Measuring Competition in Banking:

A Disequilibrium Approach*

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Abstract

The Rosse-Panzar revenue test for competitive conditions in banking is based on observation of the impact on bank revenue of variation in factor input prices. We identify the implications for the Rosse-Panzar H-statistic of misspecification bias in the revenue equation, arising when adjustment towards market equilibrium in response to factor input price shocks is partial and not instantaneous. In simulations, fixed effects estimation is shown to produce a measured H-statistic that is severely biased towards zero. A dynamic revenue equation allows virtually unbiased estimation. Empirical results are reported for the banking sectors of 19 developed and developing countries.

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1. Introduction

Competition in banking is important, because any form of market failure or anti-competitive behaviour on the part of banks has far-reaching implications for productive efficiency, consumer welfare and economic growth. At the microeconomic level, most households and businesses engage in transactions with banks, for deposits, loans and other financial services. At the macroeconomic level, banks perform a vital economic function in channelling funds from savers to investors, and in the monetary policy transmission mechanism. Accordingly, the development of indicators of market power or competition in banking that are reliable, widely understood and generally accepted is a highly relevant exercise, carrying implications for competition policy, macroeconomic policy, financial stability, and for the effective regulation and supervision of the banking and financial services sector.[1]

An approach to the measurement of competition, which is popular in the recent empirical banking literature (Berger et al., 2004), involves drawing inferences about market or competitive structure from the observation of firms' conduct (Lau, 1982; Bresnahan, 1982, 1989; Panzar and Rosse, 1982, 1987). This approach involves the estimation of equations derived from theoretical models of price and output determination under alternative competitive conditions. Inferences as to which model best describes the firms' observed behaviour are drawn from the estimated parameters.

Panzar and Rosse (1987) develop a test that examines whether firm-level conduct is in accordance with the textbook models of perfect competition, monopolistic competition, or monopoly. The Rosse-Panzar H-statistic is the sum of the elasticities of a firm's total revenue with respect to its factor

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[1] The intensity of competition in banking may have implications for the performance and turnover of firms in other sectors, through its impact on the cost and availability of credit (Cetorelli, 2003, 2004; Beck et al., 2004; Bonnaccorsi and Dell'Ariccia, 2004; Cetorelli and Strahan, 2006; Larrain, 2006; Zarutskie, 2006). Following deregulation, increased competition between banks may have implications for new firm creation and economic growth, and perhaps even for social indicators such as the crime rate (Jayaratne and Strahan, 1996; Beck et al, 2000; Black and Strahan, 2002; Garmaise and Moskowitz, 2006). Conversely, some degree of market power in banking may be beneficial for financial stability, because market power enhances a bank's charter value and moderates incentives for excessive risk-taking. However, borrowers might be inclined to accept more risk, in order to generate the returns required to service their higher interest payments (Hellman et al., 2000; Vives, 2001; Allen and Gale, 2004; Boyd and De Nicolo, 2005).

input prices. The standard procedure for estimation of the H-statistic involves the application of fixed effects (FE) regression to panel data for individual firms. Under this procedure, the correct identification of the H-statistic relies upon an assumption that markets are in long-run equilibrium at each point in time when the data are observed. In the present study, our main focus is on the implications of departures from this assumed product market equilibrium condition. Although the micro theory underlying the Rosse-Panzar test is based on a static equilibrium framework, in practice adjustment towards equilibrium might well be less than instantaneous, and markets might be out of equilibrium either occasionally, or frequently, or always.

This paper's principal contribution takes the form of an investigation of the implications for the estimation of the H-statistic of a form of misspecification bias in the revenue equation. Misspecification bias arises in the case where there is partial, not instantaneous, adjustment towards equilibrium in response to factor input price shocks. Partial adjustment necessitates the inclusion of a lagged dependent variable among the covariates of the revenue equation. Accordingly, the latter should have a dynamic structure, and the static version without a lagged dependent variable is misspecified.

A Monte Carlo simulations exercise demonstrates that when the true data generating process involves partial rather than instantaneous adjustment towards equilibrium, FE estimation of a static revenue equation produces a measured H-statistic that is severely biased towards zero. This bias has serious implications for the researcher's ability to distinguish accurately between the three theoretical market structures. In contrast, applying an appropriate dynamic panel estimator to a correctly specified dynamic revenue equation permits virtually unbiased estimation of the H-statistic. Dynamic panel estimation enables the researcher to assess the speed of adjustment towards equilibrium directly, through the estimated coefficient on the lagged dependent variable. This eliminates the need for a market equilibrium assumption, but still incorporates instantaneous adjustment as a special case.

We also report an empirical comparison between the performance of the FE and dynamic panel estimators of the Rosse-Panzar H-statistic, based on company accounts data for 19 national banking sectors. The empirical results are consistent with the main conclusions of the preceding simulations exercise, that the FE estimator of the H-statistic is severely biased towards zero.

The rest of the paper is structured as follows. Section 2 provides a brief review of the previous empirical literature on the application of the Rosse-Panzar test in banking, and makes the case for this test to be based on a dynamic or partial adjustment model, rather than a static or instantaneous adjustment model. Section 3 describes the design of a Monte Carlo simulations exercise, which identifies the implications for the standard FE estimation of the H-statistic of misspecification bias in the revenue equation, in the form of the omission of a lagged dependent variable from the list of covariates. Section 4 interprets the results of the Monte Carlo simulations exercise. Section 5 presents some empirical evidence, based on a sample of data on 5,192 banks from 19 countries. Finally, Section 6 summarizes and concludes.

2. Measuring competitive conditions using the Rosse-Panzar revenue test

The Rosse-Panzar revenue test is usually implemented through FE estimation of the following regression, using firm-level panel data:

$$\ln(r_{i,t}) = \delta_{0,i} + \sum_{j=1}^{J} \delta_j \ln(w_{j,i,t}) + \boldsymbol{\theta}'\mathbf{x}_{i,t} + \eta_{i,t} \qquad (1)$$

In (1), $r_{i,t}$ = total revenue of firm i in year t; $w_{j,i,t}$ = price of factor input j; $\mathbf{x}_{i,t}$ is a vector of exogenous control variables; and $\eta_{i,t}$ is a random disturbance term. Typically, the factor input prices are imputed from company accounts data. The H-statistic, defined as H = $\sum_{j=1}^{J} \delta_j$, is interpreted as follows. Under monopoly, H<0. An increase in average cost resulting from an equi-proportionate increase in the factor input prices, leads to an increase in equilibrium price and, since the profit-maximising firm operates on the price-elastic segment of the market demand function, a reduction in revenue. Under monopolistic competition, 0<H<1. The representative firm achieves equilibrium at Chamberlin's (1933) tangency solution, with (i) MR=MC (marginal revenue *equals* marginal cost) and (ii) AR=AC (average revenue *equals* average cost). The perceived number of competitor firms determines both the location and the price elasticity of the perceived demand function, denoted ε. Following an increase in AC, both output and the perceived number of competitor firms adjust in order to satisfy (i) and (ii). This adjustment produces a change in revenue that is positive, but proportionately smaller than the increase in the input prices. The numerical value of H is monotonic in ε, such that $H \rightarrow 1$ as $|\varepsilon| \rightarrow \infty$. In this sense, the numerical value of H within the range $0<H<1$ can be interpreted as a measure of the intensity of competition, within a spectrum of cases that are characterized by the monopolistic competition model. Under perfect competition, $H=1$. The representative firm holds its output constant and raises its price in proportion to the increase in average cost.[2] The algebraic derivations of these results are shown in Appendix I.

In applications of the Rosse-Panzar methodology to banking data, banks are treated as profit-maximizing single-product firms producing intermediation services. It is assumed there is no vertical product differentiation, and the cost structure is homogeneous across banks (De Bandt and Davis, 2000; Bikker, 2004; Shaffer, 2004). In the first such study, Shaffer (1982) obtained $0<H<1$ for a sample of New York banks.[3] In one of the most wide-ranging empirical studies to date, Claessens and Laeven (2004) report cross-sectional regressions that identify factors associated with the numerical value of H for 50 developed and developing countries. Competition is more intense in countries with low entry barriers and where there are few restrictions on banking activity.

For accurate identification of the H-statistic using an estimated revenue equation based on a static equilibrium model, it is necessary to assume that markets are in long-run equilibrium at each point in time

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[2] In addition, it has been shown $H<0$ in the case of collusive oligopoly (joint profit maximization), and $H=1$ for a natural monopolist in a contestable market, and for a sales maximizer subject to a break-even constraint (Shaffer, 2004). However, the sign of H is ambiguous across a broad class of conjectural variations oligopoly models, because the conjectural variations equilibrium could be located on either the elastic or the inelastic portion of the industry demand function (Panzar and Rosse, 1987).

[3] Using European banking data for 1986-89, Molyneux et al. (1994) obtained $0<H<1$ for France, Germany, Spain and the UK, and $H<0$ for Italy. Using 1992-96 data, De Bandt and Davis (2000) obtained $0<H<1$ for France, Germany, Italy and the US. Similar results were reported by Nathan and Neave (1989) for Canada, Coccorese (2004) for Italy; Casu and Girardone (2006) and Staikouras and Koutsomanoli‑Fillipaki (2006) for the European Union; Gelos and Roldos (2004) and Yildrim and Philippatos (2007) for Latin America; and Matthews et al. (2007) for the UK. In contrast, Molyneux et al. (1996) obtained $H<0$ using 1986-88 data for Japan.

when the data are observed. Shaffer (1982) proposed a test of the market equilibrium assumption. Competitive capital markets should equalize risk-adjusted returns across banks in equilibrium. Accordingly, the equilibrium profit rate should be uncorrelated with the factor input prices. This test is commonly implemented through FE estimation of the following regression:

$$\ln(1+\pi_{i,t}) = \gamma_{0,i} + \sum_{j=1}^{J}\gamma_j \ln(w_{j,i,t}) + \boldsymbol{\varphi}'\mathbf{x}_{\mathbf{i,t}} + \xi_{i,t} \qquad (2)$$

In (2), $\pi_{i,t}$=return on assets; $w_{j,i,t}$ and $\mathbf{x}_{\mathbf{i,t}}$ are defined as before; and $\xi_{i,t}$ is a random disturbance term. The Shaffer E-statistic is E = $\sum_{j=1}^{J}\gamma_j$. The market equilibrium condition is E=0.

Our focus in the present study is on the implications for the estimation of the H- and E-statistics of departures from the market equilibrium assumption in the product market. In order to motivate the use of a dynamic model, we conclude Section 2 by citing three alternative critiques of the comparative statics methodological approach on which (1) and (2) are based. The first critique stems from classic debates over the methodology of economic theory. The second is directed from a time-series econometrics perspective. The third is directed from a perspective articulated in the recent empirical industrial organization and banking literature.

First, according to Blaug (1980, p118), “traditional microeconomics is largely, if not entirely, an analysis of timeless comparative statics, and as such it is strong on equilibrium outcomes but weak on the process whereby equilibrium is attained”. Schumpeter (1954) regards static theory as operating at a higher level of abstraction than dynamic theory. The former ignores, while the latter takes into account, “ ... past and (expected) future values of our variables, lags, sequences, rates of change, cumulative magnitudes, expectations, and so on” (op cit., p963). That this issue remains live today in the banking literature is evidenced by Stiroh and Strahan (2003, p81). “Competition is perhaps the most fundamental idea in economics, and as firms fight for profits, the competitive paradigm makes clear dynamic predictions: strong performers should pass the market test and survive, while weak performers should shrink, exit or sell out. The transfer of market share from under-performers to more successful firms is a critical part of the competitive process, but this stylised picture is not always the reality. Regulation, uncertainty, and other entry barriers to entry can protect inefficient firms, limit entry and exit, and prevent the textbook competitive shakeout."

Second, the absence of any dynamic effects in (1) and (2) creates the possibility that specifications of this type may be criticized from a perspective of time-series econometrics. If $\ln(r_{i,t})$ is actually dependent on $\ln(r_{i,t-1})$, or if $\ln(1+\pi_{i,t})$ is similarly dependent on $\ln(1+\pi_{i,t-1})$, then the misspecification of (1) and (2) results in a pattern of autocorrelation in the disturbance terms, $\eta_{i,t}$ or $\xi_{i,t}$. This creates difficulties for either FE or random effects (RE) estimation of (1) and (2). With small T and autocorrelated disturbances, the FE and RE estimators of δ_j and γ_j are biased toward zero, creating the potential for seriously misleading inferences to be drawn concerning the nature or intensity of competition. Although the FE and RE estimators of δ_j in (1) and γ_j in (2) are consistent as $T\rightarrow\infty$, this property is of little comfort in the case where N may be quite large but T is small. This case is typical in the empirical banking literature. The implications of this critique for the measurement of competitive conditions are developed in Sections 3 and 4 below.

Third and finally, in the recent empirical industrial organization and banking literature, the estimation of dynamic models for the persistence of profit (POP) is motivated by Brozen's (1971) observation that while the relevant micro theory identifies equilibrium relationships between variables such as concentration and profitability, there is no certainty that any observed profit figure represents an equilibrium value.[4] In tests of the POP hypothesis for banking, Goddard et al. (2004a,b) find evidence that

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[4] In the POP model used by Geroski and Jacquemin (1988), the change in a firm's profit rate, denoted $\Delta\pi_t$ and suppressing i-subscripts, is a function of the lagged profit rate denoted π_{t-1}, current and past entry denoted E_{t-j}, and 'luck' denoted u_t:

$$\Delta\pi_t = \theta + \sum_{j=0}^{\infty}\beta_j E_{t-j} + \gamma\pi_{t-1} + u_t$$

Entry is a function of past realizations of the profit rate:

$$E_t = \phi + \sum_{j=1}^{\infty}\alpha_j \pi_{t-j} + e_t$$

Substituting and reparameterizing yields an autoregressive model for the profit rate:

convergence towards long-run equilibrium is less than instantaneous. Berger et al. (2000) reach a similar conclusion using non-parametric techniques to measure persistence.

3. Identification of misspecification bias in the estimated H-statistic

In Section 3, we describe the design of a Monte Carlo simulations exercise, which identifies the implications for the estimation of the H- and E-statistics of misspecification bias in (1) and (2), in the form of the omission of lagged dependent variables from the right-hand-sides of these equations.

For banks, it is natural to identify output, denoted y, with loans or assets, and price, denoted p, with the interest rate charged on the loans portfolio. An ROA (return on assets) profit rate measure is $\pi = (py–c)/y$, where c denotes total cost. For simplicity, we assume variations in c, y, p and π are driven by variations in the price of only one factor input. To generate the simulated price and output series, we feed the simulated factor input price series into the theoretical models of price and output determination under monopoly, monopolistic competition and perfect competition. In accordance with the discussion in Section 2, we allow for either instantaneous adjustment or partial adjustment towards equilibrium. The baseline parameter values used in the simulations are arbitrary and unimportant. We focus on the variation in the performance of the FE and dynamic panel estimators as the parameter values and adjustment assumptions are varied, under laboratory conditions.

The simulations procedure is described briefly below. The full technical details follow the brief description. Each replication in the simulations consists of four steps. At Step 1, we simulate the factor input price series. These simulated series are either white noise, or they are autocorrelated. At Step 2, for

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$$\pi_t = \lambda_0 + \sum_{j=1}^{\infty} \lambda_j \pi_{t-j} + v_t$$

In practice, it is common to estimate an AR(1) specification for π_t:

$$\pi_t = (1–\lambda_1)\tilde{\pi} + \lambda_1\pi_{t–1} + v_t$$

where $\tilde{\pi} = \lambda_0/(1–\lambda_1)$ denotes the long-run equilibrium profit rate.

each factor input price series we simulate the series of market equilibrium values for output, price and (in the case of monopolistic competition only) the perceived number of competitor firms, under each of the three market structures: monopoly, monopolistic competition and perfect competition.

At Step 3, for each factor input price series and for each market structure, we simulate 'actual' series for output, price and perceived number of competitor firms, under alternative assumptions of either instantaneous adjustment or partial adjustment. Under instantaneous adjustment, the 'actual' values diverge from the market equilibrium values randomly, through a stochastic disturbance term. Under partial adjustment, the 'actual' values diverge from the market equilibrium values both systematically, in accordance with a partial adjustment mechanism, and randomly through a stochastic disturbance term.

At Step 4, for each factor input price series, for each market structure, and for instantaneous and for partial adjustment, we estimate revenue and profit equations using the simulated 'actual' price and output series, the simulated factor input price series, and (for the profit equation) a simulated cost series. The equations are estimated using the standard FE panel estimator, and using a dynamic panel estimator, which, in contrast to FE, permits the inclusion of a lagged dependent variable among the covariates of the revenue and profit equations. The dynamic panel estimator is Arellano and Bond's (1991) generalized method of moments (GMM) procedure.

By repeating Steps 1 to 4 over a large number of replications, we obtain the simulated sampling distributions of the estimated FE and GMM H- and E-statistics. The results reported in Section 4 are based on 2,000 replications. In the rest of Section 3, we provide the full technical details of the procedure that has been outlined above. The notation is as follows: n=perceived number of competitor firms, w=factor input price, s=scale parameter, and y, p, c and π are as defined previously. $\tilde{y}^k$ and $\tilde{p}^k$ are the equilibrium values of y and p for k=M (monopoly), MC (monopolistic competition) and PC (perfect competition). $\tilde{n}^{MC}$ is the equilibrium value of n for monopolistic competition. The subscripts 'i,t' appended to any variable denote values pertaining to bank i in year t. The subscript 'i' appended to the scale parameter s allows for heterogeneity in the bank size distribution. For simplicity, it is assumed that the scale parameter for bank i is time-invariant. The underlying bank size distribution is assumed to be lognormal, with $s_i=\exp(z_i)$ and $z_i \sim N(0,1)$.

Step 1

For simplicity, we assume there is a single factor input. In order to simulate $w_{i,t}$, the following partial adjustment mechanism is assumed:

$$w_{i,t} = (1-\phi)\mu_w + \phi w_{i,t-1} + \varepsilon^w_{i,t}\,;\ \varepsilon^w_{i,t} \sim N(0, \nu^2_w);\ \ \nu^2_w = (1-\phi^2)\,\sigma^2_w \qquad (3)$$

The parameter μ_w represents the unconditional mean value of $w_{i,t}$. The parameter ϕ allows for autocorrelation in $w_{i,t}$. We examine ϕ = 0.0, 0.25, 0.5, 0.75, representing zero, 'low', 'medium' and 'high' autocorrelation in $w_{i,t}$, respectively.

Step 2

The following functional forms are assumed for the inverse demand function and cost function:

$$p = \alpha_1(n+1)/n - \alpha_2 s^{-1}y/n \qquad (4)$$

$$c = w(\beta_1 y + \beta_2 s^{-1}y^2 + 0.0005\beta_2 s^{-2}y^3) \qquad (5)$$

In (4) and (5), α_j are parameters of the demand function and β_j are parameters of the cost function.

For monopoly, $\tilde{y}^M$ is obtained from the condition MR=MC, with n=1 in (4). $\tilde{p}^M$ is obtained by substituting $\tilde{y}^M$ for y in (4). For monopolistic competition, $\tilde{y}^{MC}$ and $\tilde{n}^{MC}$ are obtained by solving the conditions MR=MC and TR=TC as a pair of simultaneous equations. $\tilde{p}^{MC}$ is obtained by replacing y and n in (4) with $\tilde{y}^{MC}$ and $\tilde{n}^{MC}$. For perfect competition, $\tilde{y}^{PC}$ is determined by the conditions p=MC and TR=TC. $\tilde{p}^{PC}$ is obtained by replacing y in the MC function derived from (5) with $\tilde{y}^{PC}$. Appendix II details the formulae for $\tilde{y}^M$, $\tilde{y}^{MC}$ and $\tilde{y}^{PC}$ corresponding to (4) and (5).

The Monte Carlo simulations are based on the following (arbitrary) parameter values: α_1=0.05, α_2=0.000025, β_1=0.1, β_2=0.0001, μ_w=1.1. The corresponding values for the H-statistic, against which the estimated values generated from the simulations are to be assessed, are H=–0.243 (monopoly), H=0.583 (monopolistic competition), and H=1.000 (perfect competition).

Step 3

The following partial adjustment equations are assumed for $y_{i,t}$ and $p_{i,t}$ for all three market structures, and for $n_{i,t}$ in the case of monopolistic competition:

$$y_{i,t} = (1-\lambda)\,\tilde{y}^k_{i,t} + \lambda y_{i,t-1} + s_i\,\varepsilon^y_{i,t}\,;\ \varepsilon^y_{i,t} \sim N(0, \nu^2_y)\,;\ \ \nu^2_y = (1-\lambda^2)\,\sigma^2_y - (1-\lambda)^2\,\sigma^2_{\tilde{y}}$$

$$p_{i,t} = (1-\lambda)\,\tilde{p}^k_{i,t} + \lambda p_{i,t-1} + \varepsilon^p_{i,t}\,;\ \varepsilon^p_{i,t} \sim N(0, \nu^2_p)\,;\ \ \nu^2_p = (1-\lambda^2)\,\sigma^2_p - (1-\lambda)^2\,\sigma^2_{\tilde{p}}$$

$$n_{i,t} = (1-\lambda)\,\tilde{n}^k_{i,t} + \lambda n_{i,t-1} + \varepsilon^n_{i,t}\,;\ \varepsilon^n_{i,t} \sim N(0, \nu^2_n)\,;\ \ \nu^2_n = (1-\lambda^2)\,\sigma^2_n - (1-\lambda)^2\,\sigma^2_{\tilde{n}} \qquad (6)$$

In (6), $\sigma^2_{\tilde{y}}$, $\sigma^2_{\tilde{p}}$ and $\sigma^2_{\tilde{n}}$ are the variances (within the series for bank i) of $\tilde{y}^k_{i,t}$, $\tilde{p}^k_{i,t}$ and $\tilde{n}^k_{i,t}$. Each of these variances depends on σ^2_w, because $w_{i,t}$ is the only stochastic determinant of $\tilde{y}^k_{i,t}$, $\tilde{p}^k_{i,t}$ and $\tilde{n}^k_{i,t}$. The parameter λ describes the adjustment speed for $y_{i,t}$, $p_{i,t}$ and $n_{i,t}$. In the simulations, we examine $\lambda=0$ (instantaneous adjustment) and $\lambda=0.1, 0.2, 0.3, 0.4$ (partial adjustment, at various speeds). It is possible to envisage different adjustment speeds for each of $y_{i,t}$, $p_{i,t}$ and $n_{i,t}$; but in order to avoid a proliferation of parameters, we assume λ is the same in all three cases.

For the purposes of calculating the E-statistic, a simulated total cost series is also required. This is based directly on (5) with a stochastic disturbance term added, as follows:

$$c_{i,t} = w_{i,t}(\beta_1 y_{i,t} + \beta_2 s_i^{-1} y^2_{i,t} + 0.0005\beta_2 s_i^{-2} y^3_{i,t}) + \varepsilon^c_{i,t}\,;\ \varepsilon^c_{i,t} \sim N(0, \sigma^2_c) \qquad (7)$$

Equations (3) to (7) are used to generate simulated data for $w_{i,t}$, $y_{i,t}$, $p_{i,t}$, $n_{i,t}$ and $c_{i,t}$ for a panel of N banks indexed i=1,...,N observed over T+2 years indexed t = –1,0,1,...,T.[5]

[5] Randomly generated N(0,1) deviates are used to obtain z_i, and hence s_i. Randomly generated N(0,1) deviates, scaled using ν_w, ν_y, ν_p and ν_n chosen for consistency with the (arbitrary) parameter values $\sigma_w=0.02$ in (3) and $\sigma_y=20$, $\sigma_p=0.002$ and $\sigma_n=1$ in (6), are used to obtain $\varepsilon^w_{i,t}, \varepsilon^y_{i,t}, \varepsilon^p_{i,t}, \varepsilon^n_{i,t}$ for i=1,...,N and t = –99,...,–1,0,1,...,T. The start-values for $w_{i,t}$, $y_{i,t}$, $p_{i,t}$ and $n_{i,t}$ (at t=–100) are set to μ_w, $\tilde{y}^k, \tilde{p}^k, \tilde{n}^k$, respectively. The values of the simulated series

Step 4

The partial adjustment equations for $y_{i,t}$ and $p_{i,t}$ in (6) establish $r_{i,t}=p_{i,t}y_{i,t}=f(p_{i,t-1}y_{i,t-1}, ...)$ or $r_{i,t}=f(r_{i,t-1}, ...)$, where f is a non-linear function also containing terms in p_{t-1}, y_{t-1}, $\tilde{p}^k_{i,t}$ and $\tilde{y}^k_{i,t}$. An AR(1) model for $r_{i,t}$ can be interpreted as a linear approximation to f( ). An autoregressive structure for $\pi_{i,t}$, as assumed in the standard POP model, can be similarly established. Accordingly, the following static and dynamic panel regressions are estimated using the simulated data:

Revenue equation

FE: $$\ln(r_{i,t}) = \hat{\delta}^F_{0,i} + \hat{\delta}^F_1 \ln(w_{i,t}) + \hat{\eta}^F_{i,t} \quad (8)$$

GMM: $$\Delta\ln(r_{i,t}) = \hat{\delta}^G_1 \Delta\ln(w_{i,t}) + \hat{\delta}^G_2 \Delta\ln(r_{i,t-1}) + \Delta\hat{\eta}^G_{i,t} \quad (9)$$

Profit equation

FE: $$\ln(\pi_{i,t}) = \hat{\gamma}^F_{0,i} + \hat{\gamma}^F_1 \ln(w_{i,t}) + \hat{\xi}^F_{i,t} \quad (10)$$

GMM: $$\Delta\ln(\pi_{i,t}) = \hat{\gamma}^G_1 \Delta\ln(w_{i,t}) + \hat{\gamma}^G_2 \Delta\ln(\pi_{i,t-1}) + \Delta\hat{\xi}^G_{i,t} \quad (11)$$

FE estimation is implemented using the simulated data for t=1,...,T. For GMM estimation, the individual bank effects are eliminated prior to estimation, by applying a first-difference transformation to all variables. Two observations are sacrificed in creating the lagged dependent variable and the first-differences. Therefore GMM is implemented using the simulated data for t=–1,0,1,...,T, but only the observations for t=1,...,T are used in the estimation. The FE estimator of the H-statistic is $\hat{H}^F = \hat{\delta}^F_1$ in (8). The GMM estimator is $\hat{H}^G = \hat{\delta}^G_1/(1-\hat{\delta}^G_2)$ in (9). The FE estimator of the E-statistic is $\hat{E}^F = \hat{\gamma}^F_1$ in (10). The GMM estimator is $\hat{E}^G = \hat{\gamma}^G_1$ in (11).

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for t=–100,...,–2 are immediately discarded. Randomly generated N(0,1) deviates, scaled using the (arbitrary) parameter value $\sigma_c=10$ in (7), are used to obtain $\varepsilon^c_{i,t}$.

4. Simulated sampling distributions of the FE and GMM estimators

In Section 4, we report the results of the Monte Carlo simulations exercise. For the H-statistic, Tables 1 and 2 report the results for various values of the parameters ϕ in (3) and λ in (6), in the case N=100, T=10. Within each replication, 20 sets of simulated data are generated for each of the three market structures: monopoly, monopolistic competition and perfect competition, incorporating all available permutations of the parameter values ϕ=0.0, 0.25, 0.5, 0.75 and λ=0.0, 0.1, 0.2, 0.3, 0.4.

Section 1 of Table 1 reports the results obtained by applying FE estimation, as in (8). Section 1 shows the means and standard deviations over the 2,000 replications of $\hat{H}^F = \hat{\delta}_1^F$, the FE H-statistic. For λ=0 (instantaneous adjustment), $\hat{H}^F$ yields unbiased estimates for all three market structures. The efficiency of $\hat{H}^F$, measured by its standard deviation, is greatest in the case ϕ=0, and is somewhat reduced when ϕ>0. For λ>0 (partial adjustment), $\hat{H}^F$ yields estimates that are severely biased towards zero for all three market structures. The magnitude of the bias in $\hat{H}^F$ is increasing in λ and decreasing in ϕ. The efficiency of $\hat{H}^F$ is generally decreasing in λ, and decreasing in ϕ.

For monopoly, the mean $\hat{H}^F$ is negative for all of the cases considered in Section 1 of Table 1. For monopolistic competition, the mean $\hat{H}^F$ is positive for all cases considered. Therefore for λ>0 (partial adjustment), the biases in $\hat{H}^F$ should not prevent the researcher from distinguishing correctly between these two market structures. For FE estimation, Section 1 of Table 2 shows the rejection rates over the 2,000 replications for z-tests of H_0:H≥0 against H_1:H<0 in the case where the true model is monopoly, and for z-tests of H_0:H≤0 against H_1:H>0 in the case where the true model is monopolistic competition. In both cases, H_0 should be rejected. The power of the former test is decreasing in both ϕ and λ, but the loss of power becomes severe only towards the upper end of the ranges of values considered for ϕ and λ. The power of the latter test is close to one over the full range considered.

Of more serious concern for the interpretation of the FE H-statistic is the finding that for both monopolistic competition and perfect competition with $\lambda>0$ (partial adjustment), the mean $\hat{H}^F$ is positive but less than one for all of the cases considered in Section 1 of Table 1. This downward bias in $\hat{H}^F$ has serious implications for the researcher's ability to distinguish between monopolistic competition and perfect competition.

For FE estimation, Section 1 of Table 2 reports the rejection rates for z-tests of H_0:H=1 against H_1:H<1 in the case where the true model is monopolistic competition and H_0 should be rejected; and where the true model is perfect competition and H_0 should not be rejected. Unsurprisingly since $\hat{H}^F$ is downward biased, the z-test has no difficulty in correctly rejecting H_0 under monopolistic competition. For any $\lambda>0$, however, the z-test suffers from a severe size distortion under perfect competition. If banks' pricing and output decisions are in accordance with perfect competition, but there is partial (rather than instantaneous) adjustment, it is highly likely that the test based on FE estimation will produce an incorrect diagnosis of monopolistic competition.

The remaining sections of Table 1 report the equivalent results for GMM estimation, as in (9). Sections 2 and 3 report the means and standard deviations of $\hat{\delta}_1^G$ and $\hat{\delta}_2^G$. $\hat{\delta}_1^G$ is interpreted as the short-run elasticity of revenue with respect to the factor input price. For $\lambda=0$ (instantaneous adjustment), $\hat{\delta}_1^G$ is a virtually unbiased estimator of the H-statistic. In this case, however, $\hat{\delta}_1^G$ turns out to be less efficient than the FE estimator, $\hat{\delta}_1^F$. For $\lambda>0$ (partial adjustment), $\hat{\delta}_1^G$ is insensitive to variation in ϕ. However, $\hat{\delta}_1^G$ tends toward zero as λ increases. This tendency is in accordance with the logic of the partial adjustment model. The larger is λ, the weaker is the direct relationship between the factor input price and revenue in the same period. When λ is large, the latter is driven more by its own lagged value and less by current factor input price shocks. Therefore the larger is λ, the smaller is the parameter δ_1. The partial adjustment parameter, $\hat{\delta}_2^G$, is also insensitive to variation in ϕ. As expected, however, $\hat{\delta}_2^G$ is increasing in λ. As λ increases, $\hat{\delta}_2^G$ suffers from an appreciable loss of efficiency.

Section 4 of Table 1 reports the means and standard deviations of $\hat{H}^G = \hat{\delta}_1^G/(1-\hat{\delta}_2^G)$. For λ=0 (instantaneous adjustment), GMM produces virtually unbiased estimates of the H-statistic. For λ>0 (partial adjustment), there is a small bias toward zero in $\hat{H}^G$. As λ increases, $\hat{H}^G$ suffers from an appreciable loss of efficiency. The bias in $\hat{H}^G$ is increasing in λ, but this bias is usually much smaller than the corresponding bias in the FE estimator $\hat{H}^F$. The GMM persistence coefficient $\hat{\delta}_2^G$ is a particularly useful aid for the interpretation of $\hat{H}^G$. If $\hat{\delta}_2^G$ is close to zero, $\hat{H}^G$ is virtually unbiased; but if $\hat{\delta}_2^G$ is large and positive, $\hat{H}^G$ is somewhat downward biased. FE estimation provides no equivalent aid for the interpretation of $\hat{H}^F$.

Section 2 of Table 2 reports the rejection rates for the same hypothesis tests as before, using z-tests based on the GMM estimator, $\hat{H}^G$. In the tests of H_0:H≥0 against H_1:H<0 when the true model is monopoly, and of H_0:H≤0 against H_1:H>0 when the true model is monopolistic competition, the z-tests based on $\hat{H}^G$ generally have lower power than those based on $\hat{H}^F$.[6] In evaluating H_0:H=1 against H_1:H<1 when the true model is monopolistic competition, the z-tests based on $\hat{H}^G$ have lower power than those based on $\hat{H}^F$. However, in evaluating H_0:H=1 against H_1:H<1 when the true model is perfect competition, the size distortion in the z-tests based on $\hat{H}^G$ is usually substantially smaller than in those based on $\hat{H}^F$. If the true model is perfect competition, the z-test based on GMM is more likely to provide the correct diagnosis than the equivalent test based on FE.

[6] While the bias toward zero is less severe for $\hat{H}^G$ than for $\hat{H}^F$, $\hat{H}^G$ is less efficient than $\hat{H}^F$. This loss in efficiency accounts for the reduced power of the z-tests.

Tables 3 and 4 explore the implications of variation in N and T for the performance of the FE and GMM estimators of the H-statistic, for the case ϕ=0.5 and λ=0.2 in (3) and (7). Within each of the 2,000 replications, there are 16 sets of simulated data for each market structure, comprising all available permutations of N=25, 50, 100, 200 and T=5, 10, 15, 20.

Table 3 indicates that the bias toward zero in the FE estimator $\hat{H}^F = \hat{\delta}_1^F$ is virtually unaffected by variation in N, but is severe for any T for which, realistically, the data required for an exercise of this kind are likely to be available. The GMM estimator $\hat{\delta}_1^G$ is virtually unaffected by variation in N and T. However, $\hat{\delta}_2^G$ is increasing in N and predominantly increasing in T. The downward bias in $\hat{H}^G$ under monopoly is increasing in N, but is virtually unaffected by variation in T. The downward biases in $\hat{H}^G$ under both monopolistic competition and perfect competition are decreasing in N and predominantly decreasing in T. As anticipated, the efficiency of all of the estimators considered in Table 3 is increasing in both N and T.

Table 4 reports the rejection probabilities for z-tests of the same null and alternative hypotheses as before, based on FE and GMM estimation. Under monopoly, the tests based on GMM are more likely than those based on FE to correctly reject H_0:H≥0 in favour of H_1:H<0 when N and T are both small (N=25, T=5). For both estimators, the power of these tests is rapidly increasing in both N and T. GMM does not consistently out-perform FE over all of the values of N and T considered. Similarly under monopolistic competition, the tests based on GMM are more likely than those based on FE to correctly reject H_0:H≤0 in favour of H_1:H>0, and to correctly reject H_0:H=1 in favour of H_1:H<1, when N and T are both small. Again, the power of these tests is generally increasing in N and T, and GMM does not consistently out-perform FE. Finally, under perfect competition, the size distortion for the tests of H_0:H=1 against H_1:H<1 is smaller for the tests based on FE than for those based on GMM when N and T are both small (N=25, T=5 or 10). Elsewhere, the size distortion is larger, and often much larger, in the tests based on FE. If the true model is perfect competition, the tests based on GMM are more likely, and in large samples much more likely, to provide the correct diagnosis than the tests based on FE.

Table 5 reports summary results for the estimation of Shaffer's E-statistic for the same values of the parameters ϕ in (3) and λ in (6) as in Tables 1 and 2, in the case N=100, T=10.[7] Table 5 reports the mean values for each estimated E-statistic as in (10) and (11), and the rejection probabilities for the test of H_0:E=0 against H_1:E<0. Under monopoly, the E-statistic should be negative for both λ=0 (instantaneous adjustment) and λ>0 (partial adjustment). In either case, an increase in factor prices entails a reduced rate of monopoly profit. The mean simulated values of both $\hat{E}^F$ and $\hat{E}^G$ are all negative, but H_0:E=0 is more likely to be rejected in favour of H_1:E<0 in the test based on GMM than it is in the test based on FE.

Under monopolistic competition and perfect competition, the E-statistic should be zero for λ=0 (instantaneous adjustment) and negative for λ>0 (partial adjustment). In the former case, an increase in factor prices results in instantaneous adjustment towards a new competitive equilibrium at which normal profit is once again realized. In the latter case, sub-normal profits are earned temporarily until the adjustment to the new competitive equilibrium is complete. The mean simulated values of both $\hat{E}^F$ and $\hat{E}^G$ reported in Table 5 are consistent with these conditions.

The test of H_0:E=0 against H_1:E<0 based on FE has the correct size for λ=0, but has relatively low power for λ>0. The test based on GMM is over-sized for λ=0, but has relatively high power for λ>0. On these criteria, there appears to be no clear basis for preferring either estimation method for the profit equation. However, an implication of the argument developed above is that the E-statistic is in fact superfluous. If the model used to estimate the H-statistic is correctly specified, then a market equilibrium assumption is not essential for the accurate identification of the H-statistic. With a correctly specified model, the H-statistic can be estimated, without any serious problems of bias or inconsistency, under conditions of either instantaneous adjustment or partial adjustment.

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7 For reasons that are amplified below, we do not consider the estimation of the E-statistic to be as important for the measurement of competitive conditions as has been assumed in the previous literature. To economise on space, the results for the E-statistic equivalent to those shown in Tables 3 and 4 (for constant ϕ and λ and various N and T) are not reported.

5. Empirical results: FE and GMM estimation of the H- and E-statistics

In Section 5, we report an empirical comparison between FE and GMM estimation of the H-statistic and the E-statistic. We use unconsolidated company accounts data obtained from *Bankscope* for the years 1998-2004 (inclusive). We originally downloaded 84,091 bank-year observations on 12,013 banks from 60 countries. We eliminated observations with missing data on any of the variables, and we applied rules to exclude outliers based on the 1st and 99th percentiles of the distributions of the dependent variable in the revenue and profit equations. We also eliminated countries for which fewer than 120 bank-year observations were available for the GMM estimation. The final sample is an unbalanced panel, comprising 19,556 bank-year observations on 5,192 banks from 19 countries. For presentational purposes, the countries are sub-divided into three groups. Group A contains six of the seven G7 member countries: France, Germany, Italy, Japan, UK and US. The seventh G7 member, Canada, is omitted due to insufficient data. Group B contains six other western European countries: Austria, Belgium, Denmark, Norway, Spain and Switzerland. Group C contains seven emerging, transition and developing countries: Argentina, Bangladesh, Brazil, India, Nigeria, Russia and Venezuela.

Two sets of estimations of the revenue equation are reported. The dependent variable is $\ln(r_{i,t})$ where $r_{i,t}$ is the ratio of revenue to total assets, and revenue is defined using *either* interest income *or* total (interest *plus* non-interest) income. We assume there are J=3 factor inputs: deposits, labour and fixed capital and equipment. The definitions of the factor input prices $w_{j,i,t}$ are: interest expenses / total deposits and money market funding (j=1); personnel costs / total assets (j=2); and operating and other expenses / total assets (j=3).[8] The control variables are: $x_{1,i,t}$ = natural logarithm of total assets; $x_{2,i,t}$ = equity / total assets; $x_{3,i,t}$ = net loans / total assets; and a full set of individual year dummy variables. In the profit

[8] In order to avoid possible simultaneity between input prices and revenue, which might arise if banks exercise monopsony power in their factor markets, Shaffer (2004) suggests using lagged rather than current input prices as covariates in the revenue equation. When this adjustment is made, the estimation results for the H-statistic are generally similar to those reported below.

equation, the dependent variable is $\ln(1+\pi_{i,t})$ where $\pi_{i,t}$ = return on assets. The covariates are the same as those for the revenue equation.

Table 6 reports the estimation results for both versions of the revenue equation (interest income and total income). Using FE based on (8), $\hat{H}^F$ lies between zero and one in every case. Using a significance level of 5%, we fail to reject H_0:H=1 in favour of H_1:H<1 in only one case (the interest income equation for Bangladesh); and we reject H_0:H=0 in favour of H_1:H>0 in every case.

Using GMM based on (9) with interest income as the dependent variable, $\hat{H}^G$ exceeds one in two cases, and we fail to reject H_0:H=1 in favour of H_1:H<1 in four cases: Austria, Argentina, Bangladesh and Brazil. The persistence coefficient $\hat{\delta}_2^G$ is positive for 15 of the 19 countries, and we are able to reject $H_0:\delta_2=0$ in favour of $H_1:\delta_2>0$ for nine countries. With total income as the dependent variable, $\hat{H}^G$ lies between zero and one in every case, and we fail to reject H_0:H=1 in favour of H_1:H<1 in two cases: Bangladesh and Russia. $\hat{\delta}_2^G$ is positive for 12 of the 19 countries, and we are able to reject $H_0:\delta_2=0$ in favour of $H_1:\delta_2>0$ for six countries. In both sets of estimations, we reject H_0:H=0 in favour of H_1:H>0 in every case.[9]

There is a high level of sampling error associated with both estimation methods, which produces considerable variation in the estimated H-statistics and persistence coefficients for individual countries. Nevertheless, several general conclusions can be drawn from these results.

First, the empirical results for $\hat{H}^F$ and $\hat{H}^G$, are consistent with the results of the Monte Carlo simulations reported in Section 4. $\hat{H}^G$ tends to produce estimates that are larger and closer to one than

[9] Table 6 reports the results from applying the two-step version of the GMM estimator. The validity of the over-identifying restrictions is rejected at the 1% level in one of the 19 estimations with interest income as dependent variable, and in three cases with total income as the dependent variable. The test for 2nd-order autocorrelation in the residuals is positive in 1 and 3 cases, respectively. In the GMM estimations of the revenue equation with interest income as the dependent variable, the coefficients on $x_{1,i,t}$ (= natural logarithm of total assets) are positive and significant at the 5% level for 5 countries out of 19, and negative and significant for 1 country. (These results are not reported in Table 6, but are available upon request from the authors). For the other covariates the numbers of significant coefficients are: for $x_{2,i,t}$ (= equity / total assets) 10 positive; for $x_{3,i,t}$ (= net loans / total assets) 7 positive and 3 negative. In the GMM estimations with total income as the dependent variable: for $x_{1,i,t}$, 7 positive and 2 negative; for $x_{2,i,t}$, 8 positive; for $x_{3,i,t}$, 1 positive and 11 negative.

$\hat{H}^F$. With interest income as the dependent variable $\hat{H}^G > \hat{H}^F$ for 15 countries out of 19, and with total income as the dependent variable $\hat{H}^G > \hat{H}^F$ for 12 countries out of 19. This pattern is consistent with a tendency for FE estimation to produce downward biased estimates of the H-statistic.

Second, the difference between the numerical estimates of the H-statistic that are produced by FE and GMM is related to the estimated value of the persistence coefficient, $\hat{\delta}_2^G$. The Monte Carlo simulations indicate that FE produces a downward biased estimated H-statistic when the true persistence is positive (partial adjustment), and an unbiased estimate when the true persistence is zero (instantaneous adjustment). Accordingly, in the interest income estimations, the average $\hat{H}^F$ appears to be downward biased for Groups A, B and C (average $\hat{\delta}_2^G$>0). In the total income estimations, the average $\hat{H}^F$ appears to be downward biased for Groups A and C (average $\hat{\delta}_2^G$>0), but not for Group B (average $\hat{\delta}_2^G$<0).

Third, there are some systematic differences between the estimation results for the Group A and B countries on the one hand, and Group C on the other. Using both FE and GMM estimation and using both revenue definitions, the mean estimated H-statistic is higher for Group C than for Groups A and B. Although monopolistic competition appears to be the appropriate model in almost every case, competitive conditions in the banking sectors of Group C countries lean closer to the textbook model of perfect competition than do those of the countries in Groups A and B.

Table 7 reports the estimation results for the profit equation. Using FE, $\hat{E}^F$ is negative and significantly different from zero for 13 of the 19 countries; and using GMM, $\hat{E}^G$ is negative and significant for 14 countries. These results cast serious doubts on the validity of the instantaneous adjustment or market equilibrium assumption. Furthermore, the estimated short-run POP (persistence of profit) coefficient $\hat{\gamma}_2^G$ is positive for 16 of the 19 countries, and we reject H_0:γ_2=0 if favour of H_1:γ_2>0 for 14 countries. The degree of short-run POP appears somewhat higher for Group A than for the other two groups.

Within Groups A and B, the finding that competition is less intense in Japan and in the two Scandinavian countries (Denmark and Norway) than it is elsewhere may be explained by a history, during the 1980s and 1990s, of difficulties in the banking sectors of these countries (Alley, 1993; Molyneux et al., 1996; Uchida and Tsutsui, 2005; Kim et al., 2005). High levels of bad debt may have caused banks to exercise restraint in competing for new sources of revenue.

More generally, the results reported in Table 6 follow a similar pattern to those reported by Claessens and Laeven (2004) for an earlier period, 1994-2001.[10] Levine (2003) finds that impediments to foreign bank entry, especially in developed countries, have a positive effect on the interest margins of incumbent banks. Claessens et al. (2001) and Gelos and Roldos (2004) find that despite recent consolidation, foreign bank penetration in developing countries increases competition, leading to reductions in both the costs and margins of incumbent banks. This pattern seems to be typical of the experiences of developing and developed nations more generally: foreign bank penetration in developed nations is generally low relative to many developing nations. The results reported in Table 6 appear consistent with this general pattern. Legal and economic entry barriers tend to be lower in developing banking systems, so competition tends to be more intense and short-run POP tends to be lower.

6. Conclusion

This study has examined the implications for the estimation of the Rosse-Panzar H-statistic of departures from assumed product market equilibrium conditions. Using the techniques that have been applied in the previous empirical literature on the measurement of competitive conditions in banking, a market equilibrium assumption is necessary for accurate estimation of the H-statistic. While the micro

[10] Claessens and Laeven (2004) report estimates of the H-statistic for 50 countries, including all of those shown in Table 6. They report the arithmetic mean of four estimated H-statistics for each country, obtained by estimating interest income and total income equations using FE and RE. The averages of their mean H-statistics for the countries included in the present sample are 0.582 for Group A, 0.593 for Group B, and 0.676 for Group C. To provide a direct comparison with the Claessens and Laeven results, we repeated the estimations of the static revenue equation (see Table 6) using RE. Our average H-statistics are 0.404 for Group A, 0.467 for Group B, and 0.635 for Group C.

theory underlying the Rosse-Panzar test is based on a static equilibrium framework, in practice the speed of adjustment towards equilibrium might well be less than instantaneous, and markets might be out of equilibrium either occasionally, or frequently, or always.

If the adjustment towards equilibrium in response to factor input price shocks is described by a partial adjustment equation, and not by instantaneous adjustment, the static revenue equation that has been estimated in previous applications of the Rosse-Panzar test is misspecified. Partial adjustment dictates that the revenue equation should contain a lagged dependent variable. In this case, the revenue equation should not be estimated using a 'static' panel estimator such as fixed effects (FE) or random effects, due to issues of bias and inconsistency in the estimated coefficients. Instead a dynamic panel estimation method is required. In this study, Arellano and Bond's (1991) generalized method of moments (GMM) dynamic panel estimator has been used.

In a Monte Carlo simulations exercise, we have demonstrated that when the true data generating process involves partial rather than instantaneous adjustment, FE estimation of a static revenue equation produces a measured H-statistic that is severely biased towards zero. With partial adjustment, the H-statistic is expected to be smaller than one under both monopolistic competition and perfect competition. Accordingly, it is invalid to reject the model of perfect competition in favour of one of monopolistic competition on the basis of a measured H-statistic that is smaller than one.

We have also reported empirical results obtained by applying the FE and GMM estimators of the H-statistic to unconsolidated company accounts data for 19 national banking sectors for the period 1998-2004. The measured H-statistics obtained from a static revenue equation (estimated using FE) and a dynamic revenue equation (estimated using GMM) are consistent with our main conclusion, that the FE estimator of the H-statistic is biased towards zero.

However, the proportions of countries for which we are unable to reject a null hypothesis of $H=1$ in favour of an alternative of $H<1$ are small, regardless of the estimation method. Therefore our empirical results are consistent with the most common finding from the previous literature, that competition in the banking sector is best characterized by the textbook model of monopolistic competition. Nevertheless, our results do suggest that within this category there may have been a systematic tendency towards the underestimation of the intensity of competition. Within the spectrum of competitive conditions covered by the case of monopolistic competition, banking appears to lean more towards the upper (highly competitive) part of the spectrum than has previously been suggested.

Finally, we have sub-divided the 19 countries into three groups: Group A comprising six of the seven G7 member countries, Group B comprising six other western European countries, and Group C comprising a heterogeneous set of emerging, transition and developing countries. Competitive conditions in the banking sectors of the Group C countries appear to lean further towards the textbook model of perfect competition than is the case for Groups A and B. The estimated coefficients on the lagged dependent variables in the revenue and profit equations suggest most countries are characterized by positive short-run persistence and partial adjustment. This result corroborates the present study's principal finding, that a dynamic rather than a static formulation of the revenue equation is required for the correct identification of the Rosse-Panzar H-statistic.

Appendix I: Derivation of the Rosse-Panzar H-statistic

The notation is as follows. y = output; n = perceived number of competing firms; **z** = vector of exogenous variables for demand function; w_i = price for factor input i; **w** = vector of factor input prices; x_i = x_i(y,**w**,**v**) = conditional demand function for factor input i; **v** = vector of exogenous variables for cost function; r = r(y,n,**z**) = revenue function; c = c(y,**w**,**v**) = cost function; p = p(y,n,z) = inverse demand function; $r_y = \partial r/\partial y$, $r_{yy} = \partial^2 r/\partial y^2$ evaluated at the profit-maximizing equilibrium; r_{yn}, c_y, c_{yy}, p_y, p_n, p_{yn} are similarly defined; H = Rosse-Panzar H-statistic.

Monopoly

Panzar and Rosse (1987) present the following proof of the result H≤0 for monopoly. Consider an equi-proportionate increase in all factor input prices, from **w** to (1+h)**w**. Let $\tilde{y}^M$ and $\tilde{\tilde{y}}^M$ denote the profit-maximising output levels when factor input prices are **w** and (1+h)**w**, respectively, and let $\tilde{r}^M$ and $\tilde{\tilde{r}}^M$ denote the corresponding revenues. From these definitions, it follows:

$$\tilde{\tilde{r}}^M - c(\tilde{\tilde{y}}^M,(1+h)\mathbf{w},\mathbf{v}) \geq \tilde{r}^M - c(\tilde{y}^M,(1+h)\mathbf{w},\mathbf{v}) \qquad \text{(A.1)}$$

$$\tilde{r}^M - c(\tilde{y}^M,\mathbf{w},\mathbf{v}) \geq \tilde{\tilde{r}}^M - c(\tilde{\tilde{y}}^M,\mathbf{w},\mathbf{v}) \qquad \text{(A.2)}$$

Costs are linearly homogeneous in factor input prices. Therefore (A.1) can be rewritten:

$$\tilde{\tilde{r}}^M - (1+h)c(\tilde{\tilde{y}}^M,\mathbf{w},\mathbf{v}) \geq \tilde{r}^M - (1+h)c(\tilde{y}^M,\mathbf{w},\mathbf{v}) \qquad \text{(A.3)}$$

Multiplying (A.2) by (1+h) and adding the result to (A.3) yields:

$$-h(\tilde{\tilde{r}}^M - \tilde{r}^M) \geq 0 \qquad \text{(A.4)}$$

The Rosse-Panzar H-statistic is $H = \lim_{h \to 0}\{(\tilde{\tilde{r}}^M - \tilde{r}^M)/(h\tilde{r}^M)\}$. Dividing (A.4) by $-h^2$ yields

$(\tilde{\tilde{r}}^M - \tilde{r}^M)/h < 0$. This result ensures H<0.

Monopolistic competition

For monopolistic competition, $\tilde{y}^{MC}$ denotes the profit-maximizing equilibrium output level, and the equilibrium values of other variables are denoted similarly. The tangency solution is defined by y and n which satisfy (i) marginal revenue = marginal cost; and (ii) total revenue = total cost:

$$r_y - c_y = 0 \qquad \text{(A.5)}$$

$$r(\tilde{y}^{MC}, \tilde{n}^{MC}, \mathbf{z}) - c(\tilde{y}^{MC}, \mathbf{w}, \mathbf{v}) = 0 \qquad \text{(A.6)}$$

Total differentiation of (A.5) and (A.6) with respect to w_i yields:

$$r_{yy}(\partial \tilde{y}^{MC}/\partial w_i) + r_{yn}(\partial \tilde{n}^{MC}/\partial w_i) - c_{yy}(\partial \tilde{y}^{MC}/\partial w_i) - \partial^2 c/\partial y \partial w_i = 0 \qquad \text{(A.7)}$$

$$r_y(\partial \tilde{y}^{MC}/\partial w_i) + r_n(\partial \tilde{n}^{MC}/\partial w_i) - c_y(\partial \tilde{y}^{MC}/\partial w_i) - \partial c/\partial w_i = 0 \qquad \text{(A.8)}$$

(A.7) and (A.8) can be written in matrix form as follows:

$$\begin{pmatrix} r_{yy} - c_{yy} & r_{yn} \\ r_y - c_y & r_n \end{pmatrix} \begin{pmatrix} \partial \tilde{y}^{MC}/\partial w_i \\ \partial \tilde{n}^{MC}/\partial w_i \end{pmatrix} = \begin{pmatrix} \partial^2 c/\partial y \partial w_i \\ \partial c/\partial w_i \end{pmatrix}$$

$$\begin{pmatrix} \partial \tilde{y}^{MC}/\partial w_i \\ \partial \tilde{n}^{MC}/\partial w_i \end{pmatrix} = \frac{1}{(r_{yy} - c_{yy})r_n - (r_y - c_y)r_{yn}} \begin{pmatrix} r_n & -r_{yn} \\ c_y - r_y & r_{yy} - c_{yy} \end{pmatrix} \begin{pmatrix} \partial^2 c/\partial y \partial w_i \\ \partial c/\partial w_i \end{pmatrix}$$

Using $r_y - c_y = 0$, $\partial c/\partial w_i = x_i(y,\mathbf{w},\mathbf{v})$ and $\partial^2 c/\partial y \partial w_i = \partial x_i/\partial y$:

$$\partial \tilde{y}^{MC}/\partial w_i = \frac{r_n(\partial x_i/\partial y) - r_{yn} x_i}{(r_{yy} - c_{yy})r_n} \qquad \text{(A.9)}$$

For (A.6) to be maintained, $\partial \tilde{r}^{MC}/\partial w_i = c_y(\partial \tilde{y}^{MC}/\partial w_i) + \partial c/\partial w_i = c_y(\partial \tilde{y}^{MC}/\partial w_i) + x_i$

$$H = \sum_i \{w_i c_y (\partial \tilde{y}^{MC}/\partial w_i)/\tilde{r}^{MC} + w_i x_i/\tilde{r}^{MC}\}$$

Using $\sum_i w_i x_i = \tilde{c}^{MC}$, $\tilde{r}^{MC} = \tilde{c}^{MC}$, $r_y = c_y$, $\sum_i w_i(\partial x_i/\partial y) = c_y$ and $\sum_i w_i x_i = \tilde{c}^{MC}$:

$$H = 1 + \frac{c_y\{r_n \sum_i w_i(\partial x_i/\partial y) - r_{yn}\sum_i w_i x_i\}}{\tilde{r}^{MC}(r_{yy} - c_{yy})r_n} = 1 + \frac{c_y(r_n c_y - \tilde{c}^{MC} r_{yn})}{\tilde{r}^{MC}(r_{yy} - c_{yy})r_n} = 1 + \left[\frac{r_y(r_n r_y - \tilde{r}^{MC} r_{yn})}{\tilde{r}^{MC}(r_{yy} - c_{yy})r_n}\right]$$

Using $\tilde{r}^{MC} = \tilde{p}^{MC}\tilde{y}^{MC}$, $r_n r_y - \tilde{r}^{MC} r_{yn} =$

$$(\tilde{p}^{MC} y_n + \tilde{y}^{MC} p_n)(\tilde{p}^{MC} + \tilde{y}^{MC} p_y) - \tilde{p}^{MC}\tilde{y}^{MC}(p_n + y_n p_y + \tilde{y}^{MC} p_{yn}) = \{\tilde{y}^{MC}\}^2(p_n p_y - \tilde{p}^{MC} p_{yn})$$

$$H = 1 + \left[\frac{r_y\{y^{MC}\}^2(p_n p_y - \tilde{p}^{MC} p_{yn})}{\tilde{r}^{MC}(r_{yy} - c_{yy})r_n}\right] \tag{A.10}$$

The condition $0<H<1$ under monopolistic competition follows from the assumption that the price elasticity of the perceived demand function is a non-decreasing function of the number of perceived competitors. This condition implies $e_n \geq 0$, where $e(y,n,z) = -p/(yp_y)$ = price elasticity of perceived demand function, and $e_n = \partial e/\partial n$.

$e_n = pyp_{yn}/(yp_y)^2 - p_n/(yp_y) = (pp_{yn} - p_n p_y)/(yp_y^2)$

Therefore $e_n>0$ ensures $(p_n p_y - pp_{yn})<0$ and from (A.10), $H<1$.

Perfect competition

For perfect competition, $\tilde{y}^{PC}$ denotes the profit-maximizing equilibrium output level, and the equilibrium values of other variables are denoted similarly. Perfectly competitive equilibrium requires: (i) price = marginal cost; and (ii) total revenue = total cost:

$$\tilde{p}^{PC} - c_y = 0 \tag{A.11}$$

$$\tilde{p}^{PC}\tilde{y}^{PC} - c(\tilde{y}^{PC}, \mathbf{w}, \mathbf{v}) = 0 \tag{A.12}$$

Total differentiation of (A.11) and (A.12) with respect to w_i yields:

$$(\partial \tilde{p}^{PC}/\partial w_i) - c_{yy}(\partial \tilde{y}^{PC}/\partial w_i) - (\partial c_y/\partial w_i) = 0 \tag{A.13}$$

$$(\partial \tilde{p}^{PC}/\partial w_i)\,\tilde{y}^{PC} + \tilde{p}^{PC}(\partial \tilde{y}^{PC}/\partial w_i) - c_y(\partial \tilde{y}^{PC}/\partial w_i) - (\partial c/\partial w_i) = 0 \tag{A.14}$$

Using $\partial c/\partial w_i = x_i$, (A.13) and (A.14) can be written in matrix form as follows:

$$\begin{pmatrix} 1 & -c_{yy} \\ y & p-c_y \end{pmatrix}\begin{pmatrix} \partial\tilde{p}^{PC}/\partial w_i \\ \partial\tilde{y}^{PC}/\partial w_i \end{pmatrix} = \begin{pmatrix} \partial x_i/\partial y \\ x_i \end{pmatrix}$$

Using (A.11), the solutions are as follows:

$$\begin{pmatrix} \partial\tilde{p}^{PC}/\partial w_i \\ \partial\tilde{y}^{PC}/\partial w_i \end{pmatrix} = \frac{1}{yc_{yy}}\begin{pmatrix} 0 & c_{yy} \\ -y & 1 \end{pmatrix}\begin{pmatrix} \partial x_i/\partial y \\ x_i \end{pmatrix}$$

Using r=py and (A.11):

$$(\partial r/\partial w_i) = \tilde{p}^{PC}(\partial\tilde{y}^{PC}/\partial w_i) + \tilde{y}^{PC}(\partial\tilde{p}^{PC}/\partial w_i) = c_y(x_i - y(\partial x_i/\partial y))/(yc_{yy}) + x_i$$

$$H = (1/r)\sum_i w_i(\partial r/\partial w_i) = \{c_y/(ryc_{yy})\}((\sum_i w_i x_i - y\sum_i w_i(\partial x_i/\partial y)) + (\sum_i w_i x_i)/r$$

Using $\sum_i w_i x_i = c$, $\sum_i w_i(\partial x_i/\partial y) = c_y$, (A.11) and (A.12):

$$H = p(py - yp)/(ryc_{yy}) + py/(py) = 1$$

Appendix II: Equilibrium solutions for price and output under monopoly, monopolistic competition and perfect competition

Equations (4) and (5) define the demand and cost functions on which the Monte Carlo simulations that are reported in Sections 3 and 4 of this paper are based. In the case of monopoly, the equilibrium output level satisfies the condition MR=MC, with n=1 in (4). The solution for $\tilde{y}^{M}$, as a function of w and the parameters α_j, β_j and s, is:

$$\tilde{y}^{M} = \frac{2(\beta_2 w - \alpha_2) + \{4(\alpha_2^2 + \beta_2^2 w^2 - 2\alpha_2\beta_2 w) - 0.006\beta_2 w(\beta_1 w - 2\alpha_1)\}^{1/2}}{0.003\beta_2 s^{-1} w}$$

In the case of monopolistic competition, the equilibrium conditions are MR=MC and TR=TC. The equilibrium solutions are obtained by solving these two conditions as a pair of simultaneous equations in y and n, as follows:

$$\tilde{y}^{MC} = \frac{0.001\alpha_1\beta_2 w - \{0.000001\alpha_1^2\beta_2^2 w^2 - 0.002\alpha_2\beta_2 w(\alpha_1\alpha_2 + \alpha_1\beta_2 w - \alpha_2\beta_1 w)\}^{1/2}}{0.001\alpha_2\beta_2 s^{-1} w}$$

$$\tilde{n}^{MC} = \frac{\alpha_2}{\beta_2 w(1 - 0.001 s^{-1}\tilde{y}^{MC})}$$

In the case of perfect competition, the equilibrium output level is determined by the conditions p=MC and TR=TC. The solution for $\tilde{y}^{PC}$ is:

$$\tilde{y}^{PC} = 1000s$$

As noted in Section 3, the simulations are based on the following (arbitrary) parameter values: α_1=0.05, α_2=0.000025, β_1=0.1, β_2=0.0001, μ_w=1.1. For w=μ_w=1.1 and s=1, these parameter values produce: {$\tilde{y}^{M}$=967.67, $\tilde{p}^{M}$=.0758}, {$\tilde{y}^{MC}$=955.53, $\tilde{p}^{MC}$=.0551, $\tilde{n}^{MC}$=5.11} and {$\tilde{y}^{PC}$=1000, $\tilde{p}^{PC}$ = .0550}. As noted in Section 3, the corresponding 'true' values for the H-statistic are H=–0.243 (monopoly), H=0.583 (monopolistic competition), and H=1.000 (perfect competition).

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Table 1 Simulation results for estimation of the H-statistic: various ϕ, λ and fixed N=100, T=10

$\phi \rightarrow$	Monopoly				Monopolistic competition				Perfect competition			
	0.0	0.25	0.5	0.75	0.0	0.25	0.5	0.75	0.0	0.25	0.5	0.75
$\lambda \downarrow$	Section 1. FE: Mean simulated values of $\hat{H}^F = \hat{\delta}_1^F$, Standard deviations in *italics*											
0.0	-.244	-.243	-.243	-.242	.583	.584	.584	.584	1.000	1.002	1.001	1.002
0.1	-.219	-.223	-.229	-.236	.516	.529	.540	.549	.888	.910	.929	.947
0.2	-.191	-.197	-.207	-.217	.454	.478	.498	.522	.780	.819	.855	.896
0.3	-.163	-.176	-.187	-.202	.392	.416	.448	.483	.673	.716	.770	.829
0.4	-.139	-.149	-.162	-.181	.326	.359	.398	.441	.561	.616	.680	.754
0.0	*.053*	*.056*	*.059*	*.070*	*.066*	*.069*	*.073*	*.087*	*.066*	*.068*	*.072*	*.086*
0.1	*.053*	*.058*	*.063*	*.074*	*.066*	*.072*	*.078*	*.092*	*.066*	*.071*	*.077*	*.092*
0.2	*.055*	*.059*	*.067*	*.082*	*.068*	*.073*	*.084*	*.102*	*.068*	*.072*	*.083*	*.101*
0.3	*.056*	*.061*	*.067*	*.085*	*.070*	*.076*	*.084*	*.107*	*.069*	*.075*	*.084*	*.106*
0.4	*.054*	*.061*	*.071*	*.091*	*.068*	*.076*	*.088*	*.115*	*.068*	*.075*	*.088*	*.114*
	Section 2. GMM: Mean simulated values of $\hat{\delta}_1^G$, Standard deviations in *italics*											
0.0	-.236	-.235	-.236	-.240	.566	.570	.570	.569	.976	.980	.981	.979
0.1	-.214	-.216	-.215	-.217	.506	.507	.512	.511	.873	.875	.881	.880
0.2	-.187	-.191	-.191	-.194	.452	.452	.454	.454	.778	.779	.781	.783
0.3	-.163	-.169	-.164	-.167	.395	.392	.401	.400	.680	.677	.687	.688
0.4	-.141	-.138	-.140	-.140	.336	.342	.344	.348	.578	.585	.589	.594
0.0	*.066*	*.073*	*.085*	*.111*	*.082*	*.090*	*.106*	*.137*	*.082*	*.089*	*.104*	*.136*
0.1	*.065*	*.074*	*.087*	*.115*	*.083*	*.092*	*.109*	*.142*	*.083*	*.091*	*.107*	*.140*
0.2	*.068*	*.075*	*.087*	*.117*	*.086*	*.094*	*.108*	*.145*	*.086*	*.092*	*.106*	*.143*
0.3	*.069*	*.075*	*.087*	*.113*	*.085*	*.093*	*.107*	*.142*	*.084*	*.091*	*.106*	*.140*
0.4	*.064*	*.074*	*.083*	*.110*	*.080*	*.091*	*.103*	*.139*	*.080*	*.090*	*.101*	*.137*
	Section 3. GMM: Mean simulated values of $\hat{\delta}_2^G$, Standard deviations in *italics*											
0.0	-.013	-.011	-.013	-.014	-.012	-.012	-.012	-.014	-.010	-.011	-.011	-.013
0.1	.083	.086	.087	.083	.083	.086	.085	.082	.085	.087	.086	.083
0.2	.180	.181	.179	.182	.181	.183	.180	.182	.183	.185	.182	.183
0.3	.276	.275	.275	.274	.277	.275	.276	.274	.278	.277	.277	.274
0.4	.370	.370	.369	.369	.370	.370	.369	.369	.371	.372	.370	.369
0.0	*.046*	*.046*	*.046*	*.048*	*.044*	*.045*	*.046*	*.047*	*.041*	*.043*	*.044*	*.047*
0.1	*.048*	*.048*	*.050*	*.049*	*.047*	*.047*	*.049*	*.048*	*.044*	*.045*	*.048*	*.048*
0.2	*.051*	*.050*	*.050*	*.052*	*.050*	*.049*	*.049*	*.051*	*.047*	*.048*	*.048*	*.052*
0.3	*.054*	*.053*	*.053*	*.054*	*.053*	*.052*	*.053*	*.055*	*.051*	*.051*	*.052*	*.056*
0.4	*.057*	*.058*	*.056*	*.057*	*.057*	*.058*	*.056*	*.057*	*.055*	*.056*	*.055*	*.058*
	Section 4. GMM: Mean simulated values of $\hat{H}^G$, Standard deviations in *italics*											
0.0	-.234	-.233	-.234	-.237	.561	.564	.564	.562	.968	.971	.972	.969
0.1	-.234	-.237	-.236	-.237	.554	.556	.561	.559	.957	.962	.966	.962
0.2	-.229	-.234	-.233	-.238	.555	.555	.555	.557	.956	.959	.958	.961
0.3	-.227	-.234	-.227	-.232	.550	.544	.556	.553	.947	.942	.955	.951
0.4	-.226	-.221	-.224	-.224	.538	.547	.550	.556	.928	.940	.943	.950
0.0	*.067*	*.073*	*.084*	*.110*	*.087*	*.093*	*.106*	*.136*	*.094*	*.098*	*.109*	*.136*
0.1	*.073*	*.082*	*.096*	*.126*	*.098*	*.105*	*.123*	*.157*	*.106*	*.112*	*.126*	*.158*
0.2	*.086*	*.093*	*.107*	*.144*	*.114*	*.120*	*.135*	*.180*	*.125*	*.127*	*.140*	*.182*
0.3	*.098*	*.107*	*.121*	*.158*	*.128*	*.134*	*.155*	*.199*	*.142*	*.144*	*.161*	*.202*
0.4	*.107*	*.120*	*.135*	*.178*	*.140*	*.156*	*.173*	*.229*	*.160*	*.173*	*.184*	*.236*

Table 2 Rejection probabilities for tests of H_0:H=0 and H_0:H=1: various ϕ, λ and fixed N=100, T=10

True market structure, H_0 and H_1		Section 1. FE estimation				Section 2. GMM estimation			
	$\phi \rightarrow$	0.0	0.25	0.5	0.75	0.0	0.25	0.5	0.75
	$\lambda \downarrow$								
Monopoly	0.0	1.000	.997	.991	.960	.996	.985	.962	.879
Test H_0:H≥0	0.1	.993	.990	.984	.950	.990	.979	.934	.828
against H_1:H<0	0.2	.970	.959	.943	.896	.961	.942	.898	.763
	0.3	.904	.915	.904	.828	.925	.908	.835	.686
	0.4	.809	.820	.809	.756	.887	.825	.770	.630
Monopolistic comp.	0.0	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Test H_0:H≤0	0.1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	.995
against H_1:H>0	0.2	1.000	1.000	1.000	.999	1.000	.999	1.000	.984
	0.3	1.000	1.000	1.000	1.000	1.000	1.000	.999	.972
	0.4	.998	1.000	1.000	.997	1.000	.999	.994	.936
Monopolistic comp.	0.0	1.000	1.000	1.000	.999	1.000	1.000	1.000	.984
Test H_0:H=1	0.1	1.000	1.000	1.000	.999	.999	.999	.991	.967
against H_1:H<1	0.2	1.000	1.000	1.000	1.000	.997	.996	.991	.935
	0.3	1.000	1.000	1.000	1.000	.991	.987	.968	.891
	0.4	1.000	1.000	1.000	1.000	.982	.969	.944	.840
Perfect comp.	0.0	.049	.047	.049	.044	.294	.274	.253	.245
Test H_0:H=1	0.1	.493	.354	.252	.162	.327	.294	.276	.248
against H_1:H<1	0.2	.948	.818	.592	.337	.321	.299	.279	.248
	0.3	1.000	.987	.902	.589	.350	.333	.287	.258
	0.4	1.000	1.000	.987	.808	.384	.345	.325	.268

Table 3 Simulation results: Fixed ϕ=0.5, λ=0.2 and various N, T

	Monopoly				Monopolistic competition				Perfect competition			
N →	25	50	100	200	25	50	100	200	25	50	100	200
T↓	Section 1. FE: Mean simulated values of $\hat{H}^F = \hat{\delta}_1^F$, Standard deviations in *italics*											
5	-.258	-.261	-.255	-.258	.477	.473	.480	.478	.820	.816	.823	.821
10	-.263	-.265	-.269	-.268	.502	.500	.495	.497	.859	.857	.852	.853
15	-.272	-.268	-.271	-.269	.504	.509	.504	.507	.865	.870	.866	.869
20	-.276	-.269	-.272	-.273	.504	.512	.509	.508	.868	.876	.873	.872
5	*.205*	*.148*	*.104*	*.073*	*.254*	*.183*	*.129*	*.091*	*.252*	*.182*	*.128*	*.090*
10	*.131*	*.094*	*.068*	*.047*	*.163*	*.117*	*.084*	*.058*	*.162*	*.116*	*.083*	*.058*
15	*.104*	*.075*	*.053*	*.036*	*.129*	*.093*	*.065*	*.045*	*.128*	*.092*	*.064*	*.045*
20	*.087*	*.064*	*.045*	*.033*	*.109*	*.079*	*.056*	*.040*	*.108*	*.079*	*.055*	*.040*
	Section 2. GMM: Mean simulated values of $\hat{\delta}_1^G$, Standard deviations in *italics*											
5	-.240	-.246	-.242	-.248	.451	.447	.460	.461	.776	.773	.789	.792
10	-.248	-.251	-.245	-.246	.470	.465	.455	.455	.804	.800	.783	.783
15	-.248	-.249	-.252	-.244	.478	.470	.465	.460	.816	.805	.800	.789
20	-.253	-.247	-.251	-.251	.481	.471	.467	.467	.816	.805	.801	.802
5	*.238*	*.175*	*.120*	*.084*	*.293*	*.218*	*.151*	*.105*	*.289*	*.217*	*.150*	*.104*
10	*.161*	*.114*	*.091*	*.063*	*.209*	*.141*	*.111*	*.078*	*.209*	*.138*	*.109*	*.077*
15	*.138*	*.092*	*.066*	*.050*	*.206*	*.116*	*.082*	*.062*	*.208*	*.112*	*.080*	*.062*
20	*.145*	*.078*	*.057*	*.040*	*.204*	*.096*	*.071*	*.050*	*.206*	*.095*	*.070*	*.050*
	Section 3. GMM: Mean simulated values of $\hat{\delta}_2^G$, Standard deviations in *italics*											
5	.098	.147	.173	.186	.100	.146	.175	.186	.103	.147	.175	.187
10	.121	.160	.179	.190	.124	.162	.179	.191	.128	.164	.180	.192
15	.114	.159	.183	.191	.113	.160	.183	.192	.119	.162	.184	.193
20	.128	.153	.182	.192	.126	.156	.182	.192	.129	.159	.183	.192
5	*.168*	*.131*	*.097*	*.066*	*.171*	*.132*	*.095*	*.065*	*.170*	*.132*	*.094*	*.064*
10	*.101*	*.064*	*.051*	*.037*	*.101*	*.063*	*.051*	*.037*	*.100*	*.062*	*.050*	*.036*
15	*.099*	*.054*	*.034*	*.026*	*.104*	*.053*	*.034*	*.026*	*.101*	*.053*	*.033*	*.025*
20	*.092*	*.054*	*.030*	*.019*	*.095*	*.053*	*.029*	*.020*	*.089*	*.050*	*.028*	*.019*
	Section 4. GMM: Mean simulated values of $\hat{H}^G$, Standard deviations in *italics*											
5	-.279	-.295	-.297	-.307	.523	.540	.566	.570	.904	.933	.971	.981
10	-.285	-.301	-.299	-.304	.543	.558	.556	.563	.933	.962	.959	.971
15	-.283	-.297	-.309	-.302	.546	.562	.571	.570	.938	.963	.983	.978
20	-.293	-.293	-.307	-.311	.555	.559	.572	.578	.945	.961	.982	.993
5	*.300*	*.220*	*.153*	*.108*	*.378*	*.287*	*.201*	*.140*	*.420*	*.320*	*.224*	*.155*
10	*.190*	*.139*	*.112*	*.078*	*.251*	*.174*	*.138*	*.099*	*.267*	*.179*	*.143*	*.102*
15	*.163*	*.113*	*.081*	*.061*	*.245*	*.141*	*.103*	*.079*	*.260*	*.142*	*.104*	*.081*
20	*.171*	*.094*	*.071*	*.050*	*.239*	*.119*	*.088*	*.063*	*.250*	*.126*	*.089*	*.063*

Table 4 Rejection probabilities for tests of H_0:H=0 and H_0:H=1: Fixed ϕ=0.5, λ=0.2 and various N,T

True market structure, H_0 and H_1		Section 1 FE estimation				Section 2 GMM estimation			
	N →	25	50	100	200	25	50	100	200
	T ↓								
Monopoly	5	.380	.594	.813	.980	.555	.584	.736	.921
Test H_0:H≥0	10	.680	.902	.995	1.000	.817	.963	.963	.996
against H_1:H<0	15	.867	.979	1.000	1.000	.831	.982	1.000	1.000
	20	.950	.996	1.000	1.000	.792	.992	1.000	1.000
Monopolistic comp.	5	.626	.856	.986	1.000	.751	.802	.948	.999
Test H_0:H≤0	10	.936	.998	1.000	1.000	.921	.998	.999	1.000
against H_1:H>0	15	.991	1.000	1.000	1.000	.889	1.000	1.000	1.000
	20	.999	1.000	1.000	1.000	.860	1.000	1.000	1.000
Monopolistic comp.	5	.693	.905	.994	1.000	.718	.698	.789	.926
Test H_0:H=1	10	.928	.998	1.000	1.000	.853	.979	.984	.998
against H_1:H<1	15	.987	1.000	1.000	1.000	.798	.991	1.000	1.000
	20	.998	1.000	1.000	1.000	.755	.996	1.000	1.000
Perfect comp.	5	.193	.305	.438	.664	.341	.240	.157	.126
Test H_0:H=1	10	.255	.400	.607	.849	.343	.455	.289	.199
against H_1:H<1	15	.318	.476	.718	.931	.277	.379	.451	.281
	20	.381	.543	.795	.956	.215	.348	.391	.462

Table 5 Simulation results for estimation of the E-statistic: various ϕ, λ and fixed N=100, T=10

	Monopoly				Monopolistic competition				Perfect competition			
$\phi \rightarrow$	0.0	0.25	0.5	0.75	0.0	0.25	0.5	0.75	0.0	0.25	0.5	0.75
$\lambda \downarrow$	FE: Mean simulated values of $\hat{E}^F = \hat{\gamma}_1^F$											
0.0	-.046	-.046	-.046	-.045	.001	.000	.000	.002	.001	.001	.001	.003
0.1	-.050	-.049	-.049	-.047	-.009	-.006	-.005	-.003	-.008	-.006	-.005	-.003
0.2	-.050	-.049	-.047	-.048	-.013	-.012	-.007	-.007	-.013	-.011	-.007	-.007
0.3	-.049	-.046	-.049	-.048	-.018	-.013	-.013	-.010	-.017	-.013	-.013	-.009
0.4	-.051	-.050	-.050	-.050	-.026	-.022	-.019	-.015	-.025	-.022	-.018	-.015
	FE: Rejection probs for H_0:E=0 vs. H_1:E<0											
0.0	.253	.262	.228	.181	.046	.049	.051	.049	.046	.048	.051	.048
0.1	.298	.268	.246	.194	.070	.065	.057	.053	.072	.066	.059	.052
0.2	.285	.287	.238	.194	.088	.078	.071	.067	.088	.079	.071	.067
0.3	.274	.260	.264	.206	.109	.088	.092	.070	.112	.090	.093	.070
0.4	.299	.274	.256	.193	.142	.110	.099	.088	.144	.112	.102	.088
	GMM: Mean simulated values of $\hat{E}^G = \hat{\gamma}_1^G$											
0.0	-.047	-.047	-.046	-.047	.000	.000	.001	.001	.000	.000	.001	.002
0.1	-.048	-.048	-.050	-.050	-.010	-.008	-.009	-.009	-.009	-.008	-.009	-.008
0.2	-.049	-.047	-.047	-.049	-.017	-.013	-.012	-.012	-.017	-.013	-.012	-.012
0.3	-.049	-.046	-.049	-.049	-.022	-.018	-.019	-.016	-.022	-.018	-.019	-.016
0.4	-.049	-.050	-.051	-.051	-.028	-.027	-.025	-.024	-.028	-.027	-.026	-.024
	GMM: Rejection probs for H_0:E=0 vs. H_1:E<0											
0.0	.797	.738	.706	.612	.349	.367	.350	.384	.347	.364	.349	.379
0.1	.805	.768	.722	.635	.453	.418	.434	.423	.455	.418	.433	.420
0.2	.811	.758	.710	.604	.531	.481	.454	.424	.535	.483	.455	.425
0.3	.806	.751	.711	.635	.586	.522	.506	.466	.593	.529	.509	.471
0.4	.812	.764	.715	.641	.624	.593	.550	.502	.634	.603	.556	.507

Table 6 Estimation results: revenue equation

Dependent variable →					Interest income								Total income							
Estimator →	FE		GMM		FE		GMM						FE		GMM					
	N_{obs}	N_{bank}	N_{obs}	N_{bank}	$\hat{H}^F$	s.e.	$\hat{H}^G$	s.e.	$\hat{\delta}_2^G$	s.e.	Sarg.	AR(2)	$\hat{H}^F$	s.e.	$\hat{H}^G$	s.e.	$\hat{\delta}_2^G$	s.e.	Sarg.	AR(2)
Group A																				
France	1168	309	1036	285	.367	*.024*	.716	*.078*	.201	*.094*	.839	.883	.346	*.021*	.586	*.082*	.092	*.088*	.893	.526
Germany	7618	1935	6890	1774	.435	*.010*	.537	*.029*	.120	*.035*	.000	.224	.493	*.010*	.630	*.038*	.176	*.046*	.000	.843
Italy	3174	753	2762	683	.428	*.015*	.665	*.072*	.177	*.054*	.031	.384	.518	*.014*	.574	*.055*	.081	*.036*	.365	.390
Japan	2753	705	2308	633	.246	*.016*	.209	*.047*	-.088	*.077*	.045	.982	.293	*.021*	.243	*.047*	.017	*.048*	.124	.624
UK	390	110	285	77	.426	*.041*	.632	*.104*	.001	*.052*	.450	.854	.486	*.035*	.638	*.071*	.145	*.045*	.190	.235
US	2360	581	2248	554	.393	*.016*	.701	*.052*	.172	*.053*	.423	.448	.506	*.017*	.608	*.049*	-.042	*.053*	.021	.005
Averages					*.382*		*.576*		*.097*				*.441*		*.546*		*.078*			
Group B																				
Austria	735	182	598	154	.479	*.039*	.829	*.101*	.244	*.063*	.549	.223	.779	*.039*	.716	*.104*	.121	*.108*	.405	.008
Belgium	250	62	217	55	.585	*.044*	.762	*.041*	.108	*.031*	.327	.663	.676	*.053*	.501	*.052*	-.088	*.052*	.246	.448
Denmark	393	96	341	90	.146	*.032*	.113	*.056*	-.027	*.085*	.049	.023	.421	*.046*	.356	*.059*	-.090	*.098*	.009	.743
Norway	257	66	193	52	.338	*.052*	.277	*.039*	-.087	*.092*	.909	.449	.296	*.053*	.231	*.044*	-.123	*.054*	.410	.083
Spain	406	98	354	89	.570	*.043*	.860	*.081*	.226	*.058*	.170	.530	.598	*.046*	.639	*.094*	-.016	*.045*	.070	.179
Switzerland	1387	386	926	322	.565	*.032*	.696	*.051*	.057	*.041*	.035	.003	.529	*.030*	.439	*.044*	-.102	*.039*	.000	.046
Averages					*.447*		*.590*		*.087*				*.550*		*.480*		*-.050*			
Group C																				
Argentina	269	81	204	70	.632	*.088*	1.034	*.134*	.113	*.087*	.039	.414	.556	*.090*	.588	*.107*	-.218	*.095*	.154	.540
Bangladesh	146	33	121	30	.998	*.082*	1.009	*.037*	-.023	*.018*	.212	.271	.831	*.062*	.935	*.049*	.067	*.015*	.239	.909
Brazil	461	128	370	106	.633	*.047*	.956	*.081*	.153	*.054*	.162	.437	.629	*.042*	.832	*.063*	.052	*.039*	.116	.000
India	304	71	281	65	.608	*.034*	.788	*.049*	.152	*.038*	.379	.478	.606	*.044*	.712	*.051*	.106	*.046*	.254	.040
Nigeria	184	58	122	40	.638	*.066*	.645	*.053*	.028	*.050*	.240	.743	.592	*.057*	.680	*.039*	.056	*.036*	.397	.495
Russia	399	160	151	71	.495	*.049*	.538	*.100*	.108	*.068*	.791	.639	.525	*.046*	.892	*.137*	.302	*.058*	.743	.646
Venezuela	200	57	149	42	.681	*.045*	.584	*.051*	.005	*.033*	.178	.038	.671	*.037*	.619	*.044*	.013	*.031*	.178	.042
Averages					*.669*		*.793*		*.077*				*.630*		*.751*		*.054*			

Notes to Table 6

N_{obs} is the number of bank-year observations used in each estimation. Only those countries for which at least 120 bank-year observations were available for the GMM estimation are included.
N_{bank} is the number of banks for which data were available in each estimation.
$\hat{H}^F$ is the FE estimated Rosse-Panzar H-statistic.

$\hat{H}^{G}$ is the GMM estimated Rosse-Panzar H-statistic.

$\hat{\delta}_2^{G}$ is the GMM estimated persistence coefficient (see equation (9)).

Standard errors of estimated coefficients are shown in italics.

Sarg. is the p-value for the Sargan test for the validity of the over-identifying restrictions in the GMM estimation.

AR(2) is the p-value for the test for 2nd-order autocorrelation in the residuals from the GMM estimation.

Table 7 Estimation results: profit equation

	FE estimation				GMM estimation							
	N_{obs}	N_{bank}	$\hat{E}^F$	s.e.	N_{obs}	N_{bank}	$\hat{E}^G$	s.e.	$\hat{\gamma}_2^G$	s.e.	Sargan	AR(2)
Group A												
France	1168	309	-.007	*.001*	1036	285	-.008	*.002*	.193	*.083*	.323	.490
Germany	7618	1935	-.004	*.000*	6890	1774	-.004	*.001*	.104	*.029*	.000	.186
Italy	3174	753	-.008	*.001*	2762	683	-.011	*.002*	.176	*.038*	.000	.009
Japan	2753	705	-.011	*.001*	2308	633	-.012	*.002*	-.022	*.032*	.208	.536
UK	390	110	-.013	*.002*	285	77	-.012	*.003*	.407	*.036*	.446	.832
US	2360	581	-.001	*.001*	2248	554	-.002	*.001*	.377	*.057*	.280	.728
Averages			*-.007*				*-.008*		*.206*			
Group B												
Austria	735	182	-.004	*.002*	598	154	-.006	*.004*	.321	*.074*	.280	.848
Belgium	250	62	.002	*.004*	217	55	-.008	*.002*	.104	*.040*	.215	.379
Denmark	393	96	-.005	*.003*	341	90	-.003	*.004*	.183	*.125*	.163	.292
Norway	257	66	-.012	*.004*	193	52	.005	*.002*	.200	*.073*	.194	.093
Spain	406	98	-.021	*.003*	354	89	-.019	*.002*	-.089	*.011*	.029	.243
Switzerland	1387	386	-.001	*.002*	926	322	-.006	*.003*	.260	*.070*	.079	.882
Averages			*-.007*				*-.006*		*.163*			
Group C												
Argentina	269	81	-.082	*.018*	204	70	-.044	*.013*	-.220	*.101*	.620	.046
Bangladesh	146	33	.001	*.005*	121	30	-.002	*.005*	.471	*.077*	.275	.939
Brazil	461	128	-.015	*.004*	370	106	-.005	*.006*	.016	*.047*	.151	.179
India	304	71	-.015	*.004*	281	65	-.015	*.003*	.104	*.055*	.052	.480
Nigeria	184	58	-.026	*.010*	122	40	-.037	*.009*	.199	*.095*	.282	.135
Russia	399	160	.003	*.005*	151	71	-.012	*.006*	.095	*.048*	.144	.317
Venezuela	200	57	-.015	*.009*	149	42	-.017	*.009*	.230	*.080*	.089	.507
Averages			*-.011*				*-.015*		*.128*			

Notes to Table 7

N_{obs} is the number of bank-year observations used in each estimation. Only those countries for which at least 100 bank-year observations were available for the GMM estimation are included.
N_{bank} is the number of banks for which data were available in each estimation.
$\hat{E}^F$ is the FE estimated E-statistic.
$\hat{E}^G = \hat{\gamma}_1^G$ is the GMM estimated E-statistic.
$\hat{\gamma}_2^G$ is the GMM estimated persistence coefficient (see equation (11)).
Standard errors are shown in italics.
Sargan is the p-value for the Sargan test for the validity of the over-identifying restrictions in the GMM estimation.
AR(2) is the p-value for the test for 2nd-order autocorrelation in the residuals from the GMM estimation.