as a

[29] Kashyap and Stein (1995) show for the US that after a monetary restriction different types of banks face a similar drop in deposit quantities. If some banks set prices less competitively, this implies that these banks have easier access to alternative deposits, probably because they are perceived as less risky by depositors.

buffer to insulate their loan supply, remains open. Such a setting possibly generates observationally equivalent pass-through implications. Nevertheless, we feel the evidence is highly suggestive of a bank lending channel, rather than a financial accelerator. This is based on 1) the fact that the lending rates studied are those charged to the most creditworthy borrowers, and 2) the finding of a lending pass-through smaller than one. The former argument would lead one to think that external finance premium considerations play little or no role for these borrowers. The latter is inconsistent with a rise in the external finance premium in response to increases in the market rate, as predicted by the financial accelerator. Thus, in sum, investigation of "prime" loan rates effectively resolves the identification problem.

4.4 Robustness

Bank size was not incorporated in the above model because we attempt to capture the characteristics it proxies for explicitly. We now check whether our results depend on that particular assumption. Even though we explicitly take into account variables that bank size usually proxies for, there might be some useful information in size that none of the variables in our baseline specification is able to capture. As an example, several authors have claimed that large banks predominantly serve large firms. Large banks are also most likely to be publicly traded. In view of these considerations, we first orthogonalize (the logarithm of) bank size with respect to the variables in the baseline specification. Thus, we control for the fact that e.g. small banks are typically the best capitalized and least diversified ones. Next, we include the orthogonalized size variable into our baseline specification. Table 6 (panels B and C) presents the results. First, bank size is always significant in the loan regressions. Its effect on both the pass-through and its speed is positive. One possible interpretation for this finding is that large firms, whose bank loans are granted mostly by large banks, also have access to market based funds. As a result, the larger banks face a larger degree of non-bank competition, implying closer ties with market conditions. Second, the regression casts doubt on the effect of diversification. While the previous estimates indicated a slower pass-through for diversified banks, the results in Table 6 suggest that diversified banks exhibit a higher (short and long-term pass-through). Third, all other conclusions are robust to the inclusion of the size variable.

The estimation strategy described in Section 4.1 explicitly takes into account known forms of heteroscedasticity. As an alternative approach to estimation, we ignore knowledge on the sources of cross-sectional variance and perform a simple Least Squares regression with White-corrected standard errors. On the lending side, capital retains its significantly negative effect on both short and long-term pass-through. The significance of interest rate risk is reduced but remains in regressions where insignificant variables are dropped. Although to a lesser extent, the same holds for market shares. On the deposit side, the positive effect of credit risk on the long-term pass-through is no longer significant. The effects of both capital and liquidity are very robust.

5 Conclusion

We analyse the pass-through of market conditions to retail bank interest rates in Belgium. The dataset covers bank-level interest rates for thirteen products, both assets and liabilities, with long and short maturities and oriented to both firms and consumers.

We start by measuring the extent of pass-through for each product. We find that corporate loans adjust both quicker and more complete to changes in money market rates of comparable maturity, relative to consumer loans. This finding is possibly a key element in understanding the relative response of aggregate consumption and investment to monetary policy. Concerning bank liabilities, market rates quickly transmit in both time deposits and savings bonds. Demand and savings deposits, however, exhibit a very sluggish response that is far from complete. Hence, banks appear to consider the segments of current and savings accounts versus time deposits and savings bond as two distinct savings markets. Within each product category, we find that the extent of pass-through is positively related to maturity.

Next, the paper provides an answer to three specific questions regarding the pass-through: 1) Did the introduction of the Euro affect the pass-through? We find that the launch of EMU has generally not resulted in more competitive pricing in the banking market. In particular, for consumer loans and demand and savings deposits we find that the pass-through is more sluggish and less complete in the post 1999 era. 2) Is the pass-through asymmetric? While the adjustment of loans generally does not depend on the direction of the market rate, there is some evidence that deposit rates adjust faster downward than upward. In addition, we find that the adjustment of retail loan and deposit interest rates is faster for larger deviations from long-run mark-ups. 3) Is accounting for heterogeneity in measuring the pass-through necessary? The answer is clearly yes. Our results indicate, among other things, a systematic underestimation of adjustment speeds when the analysis is either based on aggregate data or when the model fails to incorporate heterogeneity.

Finally, we verify whether bank-specific determinants can explain the heterogeneity found in banks' interest rate setting behavior. We find that banks with a relatively high degree of capital coverage and relatively liquid banks exhibit a more sluggish and less complete pass-through of market to retail interest rates. These results point to the existence of a bank lending channel**,** rather than a bank capital channel or a financial accelerator. Furthermore, we find that banks with large market shares set prices less competitively, supporting the relative market power hypothesis. This may have implications for the application of national competition policy in the banking sector.

APPENDIX A

In practice, our estimation strategy has the following implications. When measuring the pass-through we estimate a variable coefficient model. This implies that for bank *i* coefficients θ are of the form:

$$\theta_i = \theta + \varepsilon_i ,$$

where $\theta = \Sigma\, w_i \cdot \theta_i$. In words, individual coefficients are equal to the panel coefficient plus some individual effect. Typically, the weights w_i are either equal, giving rise to the mean-group estimator proposed by Pesaran and Smith (1995), or a function of the respective group-specific estimated covariances, resulting in the Swamy estimator (see e.g. Swamy, 1970; Hsiao, 2003). All estimates of dynamic coefficients referred to in the text are estimated as proposed by Swamy (1970).

The remainder of this appendix covers two aspects related to this choice. First, by means of likelihood ratio tests, we compare our variable coefficient model with a traditional pooled coefficient model. The results[30] are presented in Table 7. For each of the products we consider, the data clearly favour the variable coefficient model[31]. Second, given that the data prefer a variable coefficient model, one needs to determine whether the heterogeneity is fixed (implying mean-group estimates) or random (implying Swamy estimates). In principle, this calls for a Hausmann-type test. In Section 3.1, however, we argue that both types of variation are present in the data. Figure 6 (dotted '+' line) plots the difference in pass-through between Swamy and mean-group estimates. The figure shows that our results do not depend on the assumption of a particular type of heterogeneity. The difference in pass-through between the fixed and the random coefficient model never exceeds three basis

[30] The results in the table compare a random effects model (i.e. pooled coefficients) with a random coefficient model (i.e. variable coefficients). A fixed-fixed constellation between the pooled and variable coefficient models also favours the latter type of model.
[31] The homogeneity statistic (Swamy, 1970) also decides in favour of a heterogeneous specification.

points. This difference is of no statistical and only limited economic importance. All conclusions in the text remain.

APPENDIX B

This appendix investigates the importance of both the lagged dependent variable and the nonlinearity bias. Both these biases are theoretically plausible in a pass-through context. We here give an indication of their empirical relevance in estimation of the pass-through.

Lagged dependent variable bias

The presence of the lagged dependent variable among our regressors possibly biases the estimates of models such as (*2*). This bias is present in univariate autoregressive models, is exacerbated in "large *n*, small *T*" panels -where it is known as the Nickell (1981) bias- and might play a more limited role in panels with a large time dimension. In this subsection we assess whether this bias poses a problem for pass-through estimates. We therefore implement the Kiviet and Phillips (1994) bias corrections on the estimated coefficients. We find that coefficients hardly change as a result of the bias correction. In particular, the bias never affects a coefficient more than two percent relative to its uncorrected value. The apparent irrelevance of the lagged dependent variable bias is most probably due to the relatively long sample in our analysis. As Kiviet and Phillips (1994) show, the bias vanishes as *T* increases.

Nonlinearity bias

In general, the pass-through is a highly nonlinear function of estimated parameters. There are two exceptions, for which the pass-through is estimated directly: the immediate impact on the one hand, and the long-run effect on the other. All other measures of transmission are possibly contaminated with a bias due to nonlinearity. Within a framework similar to ours, Pesaran and Zhao (1999) suggest several correction methods, of which we implement two. The alternative estimators correct for both the lagged dependent and the nonlinear bias.

Figure 6 plots the difference between the bias-corrected and the baseline pass-through estimates. The graph reveals that the small changes due to the lagged dependent variable bias correction hardly affect the pass-through (solid line). As Pesaran and Zhao (1999) show, this “naïve” corrected estimator performs rather poorly. They prefer a bootstrap correction, which is also shown in the figure, by the broken line. Within the Engle-Granger procedure, the long-run effect is estimated directly. Hence, there is no bias due to nonlinearity in this coefficient. This is also apparent in the figure, where the corrected estimator ultimately converges to the uncorrected estimate. Intermediate estimates exhibit the largest bias within one to six months. Overall, the bias is small. From a statistical point of view, the corrected pass-through always lies within the confidence regions of Figure 2. From an economic perspective too, the bias -showing a (absolute) maximum of less than three basis points- does not seem to have an impact on any of the conclusions.

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Figure 1: Summary statistics

The figure plots the evolution of the mean product-specific interest rate (solid line) across all banks with reported rates in the sample, the evolution of the highest and the lowest (both dashed line) product-specific rate charged by any bank in a given month and the evolution of the market interest rate with the same maturity as the specific product (dotted '+' line).

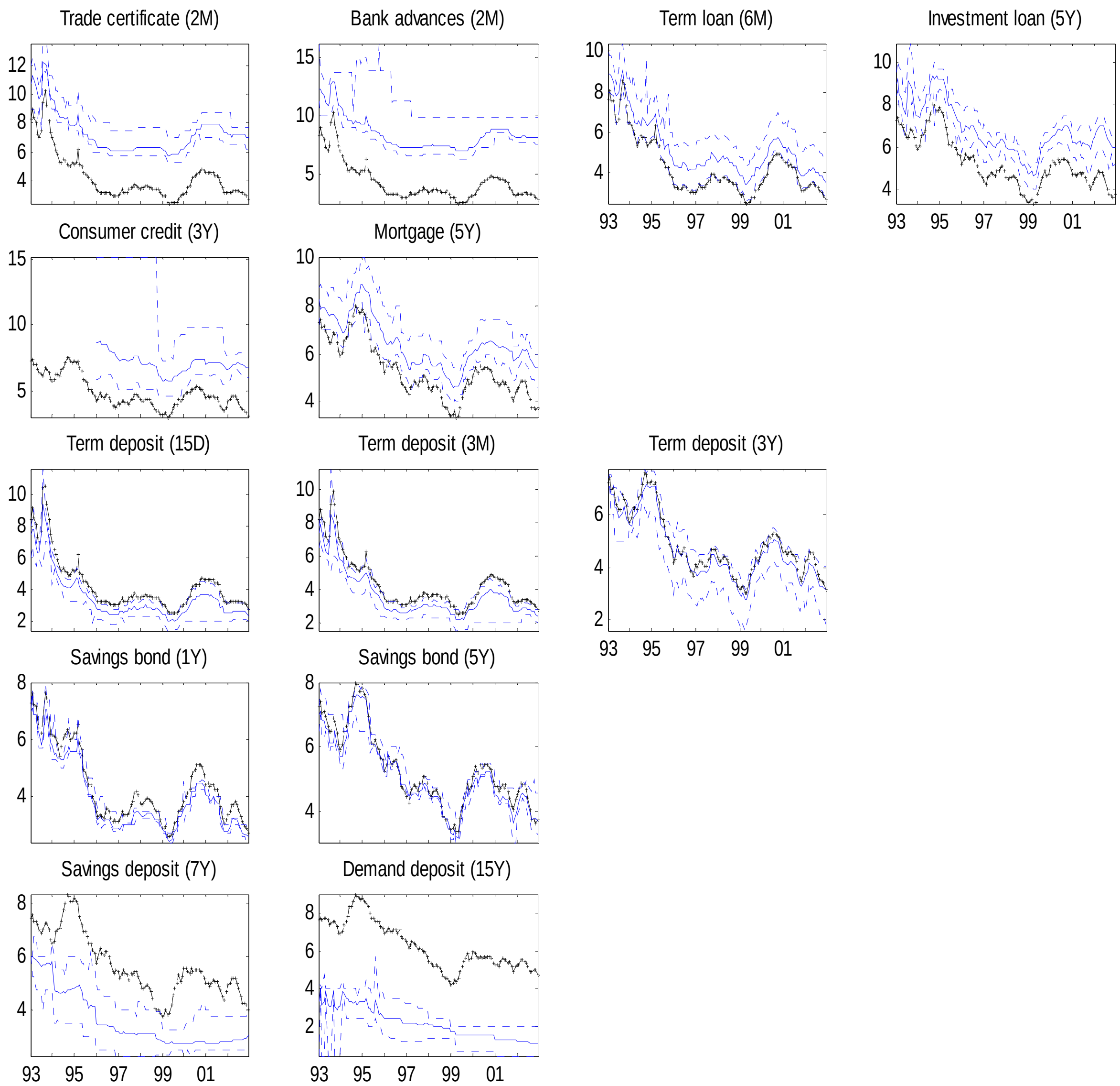

Figure 2: Pass-through

This figure plots the pass-through for the different products. At each date (x-axis, in months) the pass-through measures the contribution of a 1%-point permanent increase in the market rate to the retail bank interest rate. Confidence intervals (95%) are computed from 5000 Monte Carlo draws, ruling out explosive roots.

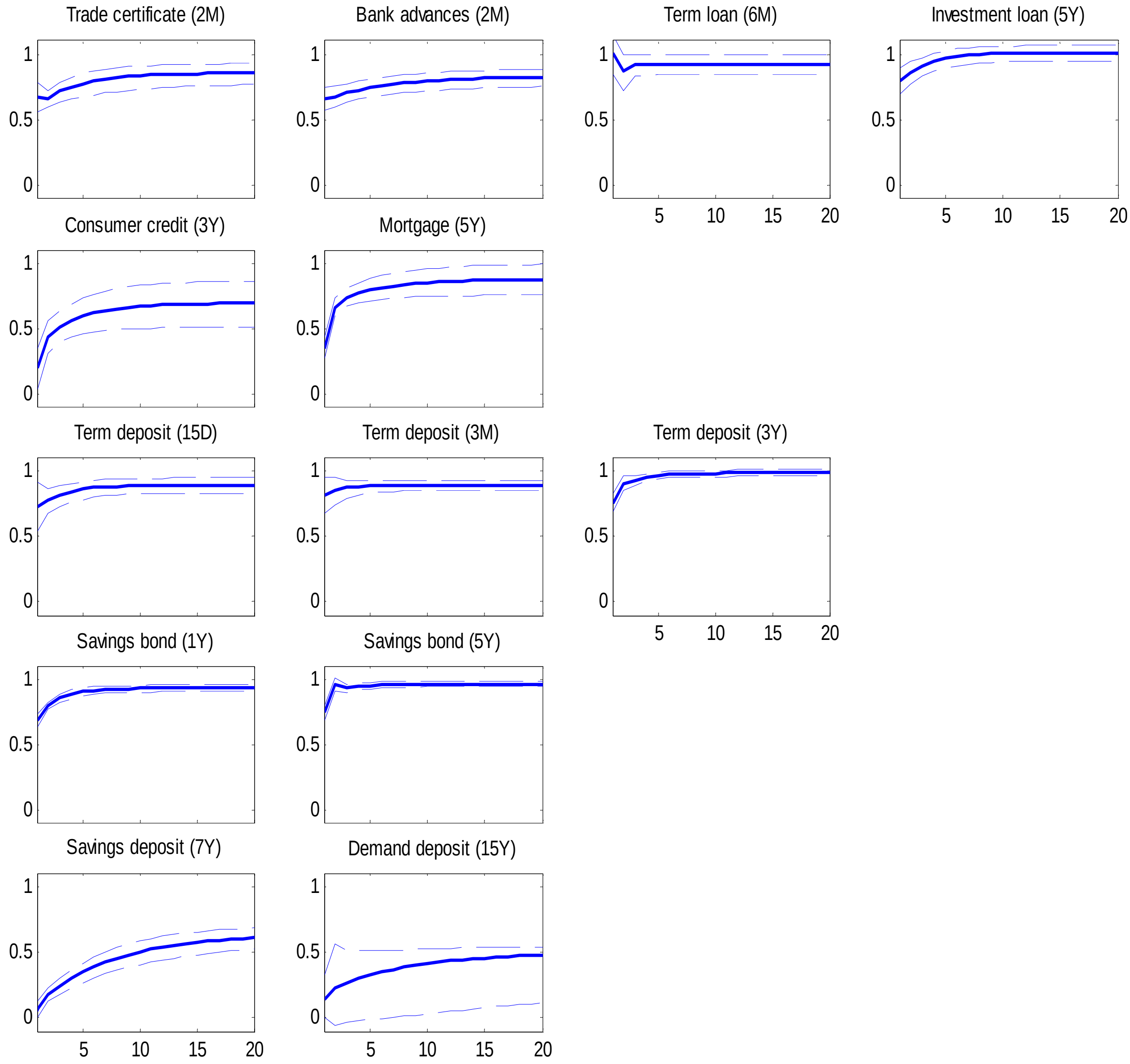

Figure 3: Pass-through in EMU

The figure compares the baseline pass-through estimates and confidence intervals (dotted lines) and the EMU-subsample pass-through estimates (solid line). The x-axis plots time in months. The y-axis plots the contribution of a 1%-point permanent increase in the market rate to the retail bank interest rate.

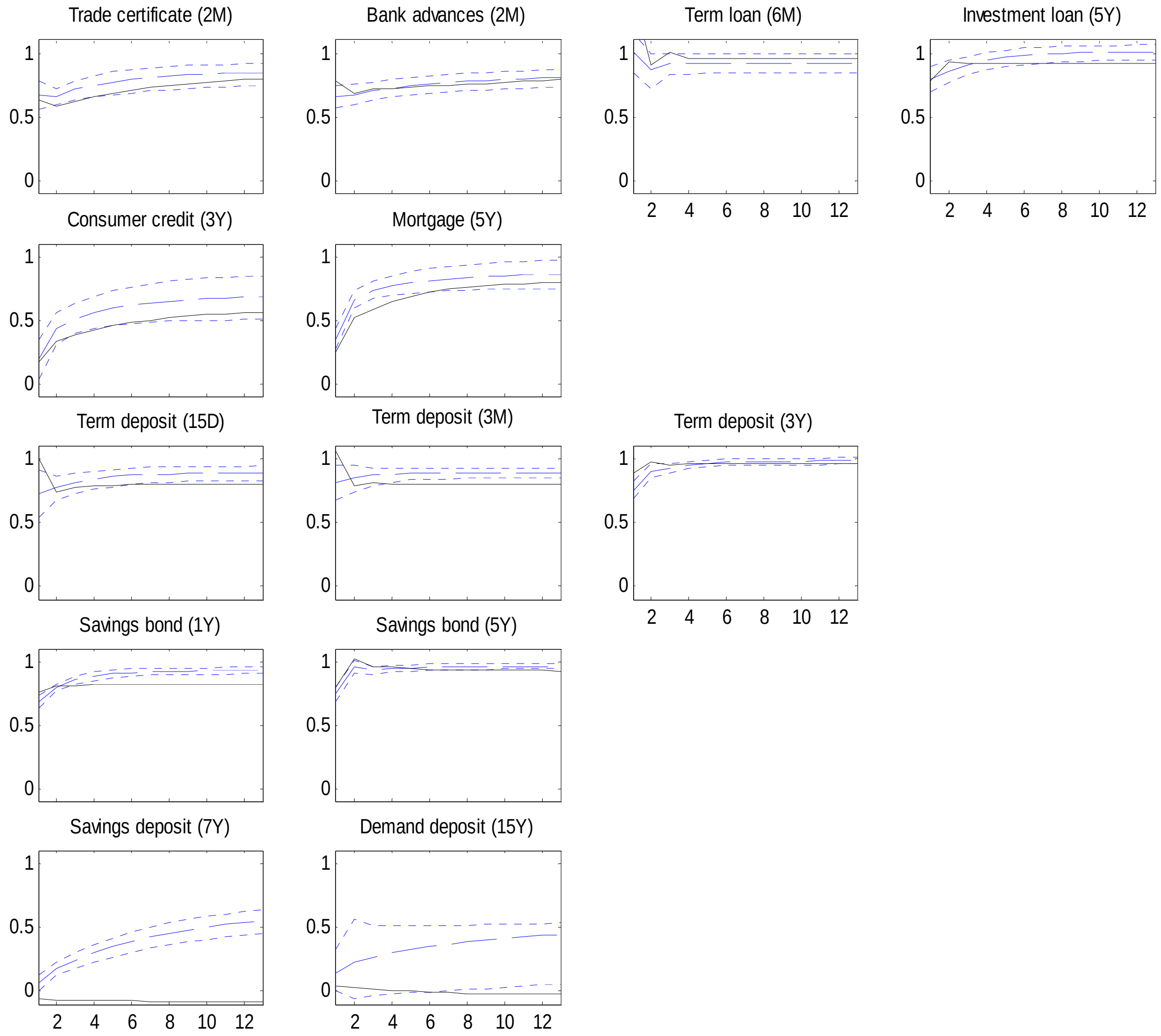

Figure 4: Nonlinear adjustment

The figure plots the implied adjustment coefficients on the y-axis, based on estimation of model (*3*). The x-axis plots the supermargins, or, in other words, residuals of equation (*1*).

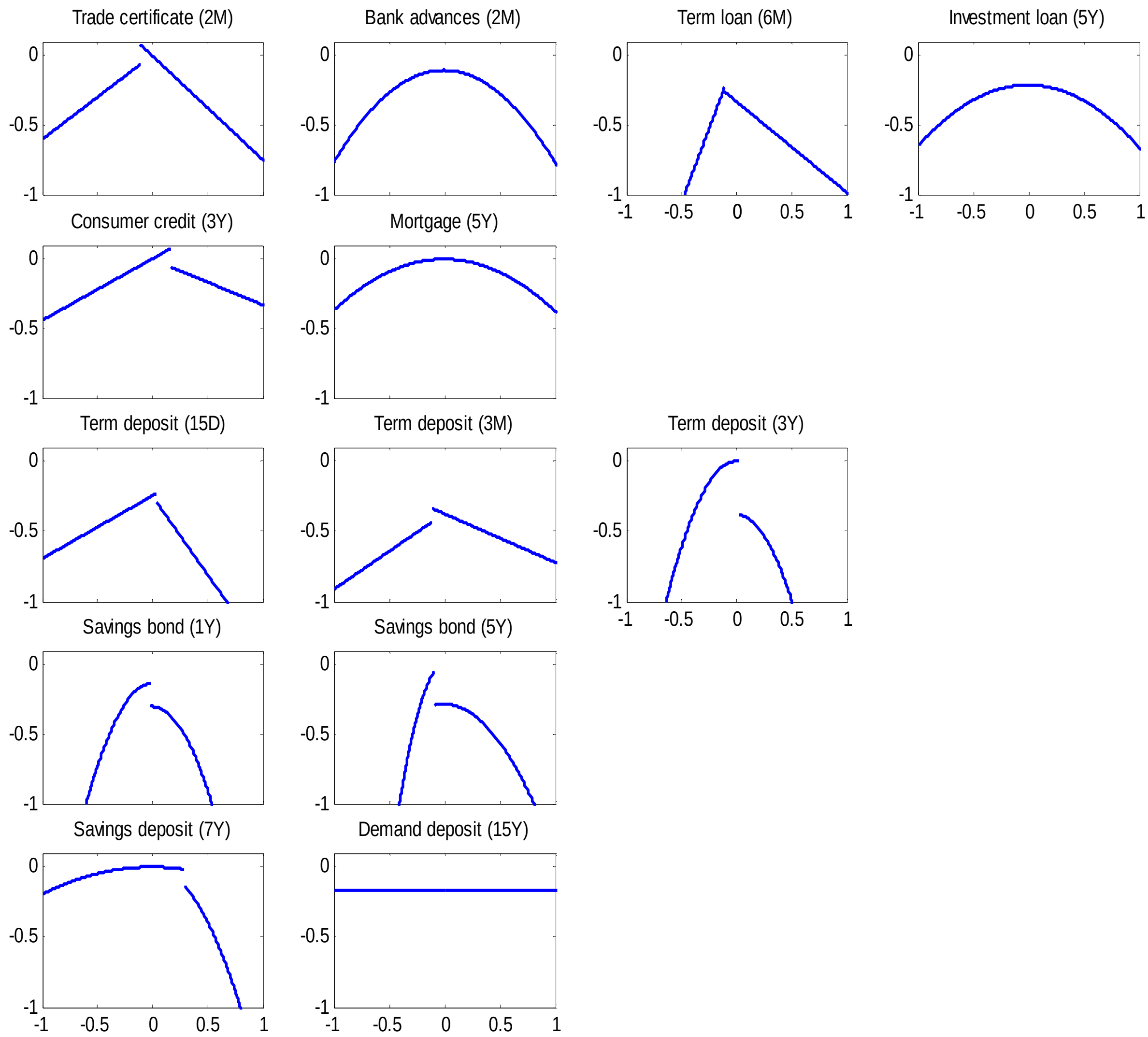

Figure 5: Heterogeneous, homogeneous and aggregate adjustment coefficients

The chart plots the absolute value of the adjustment coefficient in three different pass-through models. The first ('heterogeneous') measures the pass-through based on disaggregated series and allows for heterogeneous behavior among banks. The second ('pooled') estimates the pass-through on disaggregated series, but imposes a common reaction for all banks. The third ('aggregate') model averages interest rates into one aggregate interest rate (as reported by the ECB) and subsequently estimates the pass-through.

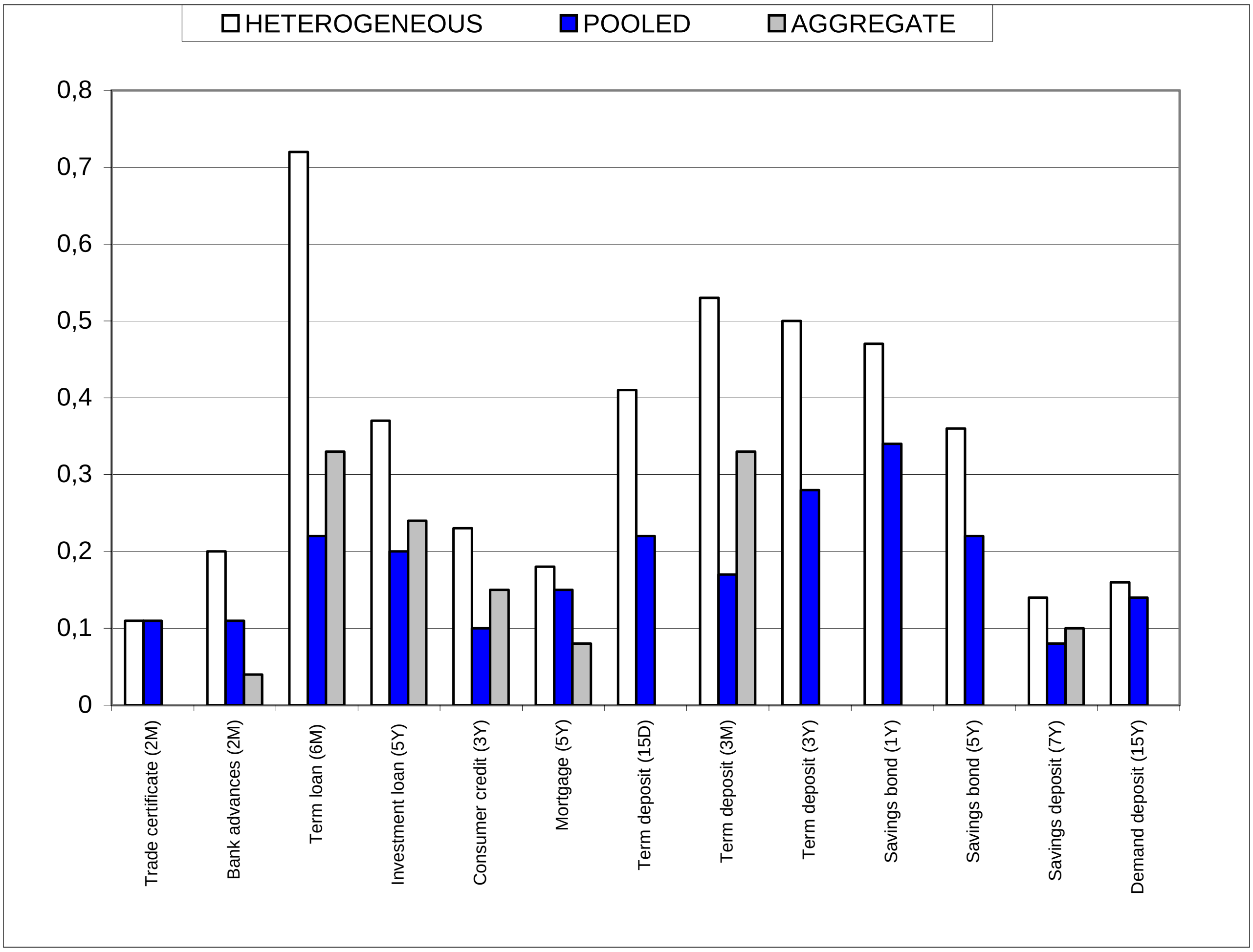

Figure 6: Alternative pass-through estimators

Mean-group (dotted '+' line), naïve bias corrected (solid line) and bootstrap corrected pass-through (broken line) expressed as deviation from the baseline model.

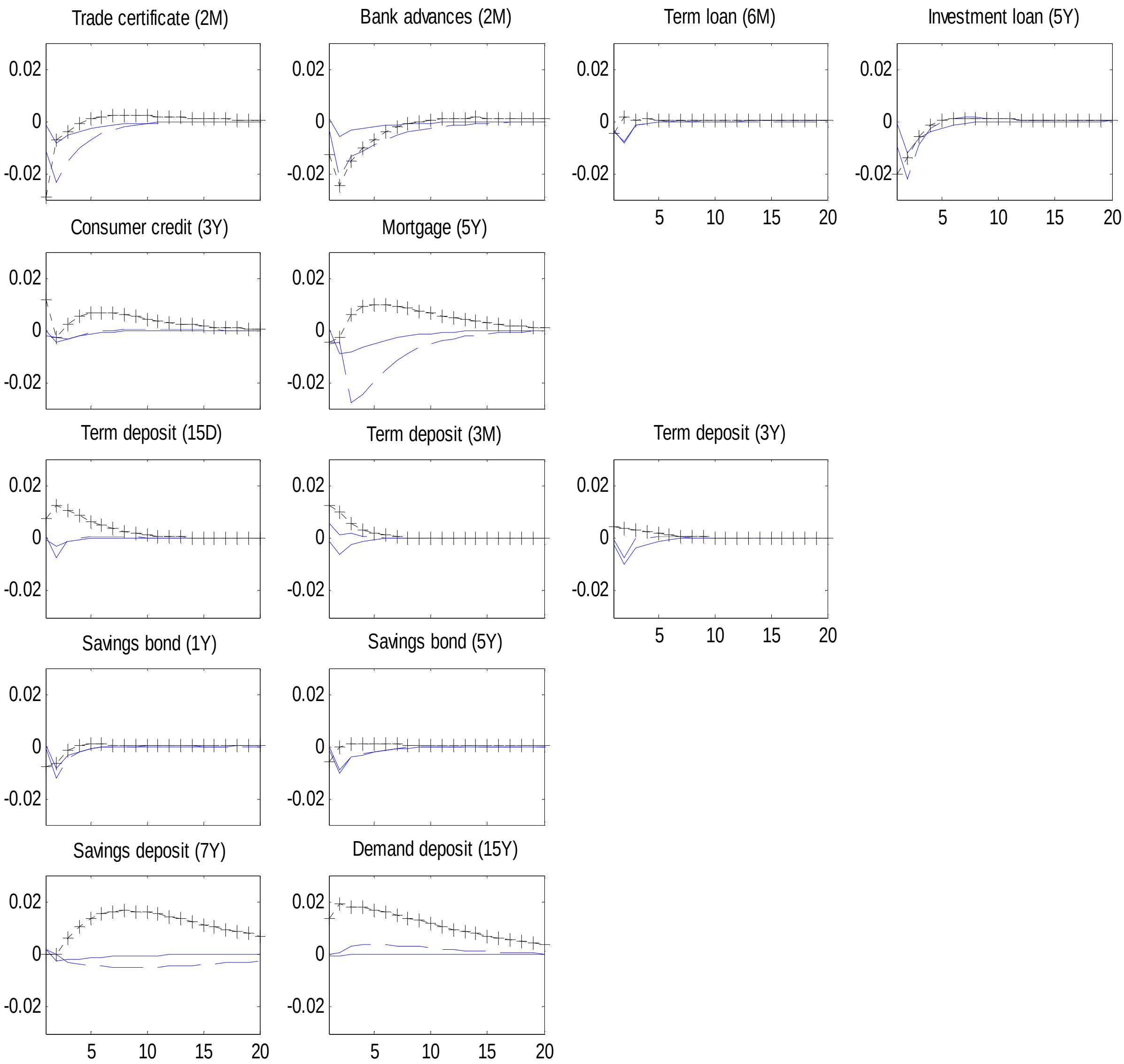

Table 1: Average correlation with market rates of different maturity

LOANS	1 mth	2 mth	3 mth	6 mth	1 y	3 y	5 y	7 y	10 y	15 y
Trade certificate (2M)	0.908	**0.908**	0.903	0.879	0.833	0.727	0.641	0.581	0.514	0.473
Bank advances (2M)	0.904	**0.905**	0.901	0.882	0.839	0.736	0.663	0.618	0.544	0.505
Term loan (6M)	0.929	0.941	0.949	**0.961**	0.955	0.867	0.761	0.692	0.601	0.552
Investment loan (5Y)	0.623	0.640	0.653	0.697	0.744	0.885	**0.921**	0.913	0.878	0.841
Consumer credit (3Y)	0.259	0.263	0.266	0.279	0.280	0.454	0.568	0.588	**0.588**	0.570
Mortgage (5Y)	0.679	0.692	0.701	0.736	0.769	0.862	**0.891**	0.879	0.854	0.827
DEPOSITS	**1 mth**	**2 mth**	**3 mth**	**6 mth**	**1 y**	**3 y**	**5 y**	**7 y**	**10 y**	**15 y**
Term deposit (15D)	**0.950**	0.949	0.946	0.929	0.890	0.768	0.679	0.627	0.554	0.517
Term deposit (3M)	0.945	0.949	**0.952**	0.946	0.919	0.803	0.709	0.653	0.569	0.527
Term deposit (3Y)	0.751	0.772	0.789	0.840	0.891	**0.974**	0.965	0.929	0.874	0.830
Savings bond (1Y)	0.920	0.936	0.946	0.969	**0.976**	0.921	0.835	0.770	0.686	0.636
Savings bond (5Y)	0.637	0.654	0.669	0.721	0.775	0.923	**0.977**	0.976	0.958	0.933
Savings deposit (7Y)	0.719	0.717	0.714	0.718	0.713	0.747	0.761	**0.785**	0.765	0.763
Demand deposit (15Y)	0.491	0.492	0.495	0.522	0.544	0.640	0.699	0.737	0.758	**0.771**

Note: For each product the maturity (when specified) of the reference contract is indicated by a coloured cell. The bold numbers indicate the maximum correlation per product.

Table 2: Cointegration tests

LOANS	mean(ADF)	t-stat		DEPOSITS	mean(ADF)	t-stat
Trade certificate (2M)	-2.4031	-1.658		Term deposit (15D)	-4.6716	-14.785
Bank advances (2M)	-2.3933	-2.1483		Term deposit (3M)	-4.8777	-17.3881
Term loan (6M)	-5.5363	-16.0173		Term deposit (3Y)	-4.4054	-13.297
Investment loan (5Y)	-4.0608	-9.6107		Savings bond (1Y)	-4.4854	-14.0676
Consumer credit (3Y)	-3.045	-5.1239		Savings bond (5Y)	-3.7246	-10.148
Mortgage (5Y)	-3.2963	-7.0992		Savings deposit (7Y)	-2.3702	-2.0133
				Demand deposit (15Y)	-2.7836	-2.0659

Note: Mean Augmented Dickey Fuller t-statistics and corrected t-statistics. The performed correction is $n^{0.5} \cdot (\text{mean(ADF)} - \mu)/\sigma$ and uses $\mu = -2.026$ and $\sigma = 0.82$ (see McCoskey and Kao (1999) for further details).

Table 3: Pass-through: measurement

The table consists of two parts, one for loans and one for deposits. Each coloured row contains the point estimates for one (product) panel. Within a panel, we restrict attention to the main coefficients of interest, i.c. the immediate pass-through, the long-run pass-through and the adjustment coefficient. Column 3 contains the actual point estimates. The adjacent Column 4 presents standard errors on these coefficients. In Column 5 we report -in percentages- how much of these standard errors is due to parameter heterogeneity. The remaining proportion is mere parameter uncertainty. Column 6 provides mean adjustment lags.

		value	standard error	heterogeneity / total uncertainty	mean lag
Loans					
Trade certificate (2M)	ST PT	0.6677	0.0634	0.82	2.1548
	LT PT	0.8546	0.0379	0.75	
	ADJ	-0.2660	0.0961	0.95	
Bank advances (2M)	ST PT	0.6588	0.0467	0.84	2.2122
	LT PT	0.8248	0.0326	0.74	
	ADJ	-0.2043	0.0629	0.93	
Term loan (6M)	ST PT	1.0063	0.0887	0.88	0.9822
	LT PT	0.9240	0.0384	0.79	
	ADJ	-0.7197	0.1527	0.92	
Investment loan (5Y)	ST PT	0.7926	0.064	0.68	1.6882
	LT PT	1.0098	0.0301	0.79	
	ADJ	-0.3727	0.0869	0.90	
Consumer credit (3Y)	ST PT	0.1906	0.0973	0.72	3.1337
	LT PT	0.6907	0.0921	0.02	
	ADJ	-0.2337	0.0514	0.89	
Mortgage (5Y)	ST PT	0.3494	0.0507	0.61	2.5175
	LT PT	0.8712	0.0602	0.96	
	ADJ	-0.1850	0.0265	0.59	
Deposits					
Term deposit (15D)	ST PT	0.7200	0.0976	0.95	1.5397
	LT PT	0.8844	0.0302	0.93	
	ADJ	-0.4107	0.0903	0.89	
Term deposit (3M)	ST PT	0.8124	0.0727	0.93	1.1494
	LT PT	0.8830	0.0207	0.91	
	ADJ	-0.5358	0.1136	0.93	
Term deposit (3Y)	ST PT	0.7527	0.0407	0.80	1.4322
	LT PT	0.9771	0.0128	0.61	
	ADJ	-0.5044	0.07	0.88	
Savings bond (1Y)	ST PT	0.6815	0.0286	0.70	1.5975
	LT PT	0.9267	0.0127	0.87	
	ADJ	-0.4736	0.0741	0.91	
Savings bond (5Y)	ST PT	0.7393	0.034	0.77	1.3281
	LT PT	0.9622	0.0113	0.80	
	ADJ	-0.3606	0.0582	0.86	
Savings deposit (7Y)	ST PT	0.0630	0.0399	0.66	6.9006
	LT PT	0.6347	0.0395	0.89	
	ADJ	-0.1490	0.0299	0.87	
Demand deposit (15Y)	ST PT	0.1433	0.1031	0.86	5.4150
	LT PT	0.4910	0.0333	0.42	
	ADJ	-0.1666	0.1044	0.96	

Table 4: Nonlinear adjustment

The table provides the estimated adjustment coefficients (and standard errors) of the pass-through model (1)-(2), where the adjustment specification is nested within the following general form:

$$\gamma_t = \gamma_1 + \gamma_1^+ \cdot \mathrm{I}(u_{t-1} \geq 0) + \gamma_2 \cdot u_{t-1} + \gamma_2^+ \cdot u_{t-1} \cdot \mathrm{I}(u_{t-1} \geq 0) + \gamma_3 \cdot (u_{t-1})^2 + \gamma_3^+ \cdot (u_{t-1})^2 \cdot \mathrm{I}(u_{t-1} \geq 0)$$

Estimation of the above adjustment specification allows for a non-zero threshold in the indicator function. The optimal threshold is given in the last column.

Loans							
	γ1	γ2	γ3	γ1+	γ2+	γ3+	threshold
Trade certificate (2M)		0.606			-1 352		-0.107
		0.062			0.383		
Bank advances (2M)	-0.106		-0.665				-0.269
	0.054		0.254				
Term loan (6M)		2 116		-0.329	-2.77		-0.108
		0.737		0.11	0.777		
Investment loan (5Y)	-0.212		-0.445				-0.192
	0.072		0.267				
Consumer credit (3Y)		0.442			-0.77		0.164
		0.145			0.268		
Mortgage (5Y)			-0.373				-0.434
			0.128				

Deposits							
	γ1	γ2	γ3	γ1+	γ2+	γ3+	threshold
Term deposit (15D)	-0.248	0.448			-1.562		0.036
	0.117	0.258			0.606		
Term deposit (3M)	-0.373	0.543			-0.889		-0.114
	0.096	0.28			0.467		
Term deposit (3Y)			-2.449	-0.378			0.025
			0.53	0.086			
Savings bond (1Y)	-0.134		-2.394	-0.167			-0.016
	0.071		0.592	0.083			
Savings bond (5Y)			-6.089	-0.282		4.987	-0.091
			1.872	0.056		1.62	
Savings deposit (7Y)			-0.195			-1.368	0.283
			0.103			0.671	
Demand deposit (15Y)	-0.167						0
	0.104						

Table 5: Determinants of pass-through heterogeneity

LOANS

Estimation Results

		Constant	Capital	Liquidity	Credit Risk	Interest Risk	Diversification	Market Share	Inefficiency	LT loans / Total loans	(Dem+Sav Dep) / Total Dep	adj R^2
ST PT	coefficient	0.233	-4.204**	0.005	-1.171	0.002**	0.357	-0.005**	-0.180	-0.020	0.154	0.151
	t-stat	0.472	-2.218	0.074	-0.937	2.333	1.408	-2.073	-0.283	-0.104	0.706	
LT PT	coefficient	-0.119	-5.452***	-0.011	1.412	0.001	0.363	-0.004*	0.049	-0.127	0.317	0.449
	t-stat	-0.219	-4.691	-0.176	1.303	1.138	1.502	-1.850	0.076	-0.828	1.634	
ADJ	coefficient	0.519	0.902	0.080*	-1.027	0.001	0.510**	-0.002	-0.784*	-0.009	-0.004	-0.011
	t-stat	1.348	0.973	1.812	-1.582	1.450	2.384	-1.297	-1.827	-0.091	-0.025	

Summary Statistics

		Capital	Liquidity	Credit Risk	Interest Risk	Diversification	Market Share	Inefficiency	LT loans / Total loans	(Dem+Sav Dep) / Total Dep
	mean	0.045	1.046	0.012	9.307	0.180	5.868	0.915	0.699	0.609
	std. dev.	0.022	0.517	0.015	22.555	0.097	10.143	0.054	0.207	0.172
	25 percentile	0.028	0.718	0.003	2.591	0.118	0.241	0.902	0.557	0.520
	75 percentile	0.053	1.346	0.013	4.387	0.193	6.301	0.959	0.872	0.720

Implied differences (value at 75 percentile - value at 25 percentile)

	Capital	Liquidity	Credit Risk	Interest Risk	Diversification	Market Share	Inefficiency	LT loans / Total loans	(Dem+Sav Dep) / Total Dep
ST PT	-0.101	0.003	-0.012	0.003	0.027	-0.033	-0.010	-0.006	0.031
LT PT	-0.131	-0.007	0.014	0.002	0.027	-0.021	0.003	-0.040	0.063
ADJ	0.022	0.050	-0.010	0.002	0.038	-0.015	-0.045	-0.003	-0.001

DEPOSITS

Estimation Results

		Constant	Capital	Liquidity	Credit Risk	Interest Risk	Diversification	Market Share	Inefficiency	adj R²
ST PT	coefficient	0.008	-3.765***	-0.104*	0.719	0.000	-0.228	-0.000	0.349	0.151
	t-stat	0.027	-5.266	-1.818	0.951	0.329	-1.445	-0.129	1.057	
LT PT	coefficient	-0.148	-4.637***	-0.094**	1.417**	0.000	-0.166	-0.003	0.431	0.403
	t-stat	-0.622	-5.611	-2.154	2.119	0.167	-1.078	-1.530	1.541	
ADJ	coefficient	0.157	2.275*	0.109**	-0.736	-0.000	0.395	-0.004	-0.467	0.014
	t-stat	0.456	1.957	2.320	-0.630	-0.166	1.237	-0.966	-1.260	
Summary Statistics										
	mean		0.050	1.036	0.013	8.633	0.168	4.525	0.908	
	std. dev.		0.024	0.503	0.016	22.144	0.088	7.827	0.068	
	25 percentile		0.031	0.718	0.002	2.380	0.111	0.115	0.870	
	75 percentile		0.068	1.300	0.014	3.848	0.184	6.235	0.961	
Implied differences (value at 75 percentile - value at 25 percentile)										
ST PT			-0.138	-0.060	0.009	0.000	-0.017	-0.002	0.032	
LT PT			-0.170	-0.055	0.017	0.000	-0.012	-0.018	0.039	
ADJ			0.083	0.064	-0.009	0.000	0.029	-0.024	-0.043	

Note: reading Table 5

The table consists of two panels, one for loans and one for deposits. Each panel is composed of three parts. The first part contains the point estimates, t-statistics and a goodness-of-fit measure. Significance of point estimates at 10, 5 and 1% level is respectively denoted with *, ** and ***. The second part shows four statistics (mean, standard deviation and the value at the 25th and 75th percentile) for each determinant included in the specification. The last part shows the implied difference on pass-through of a change in the determinant from the 25th to the 75th percentile. ST PT, LT PT and ADJ stand respectively for short term pass-through, long-term pass-through and the adjustment coefficient.

Table 6: Robustness: Panel A: bank capital channel; Panel B: size in the loan regression; Panel C: size in the deposit regression

Estimation Results

Panel			Constant	Capital	Liquidity	Credit Risk	Interest Risk	Diversification	Market Share	Inefficiency	LT loans / Total loans	(Dem+Sav Dep) / Total Dep	Size	Dummy (capital channel)
	LOANS													
	ST PT	coefficient	0.068	-4.371**	-0.028	-0.716	0.002**	0.523	-0.006**	-0.119	-0.025	0.332		0.104
		t-stat	0.134	-2.307	-0.385	-0.527	2.500	1.640	-2.182	-0.181	-0.130	1.050		0.972
A	LT PT	coefficient	0.026	-5.448***	0.013	1.074	0.001	0.227	-0.003*	0.000	-0.088	0.128		-0.101
		t-stat	0.044	-4.626	0.193	0.858	0.635	0.681	-1.678	0.000	-0.540	0.358		-0.778
	ADJ	coefficient	0.216	0.953	0.013	0.026	0.002**	0.876***	-0.001	-0.832**	-0.059	0.514***		0.304***
		t-stat	0.626	1.168	0.309	0.040	2.264	3.191	-0.256	-2.136	-0.642	2.655		3.905
	LOANS													
	ST PT	coefficient	0.103	-4.500**	-0.012	-1.422	0.002**	0.746**	-0.009***	-0.073	-0.029	0.185	0.060***	
		t-stat	0.274	-2.386	-0.201	-1.202	2.508	2.567	-3.343	-0.159	-0.170	0.853	2.981	
B	LT PT	coefficient	-0.155	-5.585***	-0.013	1.116	0.001	0.621**	-0.005**	0.024	-0.108	0.334*	0.044*	
		t-stat	-0.302	-4.705	-0.221	1.027	1.290	2.127	-2.457	0.042	-0.721	1.699	1.946	
	ADJ	coefficient	0.585	1.245	0.0904*	-0.809	0.001	0.225	0.001	-0.8071*	-0.062	-0.008	-0.051***	
		t-stat	1.576	1.233	1.916	-1.060	1.476	0.937	0.447	-1.971	-0.603	-0.051	-2.609	
	DEPOSITS													
	ST PT	coefficient	-0.001	-3.750***	-0.099*	0.681	0.000	-0.100	-0.002	0.337			0.021	
		t-stat	-0.003	-4.876	-1.715	0.917	0.093	-0.559	-0.825	1.096			1.388	
C	LT PT	coefficient	-0.157	-4.702***	-0.097**	1.411**	0.000	-0.141	-0.003	0.444			0.005	
		t-stat	-0.644	-5.556	-2.168	2.081	0.082	-0.877	-1.588	1.552			0.416	
	ADJ	coefficient	0.203	2.440**	0.115**	-0.729	0.000	0.342	-0.003	-0.531			-0.012	
		t-stat	0.560	2.101	2.419	-0.622	-0.117	0.881	-0.627	-1.361			-0.517	

Table 7: Likelihood ratio tests: Random versus pooled coefficient model

LOANS	LR	Critical value		DEPOSITS	LR	Critical value
Trade certificate (2M)	138.79	65.17		Term deposit (15D)	777.65	101.88
Bank advances (2M)	454.31	110.90		Term deposit (3M)	864.82	119.87
Term loan (6M)	262.49	69.83		Term deposit (3Y)	222.08	101.88
Investment loan (5Y)	240.77	74.47		Savings bond (1Y)	212.18	106.39
Consumer credit (3Y)	274.73	83.68		Savings bond (5Y)	256.76	115.39
Mortgage (5Y)	127.01	101.88		Savings deposit (7Y)	238.57	110.90
				Demand deposit (15Y)	77.68	26.30

Note: The table shows the likelihood ratio and the corresponding 5% Chi-square critical value. A value above the critical value indicates the restrictions of the pooled model are not valid.