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 H-statistic of misspecification bias in the revenue equation, arising when adjustment towards market equilibrium is partial and not instantaneous. In simulations, fixed effects estimation produces a measured H-statistic that is severely biased towards zero. Empirical results for the banking sectors of six developed countries corroborate our principal finding, that a dynamic formulation of the revenue equation is required for accurate identification of the H-statistic.

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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.

An approach to the measurement of competition, which is popular in the recent empirical banking literature (Berger et al., 2004; Goddard et al., 2007; Carbo et al., 2008; Dick and Hannan, 2008) involves drawing inferences about market or competitive structure from the observation of firms' conduct (Lau, 1982; Bresnahan, 1982, 1989; Panzar and Rosse, 1982, 1987). Inferences as to which model of competition best describes the firms' observed behaviour are drawn from the estimated parameters of equations derived from theoretical models of price and output determination.

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 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 is methodological and 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, used in previous studies, 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 income and balance sheet data for banks located in six countries. The empirical results are consistent with the main conclusion of the 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 develops 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 4,392 banks from six 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.[1] For algebraic derivations of these results, see Panzar and Rosse (1987).

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. 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.[2] In a recent multi-country study, Claessens and Laeven (2004) identify factors associated with the numerical value of H for 50 countries. Competition is more intense in countries with low entry barriers and where there are few restrictions on banking activity. In a similar exercise using data for 76 countries, Bikker et al. (2007) find that institutions and the foreign investment climate are important factors in explaining competition in the banking sector.

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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[1] 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).

[2] Similar results were reported by Nathan and Neave (1989) for Canada, Coccorese (2004) and Drummond et al. (2007) for Italy; Casu and Girardone (2006) and Staikouras and Koutsomanoli‐Fillipaki (2006) for the European Union; Yildrim and Philippatos (2007) for Latin America; and Matthews et al. (2007) for the UK.

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 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. In tests of the POP hypothesis for banking, Goddard et al. (2004a,b) find evidence that 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 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:

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

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

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 $\tilde{y}^{PC}$.[3]

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[3] For 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:

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

For 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:

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

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

For 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.

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 λ=0 (instantaneous adjustment) and λ=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:

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

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}. The corresponding 'true' values for the H-statistic are H=–0.243 (monopoly), H=0.583 (monopolistic competition), and H=1.000 (perfect competition).

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.[4]

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

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[4] 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 σ_w=0.02 in (3) and σ_y=20, σ_p=0.002 and σ_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 for t=–100,...,–2 are immediately discarded. Randomly generated N(0,1) deviates, scaled using the (arbitrary) parameter value σ_c=10 in (7), are used to obtain $\varepsilon^c_{i,t}$.

observations for t=1,...,T are used in the estimation. The FE estimator of the H-statistic is $\hat{H}^F = \hat{\delta}_1^F$ in (8). The GMM estimator is $\hat{H}^G = \hat{\delta}_1^G/(1-\hat{\delta}_2^G)$ in (9). The FE estimator of the E-statistic is $\hat{E}^F = \hat{\gamma}_1^F$ in (10). The GMM estimator is $\hat{E}^G = \hat{\gamma}_1^G$ in (11).

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 λ>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 λ>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.

Section 2 of Table 1 reports the means and standard deviations of $\hat{H}^G = \hat{\delta}_1^G/(1-\hat{\delta}_2^G)$ from the GMM estimation, as in (9). 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 $\hat{H}^F$. 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.

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 downward bias in the GMM estimator $\hat{H}^G$ 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.

At this stage, we examine an important issue raised by Bikker et al. (2006) concerning the selection of control variables for the estimated revenue equation. Many previous empirical studies include among the controls the log assets size measure $\ln(y_{i,t})$, or some other similarly defined measure of bank size; and many studies also scale the revenue variable, using $\ln(r_{i,t})–\ln(y_{i,t})$ (or similar) as the dependent variable for the estimating equation. However, Bikker et al. (2006) point out that it is incorrect to estimate a revenue elasticity using a specification that includes a quantity-type variable among the controls, or using a specification in which the dependent variable is, through rescaling, converted from a revenue variable into a price-type variable. In fact, if $\ln(y_{i,t})$ appears among the controls, then it is immaterial whether the dependent variable is the unscaled $\ln(r_{i,t})$, or the scaled $\ln(r_{i,t})–\ln(y_{i,t})$. In either case, the coefficients on the factor input prices $w_{j,i,t}$ should be interpreted as output price elasticities, and not as revenue elasticities.

The signs or magnitudes of the theoretical elasticities of output price with respect to factor input price for two of the three competitive models that are considered in this section differ from those of the revenue elasticities. The elasticities of output price are: greater than zero but less than one for monopoly; greater than one for monopolistic competition; and exactly one for perfect competition. Accordingly, Bikker et al. (2006) suggest that several researchers may have drawn misleading conclusions about competition by misinterpreting an estimated elasticity of output price as an elasticity of revenue. For example, an H-statistic between zero and one obtained from a correctly specified revenue equation would be indicative of monopolistic competition, but a similar value obtained from a price equation would be indicative of monopoly.

In order to examine the implications of this critique using the simulations framework developed in this paper, we repeated the simulations reported in Table 1 with an additional term in $\ln(y_{i,t})$ included on the right-hand-sides of equations [8] and [9]. For the case ϕ=0, λ=0 (corresponding to top left-hand cell of each panel in Table 1), the mean simulated values of $\hat{H}^F$, correctly interpreted as an output price elasticity due to the inclusion of $\ln(y_{i,t})$ on the right-hand-side of [8], were 0.114 (monopoly), 1.039 (monopolistic competition) and 1.001 (perfect competition). The corresponding mean simulated vales of $\hat{H}^G$ were 0.112 (monopoly), 1.010 (monopolistic competition) and 0.977 (perfect competition). For the case ϕ>0, λ>0, $\hat{H}^F$ is severely downward biased as before, while $\hat{H}^G$ remains essentially unaffected by variation in ϕ and λ. Accordingly, we concur with Bikker et al. (2006) that inadvertent misspecification of the revenue equation as a price equation, through either rescaling the dependent variable or including log-assets as a control variable, constitutes a further form of misspecification bias affecting the estimation of the Rosse-Panzar H-statistic, which is distinct from the bias arising from the omission of dynamic effects that is the main subject of this paper. The practical implications of both forms of misspecification bias are examined in the empirical application that is reported in Section 5.

Finally, 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. 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 empirical model, the H-statistic can be estimated, without any serious problems of bias or inconsistency, under conditions of either instantaneous adjustment or partial adjustment.

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) for the following six countries: France, Germany, Italy, Japan, the UK and the US. We eliminated banks 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.

Estimations of two specifications for the revenue equation are reported. In both specifications, the dependent variable is $\ln(r_{i,t})$ where $r_{i,t}$ is revenue, 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).[5] The control variable definitions are: $\ln(y_{i,t})$ where $y_{i,t}$ = natural logarithm of total assets; $x_{1,i,t}$ = equity / total assets; $x_{2,i,t}$ = net loans / total assets; and a full set of individual year dummy variables. In line with the discussion in Section 4, Specification I reported in the upper panel of Table 6 excludes $\ln(y_{i,t})$ from the list of control variables, which comprises $x_{1,i,t}$, $x_{2,i,t}$ and the year dummies only. Specification I is interpreted as a correctly specified revenue equation. Specification II, reported in the lower panel of Table 6, includes $\ln(y_{i,t})$ in the list of control variables, which also contains $x_{1,i,t}$, $x_{2,i,t}$ and the year dummies. As we have seen in Section 4, Specification II, which is comparable to the estimating equation that has been used widely in the previous literature, may produce misleading inferences for the nature of competition. Finally, the dependent variable for the profit equation is $\ln(1+\pi_{i,t})$, where $\pi_{i,t}$ = return on assets. The list of covariates, as in Specification I, comprises $w_{j,i,t}$, $x_{1,i,t}$, $x_{2,i,t}$, and the year dummies.

Table 6 reports the estimation results. For Specification I, the FE estimator $\hat{H}^F$ produces estimates between zero and one for five of the six countries (the exception being the UK) with revenue defined as interest income, and for all six countries with revenue defined as total income. In every case, the GMM estimator $\hat{H}^G$ produces estimates that are higher than the FE estimator $\hat{H}^F$. For interest income, the average $\hat{H}^G$ is 0.318 and the average $\hat{H}^F$ is 0.103. For total income, the corresponding averages are 0.339 and 0.164. For interest income, the GMM persistence coefficient $\hat{\delta}_2^G$ is positive for all

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[5] 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.

six countries, and we are able to reject H_0:δ_2=0 in favour of H_1:δ_2>0 for all six. For total income, $\hat{\delta}_2^G$ is positive for five countries (Germany being the exception), and we are able to reject H_0:δ_2=0 in favour of H_1:δ_2>0 for three countries (Italy, the UK and the US). The significance of $\hat{\delta}_2^G$ in the majority of cases suggests that the inclusion of a partial adjustment mechanism in the revenue equation is required, and that the dynamic revenue equation is preferred to the static revenue equation. This being so, the fact that in every case $\hat{H}^G$ turns out to be larger than $\hat{H}^F$ is entirely consistent with the principal conclusion of the Monte Carlo simulations reported in Section 4, that the fixed effects estimator $\hat{H}^F$ is severely biased towards zero.[6]

Using a significance level of 5% and the preferred GMM estimation results, for both revenue definitions we are able to reject H_0:H=1 in favour of H_1:H<1 for five of the six countries (Italy being the exception). For interest income we are only able to reject H_0:H=0 in favour of H_1:H>0 for two countries (Germany and Italy); although the failure to reject H_0 is borderline for a third country (France). For total income, we are able to reject H_0:H=0 in favour of H_1:H>0 for three countries (France, Germany and Italy). Therefore the implications of the GMM estimation results for Specification I for the characterization of the most appropriate competitive model for each country can be summarized as follows. For Italy, we are able to reject the null hypothesis favouring monopoly, but we are unable to reject the null favouring perfect competition. For Germany, we are able to reject the null hypotheses favouring both monopoly and perfect competition, in favour of alternatives favouring monopolistic competition. For France, the results are similar to those for Germany, except for a borderline failure to reject the null favouring monopoly with the interest income definition of revenue. Finally, for Japan, the

[6] 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 six estimations (Germany) for each of the two revenue measures. The test for 2nd-order autocorrelation in the residuals is insignificant in all cases. In the GMM estimations of the revenue equation with interest income as the dependent variable, the coefficients on $x_{2,i,t}$ (= equity/ total assets) are negative and significant at the 5% level for four countries out of six, and the coefficients on $x_{3,i,t}$ (= net loans / total assets) are positive and significant for two countries. (These results are not reported in Table 6, but are available from the corresponding author on request). In the GMM estimations with total income as the dependent variable, the numbers of countries for which the coefficients are significant are: for $x_{2,i,t}$, four negative and one positive; for $x_{3,i,t}$, two positive.

UK and the US, we are able to reject the null hypothesis favouring perfect competition, but we are unable to reject the null favouring monopoly.

The estimation results for Specification II would lead to different and possibly misleading inferences about the nature of competition, if they were to be interpreted by the same criteria regardless of the difference between Specifications I and II arising from the inclusion of $\ln(y_{i,t})$ as an additional control variable in Specification II. Using either $\hat{H}^F$ or $\hat{H}^G$, we would reject H_0:H=0 in favour of H_1:H>0 for all six countries, and we would reject H_0:H=1 in favour of H_1:H<1 for all six countries. For interest income, the persistence coefficient $\hat{\delta}_2^G$ is positive for five countries, and we would reject $H_0:\delta_2=0$ in favour of $H_1:\delta_2>0$ for four countries. For total income, $\hat{\delta}_2^G$ is positive for four countries, and we would reject $H_0:\delta_2=0$ in favour of $H_1:\delta_2>0$ for two countries. As before, the inclusion of a partial adjustment mechanism appears to be supported, and as before the average $\hat{H}^G$ is larger than the average $\hat{H}^F$, due to the downward bias in $\hat{H}^F$. $\hat{H}^G$ is larger than $\hat{H}^F$ for five of the six countries individually.

Specification II corresponds to the type of estimating equation that has been adopted in most of the previous empirical banking literature on the Rosse-Panzar statistic. Most of this literature reports 0<H<1 for most countries, and infers that monopolistic competition is the most appropriate competitive model. Therefore the results for Specification II appear to be consistent with the previous literature. For the reasons that have been outlined above, however, we believe that the Specification I estimation results represent a more reliable guide for assessing the nature of competition in banking.

Finally, Table 7 reports the estimation results for the profit equation. Using FE, $\hat{E}^F$ is negative and significantly different from zero for all six countries; and using GMM, $\hat{E}^G$ is likewise negative and significant for all six countries. Furthermore, the estimated short-run POP (persistence of profit) coefficient $\hat{\gamma}_2^G$ is positive and significant for five of the six countries (the exception being Japan). These results cast further doubts on the validity of the instantaneous adjustment or market equilibrium assumption.

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 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 reported empirical results obtained by applying the FE and GMM estimators of the H-statistic to unconsolidated company accounts data for six national banking sectors for the period 1998-

2004. In the GMM estimations, the coefficients on the lagged dependent variables in the revenue and profit equations suggest that 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. The measured H-statistics obtained from a static revenue equation (estimated using FE) and a dynamic revenue equation (estimated using GMM) are also consistent with the conclusion that the FE estimator of the H-statistic is biased towards zero.

We have noted that the choice of control variables for the estimating equation has significant implications for the interpretation of the revenue equation. Using an appropriately specified estimating equation for the H-statistic, for Italy we are unable to reject the model of perfect competition. For Germany and France, we are able to reject both monopoly and perfect competition in favour of monopolistic competition. For Japan, the UK and the US, we are unable to reject the model of monopoly. However, if the revenue equation is specified in a manner that is characteristic of much of the previous banking literature, with a quantity-type variable such as total assets included among the control variables, the empirical results would tend to point more consistently in the direction of the model of monopolistic competition if interpreted inappropriately using conventional criteria. Therefore the results of this paper raise questions over the validity of the near-universal finding in favour of the model of monopolistic competition in the previous literature on the application of the H-statistic to banking. We suggest that some further reappraisal of this empirical literature may be required.

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Tables

Table 1 Simulation results for estimation of the H-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
$\lambda \downarrow$	Section 1. FE: Mean simulated values of $\hat{H}^F = \hat{\delta}_1^F$, Standard deviations in *italics*											
0.0	-.244	-.244	-.244	-.244	.583	.583	.582	.582	1.000	1.000	1.000	1.000
0.1	-.217	-.223	-.227	-.234	.518	.530	.542	.553	.890	.910	.930	.951
0.2	-.191	-.199	-.209	-.219	.454	.475	.497	.520	.781	.816	.853	.894
0.3	-.164	-.175	-.188	-.203	.391	.417	.447	.481	.671	.717	.769	.827
0.4	-.138	-.150	-.165	-.184	.327	.357	.393	.436	.563	.613	.675	.749
0.0	*.053*	*.055*	*.058*	*.069*	*.066*	*.068*	*.073*	*.086*	*.066*	*.067*	*.072*	*.085*
0.1	*.054*	*.057*	*.062*	*.074*	*.067*	*.071*	*.077*	*.092*	*.067*	*.070*	*.076*	*.091*
0.2	*.055*	*.058*	*.064*	*.079*	*.068*	*.073*	*.080*	*.098*	*.068*	*.072*	*.080*	*.098*
0.3	*.055*	*.060*	*.067*	*.084*	*.068*	*.075*	*.084*	*.104*	*.068*	*.074*	*.083*	*.104*
0.4	*.054*	*.060*	*.069*	*.088*	*.068*	*.076*	*.087*	*.109*	*.068*	*.076*	*.087*	*.109*
	Section 2. GMM: Mean simulated values of $\hat{H}^G$, Standard deviations in *italics*											
0.0	-.234	-.234	-.234	-.234	.561	.563	.565	.566	.968	.970	.972	.971
0.1	-.233	-.233	-.233	-.233	.558	.560	.562	.564	.963	.966	.968	.968
0.2	-.231	-.232	-.232	-.232	.554	.556	.559	.562	.956	.959	.962	.963
0.3	-.229	-.230	-.230	-.230	.548	.551	.555	.558	.946	.950	.954	.956
0.4	-.226	-.226	-.227	-.227	.540	.544	.548	.552	.932	.937	.942	.945
0.0	*.067*	*.073*	*.085*	*.113*	*.087*	*.093*	*.106*	*.140*	*.094*	*.097*	*.108*	*.140*
0.1	*.076*	*.083*	*.096*	*.127*	*.098*	*.106*	*.120*	*.159*	*.107*	*.111*	*.123*	*.159*
0.2	*.085*	*.093*	*.108*	*.143*	*.111*	*.120*	*.136*	*.179*	*.122*	*.127*	*.140*	*.181*
0.3	*.096*	*.105*	*.121*	*.161*	*.126*	*.135*	*.154*	*.202*	*.139*	*.145*	*.160*	*.204*
0.4	*.108*	*.118*	*.136*	*.180*	*.142*	*.153*	*.175*	*.227*	*.160*	*.167*	*.183*	*.232*

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	.999	.994	.966	.996	.992	.967	.875
Test H_0:H≥0	0.1	.993	.989	.984	.939	.988	.974	.930	.813
against H_1:H<0	0.2	.968	.967	.957	.896	.969	.941	.889	.751
	0.3	.909	.913	.903	.843	.931	.902	.843	.694
	0.4	.795	.817	.815	.772	.891	.854	.776	.638
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	.996
against H_1:H>0	0.2	1.000	1.000	1.000	1.000	1.000	1.000	1.000	.981
	0.3	1.000	1.000	1.000	1.000	1.000	1.000	.997	.965
	0.4	.999	.999	.999	.996	1.000	.999	.989	.938
Monopolistic comp.	0.0	1.000	1.000	1.000	1.000	1.000	.999	.999	.985
Test H_0:H=1	0.1	1.000	1.000	1.000	1.000	.999	.999	.995	.963
against H_1:H<1	0.2	1.000	1.000	1.000	1.000	.998	.996	.987	.932
	0.3	1.000	1.000	1.000	1.000	.992	.987	.966	.897
	0.4	1.000	1.000	1.000	1.000	.978	.965	.944	.847
Perfect comp.	0.0	.049	.049	.049	.043	.294	.275	.250	.234
Test H_0:H=1	0.1	.495	.364	.251	.156	.306	.286	.256	.242
against H_1:H<1	0.2	.943	.814	.603	.343	.329	.300	.271	.247
	0.3	1.000	.991	.902	.597	.344	.320	.287	.251
	0.4	1.000	1.000	.993	.831	.372	.346	.313	.267

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↓	FE: Mean simulated values of $\hat{H}^F = \hat{\delta}_1^F$, Standard deviations in *italics*											
5	-.201	-.200	-.200	-.198	.477	.479	.478	.481	.819	.822	.821	.823
10	-.201	-.208	-.209	-.206	.505	.497	.497	.501	.862	.854	.853	.857
15	-.211	-.215	-.211	-.210	.505	.500	.504	.505	.866	.862	.866	.866
20	-.210	-.211	-.212	-.212	.512	.510	.509	.508	.876	.874	.873	.872
5	*.204*	*.149*	*.104*	*.071*	*.254*	*.185*	*.130*	*.088*	*.252*	*.183*	*.128*	*.087*
10	*.134*	*.094*	*.064*	*.046*	*.167*	*.117*	*.080*	*.058*	*.165*	*.116*	*.080*	*.057*
15	*.108*	*.075*	*.052*	*.036*	*.134*	*.094*	*.064*	*.045*	*.133*	*.093*	*.064*	*.045*
20	*.087*	*.064*	*.044*	*.031*	*.108*	*.080*	*.055*	*.039*	*.107*	*.079*	*.055*	*.038*
	GMM: Mean simulated values of $\hat{H}^G$, Standard deviations in *italics*											
5	-.216	-.225	-.239	-.239	.523	.543	.557	.570	.904	.934	.962	.981
10	-.222	-.230	-.232	-.233	.540	.563	.559	.571	.931	.966	.962	.979
15	-.227	-.235	-.239	-.237	.535	.553	.572	.565	.927	.957	.982	.973
20	-.231	-.228	-.237	-.243	.551	.560	.573	.576	.950	.959	.984	.992
5	*.295*	*.216*	*.155*	*.107*	*.378*	*.281*	*.202*	*.137*	*.420*	*.309*	*.225*	*.153*
10	*.188*	*.138*	*.108*	*.076*	*.255*	*.178*	*.136*	*.096*	*.266*	*.183*	*.140*	*.100*
15	*.162*	*.114*	*.077*	*.063*	*.240*	*.145*	*.098*	*.080*	*.260*	*.147*	*.099*	*.080*
20	*.163*	*.095*	*.070*	*.052*	*.240*	*.121*	*.087*	*.065*	*.250*	*.128*	*.088*	*.064*

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

$\phi \rightarrow$ / $\lambda \downarrow$	Monopoly 0.0	0.25	0.5	0.75	Monopolistic competition 0.0	0.25	0.5	0.75	Perfect competition 0.0	0.25	0.5	0.75
	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)
Specification I: Control variables are: $x_{1,i,t}$ = equity / total assets; $x_{2,i,t}$ = net loans / total assets; individual year dummies																				
France	1168	309	1036	285	.135	*.035*	.228	*.154*	.317	*.107*	.664	.259	.125	*.032*	.189	*.096*	.111	*.094*	.227	.739
Germany	7618	1935	6890	1774	.129	*.030*	.297	*.107*	.331	*.150*	.000	.348	.193	*.030*	.217	*.048*	-.181	*.138*	.000	.572
Italy	3174	753	2762	683	.252	*.030*	.882	*.281*	.575	*.083*	.038	.208	.343	*.030*	.728	*.266*	.553	*.090*	.074	.436
Japan	2753	705	2308	633	.048	*.029*	.093	*.074*	.412	*.123*	.027	.738	.094	*.032*	.106	*.053*	.127	*.128*	.047	.538
UK	374	109	260	75	-.005	*.055*	.279	*.294*	.688	*.193*	.411	.927	.046	*.055*	.388	*.216*	.506	*.179*	.421	.368
US	2360	581	2248	554	.060	*.037*	.131	*.119*	.525	*.099*	.496	.813	.181	*.037*	.404	*.222*	.614	*.133*	.689	.758
Averages					*.103*		*.318*		*.474*				*.164*		*.339*		*.288*			
Specification II: Control variables are: $\ln(y_{i,t})$ = natural logarithm of total assets; $x_{1,i,t}$ = equity / total assets; $x_{2,i,t}$ = net loans / total assets; individual year dummies																				
France	1168	309	1036	285	.367	*.024*	.716	*.124*	.201	*.094*	.839	.883	.346	*.021*	.586	*.087*	.092	*.088*	.893	.526
Germany	7618	1935	6890	1774	.435	*.010*	.536	*.034*	.120	*.035*	.000	.223	.493	*.010*	.629	*.045*	.176	*.046*	.000	.842
Italy	3174	753	2762	683	.428	*.015*	.665	*.077*	.177	*.054*	.031	.384	.518	*.014*	.574	*.058*	.081	*.036*	.365	.390
Japan	2753	705	2308	633	.246	*.016*	.209	*.032*	-.088	*.077*	.045	.982	.293	*.021*	.243	*.043*	.017	*.048*	.124	.624
UK	373	109	255	77	.276	*.037*	.298	*.052*	.025	*.079*	.113	.927	.459	*.036*	.492	*.068*	-.037	*.047*	.095	.107
US	2360	581	2248	554	.393	*.016*	.701	*.050*	.172	*.053*	.423	.448	.506	*.017*	.608	*.038*	-.042	*.053*	.021	.005
Averages					*.357*		*.521*		*.101*				*.436*		*.522*		*.048*			

Notes to Table 6

N_{obs} is the number of bank-year observations used in each estimation.
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)
France	1168	309	-.007	*.001*	1036	285	-.009	*.002*	.170	*.082*	.324	.483
Germany	7618	1935	-.004	*.000*	6890	1774	-.004	*.001*	.097	*.029*	.000	.182
Italy	3174	753	-.008	*.001*	2762	683	-.012	*.002*	.170	*.039*	.000	.011
Japan	2753	705	-.011	*.001*	2308	633	.012	*.002*	-.032	*.034*	.245	.612
UK	374	109	-.020	*.003*	260	75	-.021	*.003*	.446	*.056*	.334	.715
US	2360	581	-.001	*.001*	2248	554	-.003	*.001*	.374	*.057*	.238	.717
Averages			*-.009*				*-.010*		*.204*			

Notes to Table 7

Control variables are as for Specification I in Table 6.
N_{obs} is the number of bank-year observations used in each estimation.
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.