Assessing Competition with the Panzar-Rosse Model: The Role of Scale, Costs, and Equilibrium

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Abstract

The Panzar-Rosse test has been widely applied to assess competitive conduct, often in specifications controlling for firm scale or using a price equation. We show that neither a price equation nor a scaled revenue function yields a valid measure for competitive conduct. Moreover, even an unscaled revenue function generally requires additional information about costs and market equilibrium to infer the degree of competition. Our theoretical findings are confirmed by an empirical analysis of competition in banking, using a sample containing more than 100,000 bank-year observations on more than 17,000 banks in 63 countries during the years 1994 – 2004.

Keywords: Panzar-Rosse test, competition, scale

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1 Introduction

Empirical estimates of the degree of competition have been significantly refined by two 'new empirical industrial organization' (NEIO) techniques, the Bresnahan-Lau method (Bresnahan, 1982, 1989; Lau, 1982) and the Panzar-Rosse reduced-form revenue test (Rosse and Panzar, 1977; Panzar and Rosse, 1982, 1987). The latter method has found particularly widespread application in the literature due to its modest data requirements, single-equation linear estimation, and robustness to market definition (Shaffer, 2004a,b). Most of these applications have involved the banking industry, as summarized in Table 1, because of the special importance of banks in the economy and facilitated by the ready availability of bank-level data.

The current financial and economic crisis has highlighted the crucial position of banks in the economy. Banks play a pivotal role in the provision of credit, the payment system, the transmission of monetary policy and maintaining financial stability. The vital role of banks in the economy makes the issue of banking competition extremely important. The relevance of banking competition is confirmed by several empirical studies that establish a strong relation between banking structure and economic growth (see e.g. Jayaratne and Strahan, 1996; Levine, Loayza and Beck, 2000; Collender and Shaffer, 2003). Also, an ongoing debate has emerged in the literature as to whether banking competition helps or harms welfare in terms of systemic stability (see e.g. Smith, 1998; Allen and Gale, 2004; De Jonghe and Vander Vennet, 2008; Schaeck et al., 2009) or productive efficiency (Berger and Hannan, 1998; Maudos and De Guevara, 2007).

Theory suggests that banking competition can be inferred directly from the markup of prices over marginal cost (Lerner, 1934). In practice, this measure is often hard or even impossible to implement due to a lack of detailed information on the costs and prices of bank products. The literature has proposed various indirect measurement techniques to assess the competitive climate in the banking sector. These methods can be divided into two main streams: structural and non-structural approaches (see e.g. Bikker, 2004). Structural methods are based on the structure-conduct-performance (SCP) paradigm of Mason (1939) and Bain (1956), which predicts that more concentrated markets are more collusive. Competition is proxied by measures of banking concentration, such as the Herfindahl-Hirschman index. However, the empirical banking literature has shown that concentration is generally a poor measure of competition; see e.g. Shaffer (1993, 1999, 2002), Shaffer and DiSalvo (1994), and Claessens and Laeven (2004). Some of these studies find conduct that is much more competitive than the market structure would suggest, while others find much more market power than the market structure would imply.[1] Since the mismatch can run in either direction, concentration is an extremely unreliable measure of performance.

The Panzar-Rosse approach and the Bresnahan-Lau method can be formally derived from profit-maximizing equilibrium conditions, which is their main advantage relative to more heuristic approaches. As shown by Shaffer (1983a,b), their test statistics are systematically related to each other, as well as to alternative measures of competition such as the Lerner index (Lerner, 1934). In this paper we focus on the Panzar-Rosse (P-R) revenue test, which has been much more widely used in empirical banking studies, as well as in non-banking studies. This approach estimates a reduced-form equation relating gross revenue to a vector of input prices and other control variables. The associated measure of competition – usually called the H statistic – is obtained as the sum of elasticities of gross revenue with respect to input prices. Rosse and Panzar (1977) show that this measure is negative for a neoclassical monopolist or collusive oligopolist, between 0 and 1 for a monopolistic competitor, and equal to unity for a competitive price-taking bank in long-run competitive equilibrium. Furthermore, Shaffer (1982a, 1983a) shows that H is negative for a conjectural variations oligopolist or short-run competitor and equal to unity for a natural monopoly in a contestable market or for a firm that maximizes sales subject to a breakeven constraint. Moreover, the H statistic is also equal to unity with free entry equilibrium with full (efficient) capacity utilization (Vesala, 1995).

There is a striking dichotomy between the reduced-form revenue relation derived in the seminal articles by Panzar and Rosse and the P-R model as estimated in the empirical literature. Many published P-R studies estimate a revenue function that includes total assets (or another proxy of scale, such as equity capital) as a control variable. Other articles estimate a price function instead of a revenue equation, in which the dependent variable is total revenue divided by total assets. In both cases, the choice to control for scale effects is neither explained nor justified. As far as we

[1] Highly competitive conduct has been found in concentrated banking markets in Canada (Shaffer, 1993), a U.S. local banking duopoly (Shaffer and DiSalvo, 1994), and a banking monopoly (Shaffer, 2002). Conversely, significant monopoly power has been found in the U.S. credit card industry, despite thousands of independently pricing issuers of bank cards (Ausubel, 1991; Calem and Mester, 1995; Shaffer, 1999).

know, this inconsistency between the theoretical P-R model and its empirical translation has not been formally addressed in the economic literature. In line with Vesala (1995), Gischer and Stiele (2009) intuitively argue that the revenue and price equations will give different estimates of the H statistic. Goddard and Wilson (2009) use simulation to show that the revenue and price equations result in different estimates of the H statistic. The present paper provides a formal analysis of the consequences of controlling for firm scale in the P-R test. We prove that the properties of the price and revenue equations are identical in the case of long-run competitive equilibrium, but critically different in the case of monopoly or oligopoly. An important consequence of our findings is that a price equation and scaled revenue function – which both have been widely applied in the empirical literature – cannot identify imperfect competition in the same way that an unscaled revenue function can. This conclusion disqualifies a number of studies insofar they apply a P-R test based on a price function or scaled revenue equation. See e.g. Shaffer (1982a, 2004a), Nathan and Neave (1989), Molyneux et al. (1994, 1996), De Bandt and Davis (2000), Bikker and Haaf (2002), Claessens and Laeven (2004), Yildirim and Philippatos (2007), Schaeck et al. (2009), Coccorese (2009), and Carbó et al. (2009).

Furthermore, we show that the appropriate H statistic, based on an unscaled revenue equation, generally requires additional information about costs, market equilibrium and possibly market demand elasticity to infer the degree of competition. In particular, because competitive firms can exhibit $H < 0$ if the market is in structural disequilibrium, it is important to recognize whether or not a given sample is drawn from a market or set of markets in equilibrium. We show that the widely applied equilibrium test (Shaffer, 1982a) is essentially a joint test for competitive conduct and long-run structural equilibrium, which substantially narrows its applicability. Our findings lead to the important conclusion that the P-R test is a *one-tail* test of conduct in a more general sense than shown in Shaffer and DiSalvo (1994). A positive value of H is inconsistent with standard forms of imperfect competition, but a negative value may arise under various conditions, including short-run competition. We illustrate our theoretical results with an empirical analysis of competition, using data from the banking industry to facilitate comparison with prior literature. Our sample contains more than 100,000 bank-year observations on more than 17,000 banks in 63 countries during the period 1994 – 2004.

Although the P-R test has been applied more often to the banking industry than to any other sector, the applicability of the P-R model is much broader and not confined to banks only. See e.g. Rosse and Panzar (1977), Sullivan (1985), Ashenfelter and Sullivan (1987), Wong (1996), Fischer and Kamerschen (2003), and Tsutsui and Kamesaka (2005), who apply the P-R test to assess the competitive climate in the newspaper industry, the cigarette industry, the U.S. airline industry, a sample of physicians, and the Japanese securities industry, respectively. We emphasize that the aforementioned scale correction is also found in non-banking studies applying the P-R test to firms of different sizes; see e.g. Ashenfelter and Sullivan (1987) and Tsutsui and Kamesaka (2005). Hence, the scaling issue that we address in this paper is not confined to empirical banking studies, but applies to the entire competition literature. For this reason our theoretical analysis is formulated in terms of generic firms, and as such is not restricted to the special case of banks.

The organization of the remainder of this paper is as follows. Section 2 describes the original Panzar-Rosse model and the empirical translations found in the competition literature. Next, Section 3 analyzes the consequences of controlling for firm size in the P-R test. Section 4 focuses on the correct P-R test (based on an unscaled revenue equation) and discusses the additional information about costs and equilibrium needed to infer the degree of competition. This section also shows that the widely applied equilibrium test is essentially a test for long-run competitive equilibrium. Section 5 discusses the empirical translation of the Panzar-Rosse approach. The bank data used for the empirical illustration of our theoretical findings are described in Section 6. The corresponding empirical results can also be found in this section. Finally, Section 7 concludes.

2 The Panzar-Rosse model

The Panzar-Rosse (P-R) revenue test is based on a reduced-form equation relating gross revenues to a vector of input prices and other firm-specific control variables. Assuming an n-input single-output production function, the empirical reduced-form equation of the P-R model is written as

$$\log \mathrm{TR} = \alpha + \sum_{i=1}^{n} \beta_i \log w_i + \sum_{j=1}^{J} \gamma_j \log \mathrm{CF}_j + \varepsilon, \tag{1}$$

where TR denotes total revenue, w_i the price of the i-th input factor, and CF_j the j-th firm-specific control factor. Moreover, we assume that $\mathbb{E}(\varepsilon \mid w_1, \ldots, w_n, \mathrm{CF}_1, \ldots, \mathrm{CF}_J) = 0$. Panzar and Rosse (1977) show that the sum of input price elasticities,

$$H^r = \sum_{i=1}^{n} \beta_i, \tag{2}$$

reflects the competitive structure of the market.

The specification in Equation (1) is similar to what has been commonly used in the empirical literature, although the choice of dependent and firm-specific control variables varies. For example, the empirical banking literature often takes interest income as revenues to capture only the intermediation activities of banks (e.g. Bikker and Haaf, 2002). Larger firms earn more revenue, ceteris paribus, in ways unrelated to variations in input prices. Therefore, many studies include log total assets as a firm-specific control variable in Equation (1). Other studies take the log of revenues divided by total assets (TA) as the dependent variable in the P-R model, in which case not log revenues but log(TR/TA) – with TR/TA a proxy of the output price P – is explained from input prices and firm-specific factors. This results in a log-log price equation instead of a log-log revenue equations.

In sum, three alternative versions of the empirical P-R model have appeared in the empirical competition literature. The first one is the P-R revenue equation with log total assets as a control variable:

$$\log \mathrm{TR} = \alpha + \sum_{i=1}^{n} \beta_i \log w_i + \sum_{j=1}^{J} \gamma_j \log \mathrm{CF}_j + \delta \log(\mathrm{TA}) + \varepsilon, \tag{3}$$

yielding $H_s^r = \sum_{i=1}^{n} \beta_i$ (where r refers to 'revenue', and s to 'scaled'). In the empirical banking literature this version of the P-R model has been used by e.g. Shaffer (1982a, 2004a), Nathan and Neave (1989), Molyneux et al. (1996), Coccorese (2009), and Carbó et al. (2009). See also Ashenfelter and Sullivan (1987) and Tsutsui and Kamesaka (2005), who apply the P-R model to assess the competitive climate in the cigarette industry and the Japanese securities industry, respectively. Rosse and Panzar (1977) similarly control for scale in the newspaper industry, measured as daily circulation rather than assets. The second alternative version is the P-R price equation without total assets as a control variable:

$$\log(\mathrm{TR/TA}) = \alpha + \sum_{i=1}^{n} \beta_i \log w_i + \sum_{j=1}^{J} \gamma_j \log \mathrm{CF}_j + \varepsilon, \tag{4}$$

yielding $H^p = \sum_{i=1}^{n} \beta_i$ (where p refers to 'price'). See e.g. De Bandt and Davis (2000), Koutsomanoli-Fillipaki and Staikouras (2005), and Mamatzakis et al. (2005). The last version is the P-R price equation controlling for firm size:

$$\log(\mathrm{TR/TA}) = \alpha + \sum_{i=1}^{n} \beta_i \log w_i + \sum_{j=1}^{J} \gamma_j \log \mathrm{CF}_j + \delta \log(\mathrm{TA}) + \varepsilon, \tag{5}$$

yielding $H_s^p = \sum_{i=1}^{n} \beta_i$ (where p refers to 'price', and s to 'scaled'). This specification has been used by e.g. Molyneux et al. (1994), Bikker and Groeneveld (2000), Bikker and Haaf (2002), Claessens and Laeven (2004), Yildirim and Philippatos (2007), and Schaeck et al. (2009). When log assets are included, the empirical estimates from a log-log price equation are equivalent to those of the corresponding log-log revenue equation, with the sole distinction that the coefficient on log(TA) will differ by 1. The key issue addressed in this paper is the relation between the H statistics based on the scaled and unscaled versions of P-R price and revenue equation. Furthermore, several studies estimate a revenue or price equation with another proxy for bank size as a control variable (such as equity capital), see e.g. Vesala (1995), De Bandt and Davis (2000) and Gischer and Stiele (2009). This also results in a scale correction. Table 1 provides a detailed overview of published P-R studies in the field of banking and the type of scaling used in these studies.

3 Controlling for scale in the P-R model

This section analyzes the consequences of controlling for firm scale in the P-R test. Because elasticities are required to compute the value of the H statistic, and the coefficients in a log-log equation correspond directly to elasticities, virtually all empirical applications of the P-R test have relied on the log-log form discussed in Section 2. Accordingly, our analysis below will address this form exclusively. In addition, the original derivation of the P-R result assumes that production technology remains unchanged across the sample, and we likewise maintain that assumption throughout.

3.1 Prerequisites

As a preliminary step, we focus on the unscaled revenue equation and note the basic property that marginal cost, like total cost, is homogeneous of degree 1 in all input prices.[2] That is,

$$\sum_{i=1}^{n} \partial \log \mathrm{MC} / \partial \log w_i = 1 \tag{6}$$

for all inputs i and input prices w_i. Hence, the summed revenue elasticities of input prices must equal the elasticity of revenue with respect to marginal cost. That is, we have

$$\frac{\partial \log \mathrm{TR}}{\partial \log \mathrm{MC}} = \sum_{i=1}^{n} \frac{\partial \mathrm{TR} / \partial \log w_i}{\partial \log \mathrm{MC} / \partial \log w_i} = \sum_{i=1}^{n} \frac{\partial \log \mathrm{TR}}{\partial \log w_i} = H^r. \tag{7}$$

Thus, the P-R statistic H^r actually represents the elasticity of revenue with respect to marginal cost, under the assumption of a stable cost function so that all changes in marginal cost are driven by changes in one or more input prices. We shall make use of this result at various points in this section by referring interchangeably to H^r and $\partial \log \mathrm{TR} / \partial \log \mathrm{MC}$. A similar property holds for H^p, the H statistic obtained from the P-R price equation without scaling. Moreover, we have

$$\begin{aligned} \partial \log \mathrm{P} / \partial \log w_i &= \partial \log(\mathrm{TR}/\mathrm{TA}) / \partial \log w_i \\ &= \partial \log \mathrm{TR} / \partial \log w_i - \partial \log(\mathrm{TA}) / \partial \log w_i . \end{aligned} \tag{8}$$

In the sequel we distinguish between short-run and long-run competitive equilibrium. Short-run competitive equilibrium occurs before entry and exit have taken place in response to shocks to cost or demand. In such a situation firms are pricing at marginal cost, but the number of firms is not in equilibrium, so that entry or exit would be expected to occur subsequently. In case of positive profits, more competitors will enter the market. Similarly, negative profit will drive some of them out of the market. By contrast, long-term competitive equilibrium takes place after entry and exit have fully adjusted to any changes in cost or demand, in which case both the number of firms and each firm's output are in equilibrium.

[2]Rosse and Panzar (1977, page 7) provide a proof of this property.

3.2 Revenue equation

First, we address the common practice of including the log of total assets (or similar measure of scale) as a separate regressor in a reduced-form revenue equation such as Equation (3). This practice appears ubiquitous in the empirical P-R literature, even going back to the seminal study by Rosse and Panzar (1977), yet without explicit discussion or analysis. This point is important because the formal derivation of the H statistic does not include scale as a separate regressor, so it is necessary to rigorously explore the effects of such inclusion.

Intuitively, controlling for scale makes apparent sense because larger firms earn more revenue, ceteris paribus, in ways unrelated to variations in input prices. If we estimate a reduced-form revenue equation across firms of different sizes without controlling for scale, the standard measures of fit will be quite poor. Indeed, this fact has been used to justify the choice of log(P) $=$ log(TR/TA) instead of log (TR) as the dependent variable, especially when scale has been omitted as a regressor in the price equation (see, for example, Mamatzakis et al., 2005).

The main problem arises in the case of imperfectly competitive firms. The standard proof that $H^r < 0$ for monopoly relies on the monopolist's quantity adjustment in response to changes in input prices. If a monopolist faced a perfectly inelastic demand curve, there would be no quantity adjustment and so total revenue would move in the same direction as P, which is the same direction as marginal costs. See, for example, Milgrom and Shannon (1994) and Chakravarty (2002). Hence, total revenue would move in the same direction as input prices, so we would observe $H^r > 0$.[3] The condition that rules this out is the firm's profit-maximizing condition MR $=$ MC > 0 (where MR stands for marginal revenue), which implies elastic demand at equilibrium output levels. But if the regression statistically holds the output quantity constant by controlling for log(TA), then the coefficients that comprise H^r_s will represent the response of total revenue to input prices at a fixed output scale, which is just the change in price times the fixed output. Thus, the estimates will yield $H^r_s > 0$ for any monopoly when the revenue equation controls for scale. The same argument also applies to oligopoly and to the price equation. This leads to the following result.

Proposition 3.1 *Estimates of conduct for monopoly or oligopoly that control for scale, will yield*

[3] The same result also occurs whenever the monopoly demand curve is inelastic, even if imperfectly so.

$H_s^r > 0$.

Later we will turn back to the P-R revenue equation, but we first discuss the price equation.

3.3 Price equation

A few studies have used log(P) as the dependent variable without controlling for log(TA), and this is the case we address next. Under the standard assumptions of duality theory and the neoclassical theory of the firm, as used in the original proof of the parametric version of the P-R test (Rosse and Panzar, 1977), convexity of the production technology implies U-shaped average costs. Then, in long-run competitive equilibrium, we have $\partial \mathrm{TA}/\partial w_i = 0$ because the output scale at which average costs are minimized is not affected by input prices under the assumption of a stable production technology. Then $\partial \log(\mathrm{TA})/\partial \log w_i = 0$ and so

$$H^p = \sum_{i=1}^{n} \partial \log \mathrm{P}/\partial \log w_i = \sum_{i=1}^{n} \partial \log \mathrm{TR}/\partial \log w_i = H^r. \tag{9}$$

Therefore, the price equation and the revenue equation both yield the same result ($H^r = H^p = 1$) in the case of long-run competition with U-shaped average costs, with or without log(TA) as a control variable. We thus obtain the following result.

Proposition 3.2 $H^p = H_s^p \equiv H_s^r = H^r = 1$ *for firms in long-run competitive equilibrium with U-shaped costs.*

Next, we address the sign and magnitude of H^p in the monopoly case. We know that the monopoly price is an increasing function of marginal cost (see, for example, Milgrom and Shannon, 1994, page 173; Chakravarty, 2002, page 352).[4] That is, $\partial \mathrm{P}/\partial \mathrm{MC} > 0$ and so $\partial \log \mathrm{P}/\partial \log \mathrm{MC} > 0$. By linear homogeneity of MC in input prices,

$$\partial \log \mathrm{P}/\partial \log \mathrm{MC} = \sum_{i=1}^{n} \partial \log \mathrm{P}/\partial \log w_i = H^p. \tag{10}$$

The conclusion here is that $H^p > 0$ for monopoly – a contrasting property to $H^r < 0$ if based on an unscaled revenue equation. That is, a price equation fitted to data from a monopoly sample in equilibrium should always yield a positive sum of input price elasticities. Because this result is

[4]For either monopoly or oligopoly, the condition for profit maximization is MR = MC so we always have $\partial \mathrm{MR}/\partial \mathrm{MC} = 1$ in equilibrium.

also true for a competitive sample, by continuity it also holds for oligopoly. Clearly, this property holds whether or not log(TA) is included as a separate regressor. This yields the following result.[5]

Proposition 3.3 $H^p > 0$ *and* $H_s^p > 0$ *for monopoly or oligopoly.*

Since the scaled price equation is equivalent to the scaled revenue equation, the same conclusion applies to H_s^r based on the scaled revenue equation.

Corollary 3.1 $H_s^r > 0$ *for monopoly or oligopoly.*

An important implication of Prop. 3.2 and 3.3 is that the sign of H^p and H_s^r cannot distinguish between perfect and imperfect competition and thus fails as a test for market power.

3.4 The case of constant marginal and average costs

Next, we address the case of constant MC = AC (where MC stands for marginal cost and AC for average cost). This case is important to consider separately for two reasons. First, in long-run competitive equilibrium, the firm's output quantity is indeterminate within the range over which the minimum average cost is constant, thus implying potentially different responses to exogenous shocks than assumed in the traditional P-R derivation. Second, substantial empirical and anecdotal evidence suggests that many firms are in fact characterized by significant ranges of constant marginal and average cost. Johnston (1960) reports evidence that many industries exhibit constant marginal cost. In banking, several decades of studies have yielded contrasting conclusions regarding economies or diseconomies of scale, but the market survival test suggests that marginal and average costs cannot deviate significantly with size, as banks have demonstrated long-term economic viability over a range of scales on the order of 100,000:1 in terms of total assets.[6]

[5]Interestingly, the same property also applies to the value of H_s^r if the estimated coefficient on log(TA) is unity (in which case the scaled revenue equation is equivalent to the unscaled price equation), as is often the case empirically. Possible explanations for a unit coefficient on log(TA) could include the law of one price when firms sell homogeneous outputs within the same market. Then all firms face the same output price, so total revenue is proportional to scale.

[6]U.S. data from the Federal Reserve Bank of Chicago (http://www.chicagofed.org/webpages/banking/financial_institution_reports/commercial_bank_data_complete_2001_2009.cfm) indicate that, as of year-end 2008, the smallest long-established general-purpose commercial bank, chartered in 1909, had $ 3.1 million in assets. Another, chartered in 1900, had $ 3.4 million in assets, as did two banks chartered in 1996. Several other established banks were of similar size. By contrast, three U.S. banks reported total assets in excess of $ 1 trillion in the same quarter. These cases span a range of about 300,000:1.

In the case of monopoly or oligopoly, the imposition of constant average cost will not change the properties of H^p or H^r. The reason is that the firm's output quantity is uniquely determined under imperfect competition (downward sloping firm demand) even when marginal cost is constant. Appendix A provides full details of the proof.

Proposition 3.4 *Constant AC does not alter the sign of H^r or H^p for monopoly or oligopoly, compared to the standard case of U-shaped average costs.*

Also the case of long-run competition yields the same results for H^p whether with constant average cost or with U-shaped average costs. Again Appendix A explains the details of the proof.

Proposition 3.5 $H^p = H_s^p = 1$ *in long-run competitive equilibrium with constant AC.*

However, constant average cost poses a problem for H^r in long-run competitive equilibrium.

Proposition 3.6 $H^r < 1$, *or even* $H^r < 0$, *is possible for firms in long-run competitive equilibrium with constant AC.*

A detailed proof is given in Appendix A. Hence, a unique local minimum average cost (U-shaped average cost curve) is necessary to ensure that $H^r = 1$ under long-run competitive equilibrium in the unscaled reduced-form revenue equation. Previous literature has not considered the effect of alternate cost structures on the P-R test. It should be noted that the standard functional forms employed in most empirical cost studies (such as translog, flexible Fourier, and minflex Laurent) are not very useful in testing for constant average cost. If marginal and average cost are constant, one could contemplate estimating the elasticity of market demand as a further input to properly interpreting H^r (Shaffer, 1982b). However, in that case an overall market must be defined, which is an extra step that is not necessary in a standard P-R test. We leave this as an important topic for future research.

3.5 Scaled versus unscaled H statistics

Table 2 summarizes the various conclusions about H^r, H_s^r and H^p. In addition to Table 2, we can draw on theory to predict which types of samples might be likely to generate specific differences across the three measures of H. One possible case would be a sample containing firms of widely differing sizes in the same market. This case could be evidence of a flat average cost curve, which suggests that we should observe $H^r < 1$ or perhaps even $H^r < 0$, while also observing $H^p > 0$ or even $H^p = 1$ (if in long-run competitive equilibrium). However, it is also possible that such a sample could reflect a disequilibrium number of firms, in which case some short-run equilibrium (but not long-run equilibrium) could exist. In that case, we should observe $H^r < 0$, but $H^p > 0$. Another possible case would be an industry or market containing only firms of identical or closely similar size. This case could reflect an equilibrium with a U-shaped average cost curve. Then three possibilities arise. First, if the sample is in long-run competitive equilibrium, we should observe $H^r = H^r_s \equiv H^p_s = H^p = 1$. Second, if the sample is in an imperfectly competitive equilibrium, the analysis here indicates that we would expect to see $H^r < 0$, but $H^r_s > 0$ and $H^p > 0$. Finally, the sample might be in short-run but not in long-run competitive equilibrium; then we should observe $H^r < 1$ or possibly even $H^r < 0$, but $H^r_s > 0$ and $H^p > 0$.

4 Assessing competition with the unscaled P-R model

The previous section has made clear that a price or scaled revenue equation cannot be used to infer the degree of competition. Only the unscaled revenue function can yield a valid measure for competitive conduct. However, even if the competitive climate is assessed on the basis of the correct H statistic, there are still some caveats to consider.

4.1 Interpretation of the H statistic

Given an estimate of the H statistic based on the unscaled revenue equation, several situations may arise. A significantly positive value of H^r is inconsistent with standard forms of imperfect competition, whether the sample is in equilibrium or not.[7] Hence, in this case we do not need any additional information to reject imperfect competition. In particular, if we reject the null hypothesis $H^r < 0$, then no further tests are required to rule our the possibility of monopolistic, cartel, or

[7] Panzar and Rosse (1987, p. 447) note the less general result that any positive H^r is inconsistent with pure monopoly conduct.

profit-maximizing oligopoly conduct.[8] Furthermore, $H^r = 1$ reflects either long-run competitive equilibrium, sales maximization subject to a breakeven constraint, free entry equilibrium with full (efficient) capacity utilization, or a sample of local natural monopolies under contestability (Rosse and Panzar, 1977; Shaffer, 1982a; Vesala, 1995).[9] A negative value of H^r may arise under various conditions. Table 2 shows that, in addition to the correct H statistic, additional information about costs is generally needed to infer the degree of competition. A finding of $H^r < 0$ cannot by itself distinguish reliably between perfect and imperfect competition. First, Shaffer (1982b, 1983a) showed that, in any profit-maximizing equilibrium in which a firm faces a fixed demand curve with locally constant elasticity and locally linear cost, H^r is negative because it equals 1 plus the firm's perceived elasticity of demand, which is less than -1.[10] Second, if the firm's cost curve is flat over some range within which the firm chooses to produce, it is possible to observe $H^r < 1$ or even $H^r < 0$ under long-run competitive conduct; that is, a unique local minimum average cost is necessary to ensure $H^r = 1$ under long-run competitive equilibrium (see Prop. 3.6).[11]

Only when the hypothesis of constant average cost is ruled out, can we be assured that long-run competition would generate $H^r > 0$; see Prop. 3.6. Similarly, if we reject $H^r = 1$, this does not mean that we reject long-run competitive equilibrium. Rather, independent information about the shape of the cost function is required in addition; see again Prop. 3.6. Since short-run competition may yield $H^r < 0$ as well, even under standard cost conditions (Shaffer, 1982a, 1983a; Shaffer and DiSalvo, 1994), we also need more information about long-run structural equilibrium to distinguish between perfect and imperfect competition. In sum, the P-R test boils down to a *one-tail* test of conduct, subject to additional caveats.

Some studies, including Bikker and Haaf (2002), Claessens and Laeven (2004), and Coccorese (2009) have interpreted the H statistic as a continuous monotonic index of conduct. See also the column captioned 'continuous measure of competition' in Table 1. Indeed, for certain market structures it is possible to show that H^r is a monotonic function of the demand elasticity (Panzar

[8]Panzar and Rosse (1987, p. 447) similarly note that the predictions of $H^r > 0$ for either perfect or monopolistic competition 'depend quite crucially on the assumption that the firms in question are observed in long-run equilibrium.'

[9]Appendix B shows that H^r need not equal unity under fixed markup pricing, in contrast to what is claimed in Rosse and Panzar (1977).

[10]This result is true even with marginal-cost (fully competitive) pricing.

[11]As reported in Table 2, a flat average cost curve does not alter the properties of H^r in other, non-competitive equilibria.

and Rosse, 1987; Shaffer, 1983b; Vesala, 1995). If the demand elasticity is constant over time, H^r corresponds to a monotonic function of the degree of competition in these special cases. However, H^r can be either an increasing or a decreasing function of the demand elasticity, depending on the particular market structure. Consequently, H^r is not even an *ordinal* function of the level of competition. In particular, smaller values of H^r do not necessarily imply greater market power, as also recognized in previous studies (Panzar and Rosse, 1987; Shaffer, 1983a,b; 2004b).

4.2 Further testing

Because it has been shown that even competitive firms can exhibit $H^r < 0$ if the market is in structural disequilibrium, it is important to recognize whether or not a given sample is drawn from a market or set of markets in equilibrium. Empirical P-R studies have long applied a separate test for market equilibrium in which a firm's return on assets (ROA) replaces total revenue as the dependent variable in a reduced-form regression equation using the same explanatory variables as the standard P-R revenue equation (that is, input prices and usually other control variables). The argument is that, in a free-entry equilibrium among homogeneous firms, market forces should equalize ROA across firms, so that the level of ROA is independent of input prices (Shaffer, 1982a). That is, we define an H^{ROA} analogously to H and fail to reject the hypothesis of market equilibrium if we cannot reject the null hypothesis $H^{ROA} = 0$. Since its introduction, this test has been widely used, largely without further scrutiny (see e.g. Bikker and Haaf, 2002; Claessens and Laeven, 2004).

Recall that long-run competitive equilibrium implies P = MC = AC with zero economic profits for any set of input prices. If accounting profits are sufficiently correlated with economic profits, then we should observe $H^{ROA} = 0$ in this case and the test would be valid, subject to similar caveats and critiques as the original H^r test discussed above. However, under imperfect competition, economic profits are positive and the observed accounting ROA may vary across firms or over time (think, for instance, of asymmetric Cournot oligopoly or a monopoly with blockaded entry). In particular, ROA may respond to input prices under imperfect competition, so H^{ROA} need not (and in general would not) equal zero even if the market is in structural equilibrium. In Appendix A we prove the following theorem:

Proposition 4.1 *$H^{ROA} < 0$ for monopoly, oligopoly, or short-run competitive equilibrium, whether or not log(TA) is included as a separate regressor.*

Therefore, we may think of H^{ROA} as a joint test of both competitive conduct and long-run structural equilibrium (i.e., a test of long-run competitive equilibrium). Whenever $H^r = 1$ and $H^{ROA} = 0$, both the revenue test and the ROA test provide results consistent with long-run competitive equilibrium. Where $H^{ROA} < 0$, this would be consistent with monopoly, oligopoly, or short-run (but not long-run) competition, all of which would also imply $H^r < 0$. Where $H^{ROA} < 0$ but $H^r > 0$, the conclusion would be that conduct is largely competitive but some degree of structural disequilibrium exists in the sample, though not enough to cause $H^r > 0$.

5 Empirical method

We would like to provide an empirical illustration of the theoretical results obtained in Section 3 using bank data. We opt for the banking industry, as there is no other sector to which the P-R test has been applied so often, which facilitates comparison. This section discusses the empirical translation of the theoretical Panzar-Rosse model.

To assess bank conduct by means of the P-R model, inputs and outputs need to be specified according to a banking firm model (Shaffer, 2004a). The model usually chosen for this purpose is the intermediation model (Klein, 1971; Monti, 1972; Sealey and Lindley, 1977), according to which a bank's production function uses labor and physical capital to attract deposits. The deposits are then used to fund loans and other earning assets. The wage rate is usually measured as the ratio of wage expenses and the number of employees, the deposit interest rate as the ratio of interest expense to total deposits, and the price of physical capital as total expenses on fixed assets divided by the dollar value of fixed assets. In practice, accurate measurement of input prices may be difficult. For example, the price of physical capital has been shown to be unreliable when based on accounting data (Fisher and McGowan, 1983).

5.1 Dependent variable, input prices and control variables

In the P-R model the dependent variable is the natural logarithm of either interest income (II) or total income (TI), where the latter includes non-interest revenues (to account for the increase in revenue coming from fee-based products and off-balance sheet activities, particularly in recent years). In the P-R price model the dependent variable is either log(II/TA) (with II/TA a proxy of the lending rate) or log(TI/TA). We use the ratio of interest expense to total funding (IE/FUN) as a proxy for the average funding rate (w_1), the ratio of annual personnel expenses to total assets (PE/TA) as an approximation of the wage rate (w_2), and the ratio of other non-interest expenses to fixed assets (ONIE/FA) as proxy for the price of physical capital (w_3). The ratio of annual personnel expenses to the number of fulltime employees may be a better measure of the unit price of labor, but reliable employee figures are only available for a limited number of banks. We therefore use total assets in the denominator instead, following other studies that use BankScope data; see e.g. Bikker and Haaf (2002) and Goddard and Wilson (2009). We include (the natural logarithm of) a number of bank-specific factors as control variables, mainly balance sheet ratios that reflect bank behavior and risk profile. The ratio of customer loans to total assets (LNS/TA) represents credit risk. Furthermore, the ratio of other non-earning assets to total assets (ONEA/TA) reflects certain characteristics of the asset composition. The ratio of customer deposits to the sum of customer deposits and short term funding (DPS/F) captures important features of the funding mix. The ratio of equity to total assets (EQ/TA) accounts for the leverage, reflecting differences in the risk preferences across banks.

The sign of the input prices in the revenue equation will depend on the competitive environment as explained in Section 3. The sign of log(LNS/TA) is expected to turn out positive in the revenue equation. Generally, banks compensate themselves for credit risk by means of a surcharge on the prime lending rate, which increases interest income. The variable log(ONEA/TA) is likely to have a negative influence on interest income, since a higher value of this ratio reflects a larger share of non-interest earning assets. The influence of log(DPS/F) on interest income is more difficult to predict. Banks with customer deposits as their main source of funding may behave differently from banks that find their funding mainly in the wholesale market. However, the precise influence of log(DPS/F) on interest income is unclear. Finally, the ratio of equity to total assets log(EQ/TA) is expected to have a negative impact on interest income. A lower equity ratio implies more leverage and hence more interest income (Molyneux et al., 1994). On the other hand, capital requirements increase proportionally with the risk on loans and investment portfolios, suggesting a positive coefficient (Bikker and Haaf, 2002). If total income is the dependent variable in the revenue equation, the sign of log(ONEA/TA) becomes ambiguous. A larger share of non-interest earning assets is likely to decrease interest income, but may increase other income. The overall effect is unclear. Using similar arguments, we expect the influence of log(LNS/TA) on total income to be smaller. We expect the bank-specific control variables to have the same sign in the scaled revenue and price equations, following similar lines of reasoning. However, we expect the significance of the explanatory variables to be much higher in the models that control for scale.

It may seem odd to use explanatory variables in the unscaled revenue equation that have total assets in the denominator. For example, we use $\log(\text{PE/TA}) = \log(\text{PE}) - \log(\text{TA})$ as a proxy of the price of labor. By including this variable in the revenue equation, we actually include the log of total assets in our model (with a restricted coefficient). Our theoretical analysis in Section 3 makes clear that this may distort the estimates of H. We will address this issue in detail in Section 6.2.

5.2 Estimation method

We use several estimation techniques to estimate the various versions of the P-R model. All models in this section include year dummies to account for time fixed effects. To deal with any unobserved bank-specific factors, we include fixed effects in the P-R models of Equations (1), (3), (4), and (5). We estimate the panel P-R models using the within-group estimator.[12] This approach is in line with e.g. De Bandt and Davis (2000) and Gunalp and Celik (2006). In the unscaled P-R revenue equation the scale differences in revenues across banks of different sizes affect the error term, which becomes heteroskedastic with a relatively large standard deviation. This also inflates the standard errors of the model coefficients and of the resulting H statistic. Imprecise estimates of the H measure reduce the power of statistical tests for the competitive structure of the market, which is clearly undesirable. Therefore, we estimate the P-R revenue and price models by means of pooled feasi-

[12] Throughout, we only use bank-specific fixed effects, as random effects are strongly rejected by a Hausman test in all cases.

ble generalized least squares (FGLS) to cope with the heteroskedasticity problem.[13] A large part of the P-R literature applies pooled OLS estimation. Therefore, we also consider this estimation method. All our specifications include time dummies. We allow for general heteroskedasticity and cross-sectional correlation in the model errors and use clustered standard errors to deal with this (Arellano, 1987). In Section 6.6 we will also obtain dynamic panel estimators for the H statistic.

We have to ensure that the use of FGLS does not result in a harmful (implicit) scale correction. Also the use of bank-specific fixed effects may lead to a correction for scale. That is, if total assets vary only little over time, the fixed effect could act as a dummy for bank size. We will come back to this issue in Section 6.3.

6 Empirical results

For each country in our sample we estimate the H statistic using three different versions of the P-R model: H^r based on Equation (1), an unscaled revenue function, H_s^r based on Equation (3), a revenue function with total assets as explanatory variable; and H^p based on Equation (4), a price function with total revenue divided by total assets as the dependent variable. In line with the empirical banking literature, we estimate the P-R model separately for each country, yielding country-specific H statistics. Since some banks operate in multiple countries, our measure of competition in a particular country reflects the average level of competition on the markets where the banks of this country operate. In Section 6.6 we will run a robustness test with respect to the extent of the market.

6.1 The data

The empirical part of this paper uses an unbalanced panel data set taken from BankScope, covering the period 1994 – 2004.[14] We focus on data from commercial, cooperative and savings banks. We remove all observations pertaining to other types of financial institutions, such as securities houses, medium and long-term credit banks, specialized governmental credit institutions,

[13]The FGLS estimator has the same properties as the GLS estimator, such as consistency and asymptotic normality (White, 1980).

[14]We confine our sample to years prior to the International Financial Reporting Standards.

and mortgage banks. The latter types of institutions may be less dependent on the traditional intermediation function and may have a different financing structure compared to our focus group. We only consider countries for which we have at least 100 bank-year observations (a somewhat arbitrary minimum number needed to obtain a sufficiently accurate estimate of a country's H statistic). If available, we use consolidated data. About 14% of the banks in our total sample is consolidated. Our total sample consists of 104,750 bank-year observations on 17,131 different banks in 63 countries. As in most other such studies, the data have not been adjusted for bank mergers, which means that merged banks are treated as two separate entities until the point of merger, and thereafter as a single bank. As also noted by other authors (Kishan and Opiela, 2000; Hempell, 2002), our approach implicitly assumes that the merged banks' behavior in terms of their competitive stance and business mix does not deviate from their behavior before the merger and from that of the other banks. Since most mergers take place between small cooperative banks that have similar features, this assumption seems reasonable. We leave further testing of this assumption as a topic for further research, as it is well beyond the scope of this paper.

Table 3 provides relevant sample statistics for the dependent variables, input prices and control variables across the major countries, whereas the number of banks and bank-year observations for each country are given in Tables 4 and 5. All figures in Table 3 (apart from the quantiles) are averages over time and across banks. Average interest income, total income, and total assets are expressed in units of millions of US dollars (in year-2000 prices). The sample statistics provide information on the banking market structure in terms of average balance sheet sizes, levels of credit and deposit interest rates, relative sizes of other income and lending, type of funding, and bank solvency (or leverage), reflecting typical differences across the countries considered. The reported 5% and 95% quantiles demonstrate that all variables vary strongly across individual banks. In particular, bank size – as measured by total assets or revenues – exhibits substantial variation across banks, explaining the tendency in the economic literature to scale revenues.

6.2 Implicitly controlling for scale

As mentioned in Section 5.1, we have to verify that the explanatory variables have low correlation with total assets to avoid any implicit scale corrections. For all countries the absolute correlation between the explanatory variables and log(TA) is relatively small; on average below 0.20. Only the absolute correlation between log(EQ/TA) and log(TA) is relatively high, with an average value of 0.48 over the 63 countries. Therefore, we only include in the unscaled revenue equation the part of log(EQ/TA) orthogonal to log(TA).[15] In Section 6.6 we will correct all explanatory variables for any dependence on log(TA) as a robustness test.

6.3 Estimation results for H

Tables 4, 5, 6, 7, 8, and 9 contain the estimation results for the 63 countries in our sample. For each country, we report H^r, H^r_s and H^p and corresponding standard errors. We first consider the differences in H statistics between various estimation methods (within, pooled FGLS, and pooled OLS). Regardless of the estimation method, the average H statistics based on the price and scaled revenue equation are substantially higher than the average H statistic derived from the unscaled revenue model. For all countries FGLS and OLS yield about the same point estimates of H; only their standard errors differ substantially. The use of FGLS reduces the standard errors dramatically. Apparently, FGLS does not lead to a harmful scale correction, which would result in a substantial upward bias of H. On average the H statistic based on the within estimator is very close to the H statistic based on the pooled methods. This holds particularly for the unscaled revenue equation. The difference between the within and pooled methods is somewhat larger for the price and scaled revenue equations than for the unscaled revenue model. However, it does not seem likely that the fixed effects pick up scale differences in these cases, since the scaled revenue and price equation already correct for scale. On average the H statistics based on within estimation have considerably lower standard errors than the H measures based on pooled OLS; the use of only within-variation solves part of the heteroskedasticity problem.

All in all, we consider within estimation as our preferred estimator. Importantly, it corrects for unobserved bank-specific effects, which are ignored by the pooled methods. Moreover, the use of only within-group variation solves part of the heteroskedasticity problem. Therefore, we confine the subsequent analysis to the H statistics based on this method. Nevertheless, we emphasize that

[15] We do this by regressing log(EQ/TA) on log(TA) and log(TA)^2. The resulting error term , i.e. log(EQ/TA) $-$ $\mathbf{E}$(log(EQ/TA) $\mid$ log(TA)), in the corresponding regression model is included in the P-R model. By construction the error term is orthogonal to log(TA).

each of the three other estimation methods would yield qualitatively the same result, namely a substantial difference between the H statistics based on the scaled and unscaled P-R models.

We first consider the P-R model with the dependent variable based on interest income. The average value of H^r over 63 countries equals 0.22 (with average standard error 0.12), versus 0.76 (0.06) and 0.75 (0.06) for H_s^r and H^p, respectively (all based on the within estimator). With total income as the dependent variable, the averages are very similar. Several other summary statistics underscore the substantial differences between H^r on the one hand, and H_s^r and H^p on the other hand. For example, the correlation between H^r and H_s^r equals only 0.35. Similarly, the correlation between H^r and H^p is 0.39. By contrast, the correlation between H_s^r and H^p is 0.93. We apply a Wilcoxon signed rank test to the 63 differences between each country's H^r and H_s^r. This test rejects the null hypothesis that the median of the differences is zero at each reasonable significance level, confirming the difference between the two H statistics. We find the same test result for the differences between H^r and H^p. Throughout, the differences in H between the P-R models based on interest income and total income are small. We emphasize that the cross-country averages are provided to illustrate the differences between the scaled and unscaled P-R models. As is explained in Section 4.1, these averages do not reflect the average level of competition, or the relative ranking of the strength of competition, in the countries under consideration.

We estimate 'aggregate' H statistics for several world regions.[16] It turns out that there are substantial differences in H^r across regions. We establish the following values for H^r based on the within estimator (with the standard error in parentheses): North-America (United States, Canada and Mexico) 0.43 (0.01), South and Central America 0.38 (0.03), Western Europe 0.22 (0.01), Eastern Europe (including former Soviet Republics) 0.26 (0.04), Australia 0.97 (0.14), Asia 0.32 (0.02), Middle East (including Turkey) 0.15 (0.06), and Africa 0.48 (0.08).

The significant differences in H between the unscaled revenue equation and the scaled P-R model confirm our theoretical results. H_s^r and H^p are positively biased relative to H^r. To visualize the differences in H statistic between the three versions of the P-R model, Figure 1 depicts H^r in increasing order for all countries in the sample ('unscaled P-R'), together with the corresponding

[16]We divide our sample of countries into world regions. For each world region, we estimate a P-R (unscaled) revenue model. This yields a single value of H^r for each region.

H_s^r ('scaled P-R'). H^p is not displayed since its values are very close to those of H^r.[17] Figure 1 illustrates very clearly the positive bias in H_s^r relative to H^r. Figure 1 also shows that, unlike the unscaled H estimates – which span a range of values, both positive and negative – the scaled H statistics are always fairly close to unity.

We briefly address the role of the control factors in the unscaled revenue equation. If interest income is the dependent variable, the coefficient of loans to total assets (LNS/TA) turns out significantly positive (negative) in 36 (2) out of 63 countries. Other non-interest earning assets to total assets (ONEA/TA) has a significantly negative (positive) effect in 13 (11) countries, while deposits to funding (DPS/F) have a significantly negative (positive) influence in 16 (12) countries. Finally, the coefficient of equity to total assets (EQ/TA) is significantly negative (positive) in 29 (8) countries. For many countries one or more control variables do not turn out significant. With total income as the dependent variable, the results are very similar. As mentioned in Section 5.1, we expect the coefficients of the control variables to be much more significant in the scaled revenue and price equations. Indeed, with interest income as the dependent variable in the price equation, LNS/TA turns out significantly positive (negative) for 42 (1) countries, ONEA/TA significantly negative for 21 (3) countries, DPS/F significantly negative (positive) for 15 (10) countries and EQ/TA significantly positive (negative) for 18 (8) countries. Again the results are similar if the dependent is based on total income instead of interest income, although in this case ONEA/TA has a significantly negative (positive) coefficient for 17 (12) countries. The adjusted R^2's are on average around 0.40 for the unscaled revenue equations and on average about 0.98 for the scaled revenue and price equations.

Our unscaled estimates of the H statistic are generally lower than the scaled ones found in the literature, but our scaled estimates are much more in line with previous findings. For example, Claessens and Laeven (2004) find an average value of H^p equal to 0.69, where the average is taken over 50 countries. Staikouras and Koutsomanoli-Fillipaki (2006) establish a value of H^p equal to 0.54 (0.78) for the EU10 (EU15) during the 1998 – 2002 period. Carbo et al. (2009) find an average value of H_s^r equal to 0.70 for 14 EU countries during the period 1995 – 2001. Goddard and Wilson (2009) use the unscaled revenue to estimate the H statistic for seven developed countries.

[17] Since the coefficient of log(TA) in the revenue equation is virtually equal to unity for all countries in our sample, the estimates for H_s^r and H^p turn out to be almost identical.

Using fixed-effects and dynamic panel estimation, they report average values for H^r between 0.18 and 0.37. Delis et al. (2008), who also estimate the unscaled revenue equation using within and dynamic panel estimation, establish H statistics between -0.12 and 0.45 for Greece, Spain and Latvia during the 1993 – 2004 period. Clearly, any comparison between our results and the studies in Table 1 is somewhat loose, given the differences in sample period.

6.4 Statistical tests for market structure

To assess how the bias in H^p and H_s^r impairs assessment of market structures, we follow the approach generally adopted in existing banking literature. For each country we consider the H statistic based on either the price or scaled revenue equation and estimated by means of the within estimator. Subsequently, we draw conclusions about bank conduct on the basis of the theoretical values of H^r. That is, we consider the null hypotheses $H^r < 0$ (corresponding to a neoclassical monopolist, collusive oligopolist, or conjectural-variations short-run oligopolist), $H^r = 1$ (competitive price-taking bank in long-run competitive equilibrium, sales maximization subject to a breakeven constraint, a sample of local natural monopolies under contestability, or free entry equilibrium with full (efficient) capacity utilization), and $0 < H^r < 1$ (monopolistic competitor). We apply t-tests to test each of the three null hypotheses. We compare the resulting test outcomes to those based on H_s^r and H^p.

We only discuss the test results for the P-R model in terms of interest income, as we establish very similar outcomes for the P-R model with total income as dependent variable. The null hypotheses $H^p < 0$ and $H_s^r < 0$ are rejected for all 63 countries, whereas $H^r < 0$ is rejected for 44 countries only. On the basis of H^r and H^p monopolistic competition is never rejected, whereas H^r rejects monopolistic competition for 10 countries. The three versions of the P-R model yield comparable results for the null hypothesis that the H statistic is equal to unity. This hypothesis is rejected for 56 countries according to the P-R price equation, for 54 (of the same) countries on the basis of the scaled revenue equation, and for 56 countries on the basis of the unscaled revenue function. The statistical tests for bank conduct confirm our main theoretical result, namely that scaling of the P-R equation results in substantially larger estimates of the H statistic in case of imperfect competition, but not in case of perfect competition. The positive bias in H_s^r and H^p

is also apparent from the fact that imperfect competition is rejected more often and monopolistic competition is rejected less often in the scaled P-R models than in the unscaled ones.

Despite the regional differences in the value of the H statistic as established in Section 6.3, we cannot rejected the null hypothesis $0 < H^r < 1$ for any region. By contrast, the null hypotheses $H^r < 0$ and $H^r = 1$ are rejected for all regions.

6.5 Interpretation of test results

Table 10 provides the outcome of the ROA test as discussed in Section 4.2.[18] For 26 countries we reject $H^{ROA} = 0$ in favor of $H^{ROA} < 0$ and reject $H^r < 0$ in favor of $H^r \geq 0$, suggesting that there is generally competitive conduct but some structural disequilibrium in these countries. For 4 countries we cannot reject $H^{ROA} = 0$ and $H^r = 1$, providing strong evidence for long-run competitive equilibrium. For 10 other countries we reject $H^{ROA} = 0$ in favor of $H^{ROA} < 0$ but cannot reject $H^r < 0$, both consistent with monopoly, oligopoly, or short-run (but not long-run) competition. For the remaining 23 countries we cannot reject $H^{ROA} = 0$, although we reject $H^r = 1$ in favor of $H^r < 1$. Failure to reject $H^{ROA} = 0$ could result from large standard errors without 'proving' long-run competition (this interpretation, of course, holds for any hypothesis that we cannot reject). On the other hand, $H^r < 1$ can also occur in a competitive market and the outcome of the ROA test, if it rejects structural equilibrium, may be an additional indication for this.

6.6 Robustness checks

We performed several robustness checks to assess whether the scaling bias remains present if we use a different model specification. In particular, we estimated the scaled and unscaled P-R model separately for small and large banks in the countries Germany, France, Italy, Luxembourg, Spain, Switzerland, and the United States. The data samples for these banks are sizeable enough to create sufficiently large groups of small and large banks. Similar to Bikker and Haaf (2002), we define large banks as banks with average total assets (in real terms) during the 1994 – 2004 period in

[18] We estimate H^{ROA} by regressing ROA on (log) input prices, (log) control variables, log(TA), and year dummies. We use the within estimator, dealing with bank-specific fixed effects. We use clustered standard errors to deal with general heteroskedasticity and cross-sectional correlation in the model errors (Arellano, 1987).

excess of the 90% quantile of total assets. Similarly, small banks are defined as banks with average total assets less than the 50% quantile. The results are displayed in the first part of Table 11. Next, we assess to what extent the bias in the scaled H statistics depends on the sample period. For the aforementioned set of seven countries, we estimate separate H statistics for the period 1994 – 1999 and 2000 – 2004 using the within estimator. See the second part of Table 11. As a third robustness check, we estimate a single P-R revenue and price model for several world regions, using the within estimator (similar to Section 6.3). Since several banks (e.g. in Switzerland and the United Kingdom) also operate in other European countries, this can be considered a robustness check with respect to the extent of the market. The last part of Table 11 displays the estimation results. Table 11 confirms our main conclusion by consistently highlighting a substantial positive bias in the H statistics based on price and scaled revenue equations, with the only exception of large banks in France.[19]

If log interest income is the dependent variable in the P-R model, it seems theoretically more correct to take the total of loans, investments in securities, and deposits at other banks as a measure of scale. However, the empirical banking literature generally uses log total assets to control for scale. For this reason, our main analysis uses log total assets as a scaling factor. As a robustness check, we have taken the log of the aforementioned interest earning assets as the scaling factor in the regressions with log interest income as the dependent variable. This yields virtually identical results. This can be explained by the fact that the correlation between log interest earning assets and log total assets is very high for all countries under consideration (the average correlation over all 63 countries equals 0.84). If log total income is the dependent variable in the P-R model, log total assets may seem a natural measure of scale. However, certain off-balance sheet (OBS) activities may result in additional earnings that are included in total income. Hence, a better measure of scale would be the log of total assets plus OBS items. As a robustness check, we have taken the log of total assets plus OBS items as a scaling factor for several major countries for which our data sample remains large enough after deleting the missing values on OBS items. This yields very similar results. Again this can be explained by looking at the correlation between log total

[19] Subperiods other than 1994 – 1999 and 2000 – 2004 yield qualitatively the same result: a large positive bias for the H statistics based on the price and scaled revenue equations.

assets and the log of total assets plus OBS items. On average this correlation equals 0.71.[20]

Following Delis et al. (2008) and Goddard and Wilson (2009), we estimate dynamic panel versions of the models of Equations (1) and (3). We only do this for a selection of countries for which the number of banks is much larger than the number of years, which is required for the GMM estimation of the dynamic panel model (Arellano and Bover, 1995; Blundell and Bond, 1998). With relatively few banks, the number of orthogonality conditions will exceed the number of banks, which may result in biased estimates and other problems (Roodman, 2009). The countries under consideration are Austria, Denmark, France, Germany, Italy, Japan, Luxembourg, Spain, Switzerland, and the United States. We use Windmeijer (2005)'s robust standard errors to account for general heteroskedasticity and autocorrelation in the model residuals. For all countries under consideration the persistence in the dependent variable is relatively low (below 0.20) and often insignificant, providing only weak evidence for the need of a dynamic panel approach. Furthermore, the underlying estimation method lacks robustness and the resulting standard errors are relatively large. Nevertheless, dynamic panel estimation qualitatively yields the same results as the other estimation methods, namely a positive bias in the H statistic based on the scaled revenue equation.

Finally, we correct all control factors for any correlation with log(TA), following the approach of Section 6.2. This hardly affects the estimates of the H statistic.

7 Conclusions

This paper has shown that a Panzar-Rosse price function or scaled revenue equation – which have both been widely applied in the empirical competition literature – cannot be used to infer the degree of competition. Only an unscaled revenue equation yields a valid measure for competitive conduct. Our theoretical findings have been confirmed by an empirical analysis of competition in the banking industry, based on a sample containing more than 100,000 bank-year observations on more than 17,000 banks in 63 countries during the 1994 – 2004 period.

Even if the competitive climate is assessed on the basis of an unscaled revenue equation,

[20]Detailed estimation results in the remainder of this section are available from the authors upon request.

there are still some caveats that must be considered. In particular, the Panzar-Rosse H statistic generally requires additional information about costs, market equilibrium and possibly market demand elasticity to allow meaningful interpretations. However, it is not a straightforward exercise to obtain such additional information.

The coexistence of firms of different sizes within the same market is strong evidence either of disequilibrium or of locally constant average cost. Since constant average cost and disequilibrium undermine the reliability of the P-R test, a sample of firms of widely differing sizes within a single market may be intrinsically unsuitable for application of the P-R test. Samples of firms from multiple markets, by contrast, could exhibit a wide range of sizes without apparent problems in the P-R test, although then a separate test for market boundaries (which is not otherwise important in the P-R framework) may be required to rule out a single market for such a sample. If a single market is found for a sample of different-sized firms, then one should test further for evidence of a flat average cost curve before estimating a P-R model. We leave this empirical refinement for future implementation.

Our findings lead to the important overall implication that the unscaled P-R test is a *one-tail* test of conduct. A positive value of the H statistic is inconsistent with standard forms of imperfect competition, but a negative value may arise under various conditions, including short-run or even long-run competition. In this way, the Panzar-Rosse revenue test results in a non-ordinal statistic for firm conduct that is less informative than prior literature has suggested.

Appendix A Proofs of propositions

In the following analysis, we denote average cost by AC and the output quantity by q.

Proposition 3.4 Constant AC does not alter the sign of H^r or H^p for monopoly or oligopoly, compared to the standard case of U-shaped average costs.

Proof: Since MR $=$ MC > 0 in equilibrium, an increase in input prices will drive up marginal cost by linear homogeneity. The increase in marginal cost will reduce the firm's equilibrium output quantity by the downward-sloping demand curve. The reduction in output will reduce the firm's total revenue by the definition of positive MR. Thus $H^r < 0$. At the same time, however, the reduction in output quantity will increase the output price by the downward-sloping demand condition, so $H^p > 0$.

Proposition 3.5 $H^p = H_s^p = 1$ in long-run competitive equilibrium with constant AC.

Proof: P = MC in long-run competitive equilibrium, so $\partial\mathrm{P}/\partial\mathrm{MC} = (\mathrm{MC}/\mathrm{P})\partial\mathrm{P}/\partial\mathrm{MC} = 1 \times 1 = 1$ and thus, by linear homogeneity of marginal cost in input prices, $H^p = 1$.

Proposition 3.6 $H^r < 1$, or even $H^r < 0$, is possible for firms in long-run competitive equilibrium with constant AC.

Proof: To see this, consider separately the cases of increasing and decreasing marginal cost. First, suppose input prices rise so that marginal cost rises. Starting from an output price equal to the original marginal cost, firms now find P $<$ MC. But competitive firms are price takers and thus cannot unilaterally raise price to the new long-run equilibrium level. In the short run, firms will suffer losses until exit by some firms reduces aggregate production. Since market demand curves are downward-sloping, the reduction in aggregate production drives up the price. A new equilibrium is restored when exit has progressed to the point where the new P equals the new marginal cost. The indeterminate aspect of firms' response here is the production quantity chosen by surviving firms. Since MC = AC = constant, firms can mitigate their losses by reducing output. In that case, a new equilibrium may be restored with little or no exit. Then each firm will be producing less at the new equilibrium, possibly to the point where total revenue is lower than before despite the higher output price. This scenario would yield an empirical measure of $H^r < 0$, which cannot be distinguished from the imperfectly competitive outcome.[21] Now consider the other possibility, a decline in input prices causing a decline in marginal cost. At the old output price, P > MC and positive profits will attract entry. However, with constant MC = AC, incumbent firms are likely to expand production before entry occurs to take advantage of the incremental profits. Either way, aggregate output expands and the market price falls. At the new equilibrium (where P = MC), incumbent firms are producing more than before, but by an amount that is indeterminate. Again, it is possible to observe $H^r < 0$.[22] In both cases, $H^r < 1$ if firms make any adjustment of production quantity in the transition to the new equilibrium. With constant marginal cost, we should expect some output adjustment in general. Therefore, unless we can rule out constant marginal cost as a separate hypothesis, a rejection of $H^r = 1$ does necessarily correspond to a rejection of long-run competitive equilibrium, contrary to the standard results under the assumption of U-shaped average cost.

Proposition 4.1 $H^{ROA} < 0$ for monopoly, oligopoly, or short-run competitive equilibrium, whether or not log(TA) is included as a separate regressor.

Proof: Consider a monopoly facing any demand function that is not perfectly inelastic. If input prices rise, thus increasing marginal cost, the monopolist reduces production and raises the price of its output in order to re-equilibrate at the new profit-maximizing condition $\text{MC} = \text{MR} = \text{P} + q\partial\text{P}/\partial q$. But, as market demand is not perfectly inelastic in general (and never perfectly inelastic at the point of monopoly equilibrium), the monopolist cannot pass along the entire increase in cost to its customers. That is, $\Delta\text{P} < \Delta\text{MC}$. Since the resulting margin $\text{P} - \text{MC}$ is therefore lower after this adjustment, ROA is lower, and hence $H^{ROA} < 0$. This result does not depend on the specific form of demand or cost, and likewise generalizes to oligopoly. In the case of short-run competitive equilibrium, firms are output price takers and cannot pass along any increase in input prices in the short run, so that we would also observe $H^{ROA} < 0$. If input prices fall, firms in a competitive market may earn temporary profits until new entry occurs, again implying $H^{ROA} < 0$. In no case

[21] It is also possible that the reduction in output may be less severe, in which case $0 < H^r < 1$. Any reduction in the firm's output would cause $H^r < 1$.

[22] A milder increase in output would cause $0 < H^r < 1$. Any increase in output by individual firms would cause $H^r < 1$.

would we expect to observe $H^{ROA} > 0$.

Finally, we address the conditions under which our results are valid. We do this by going back to the seminal work of Rosse and Panzar (1977) and Panzar and Rosse (1987). Since we employ the same approach to derive our theoretical results, our propositions are valid under the same conditions. The monopoly analysis is valid for any production function satisfying the firm's second-order condition. The long-run competitive analysis requires increasing marginal cost; this is a technical restriction on the existence of long-run competitive equilibrium, rather than a limitation of the Panzar-Rosse test. The static oligopoly analysis is valid for any production function satisfying the firm's second-order condition.

Appendix B The administered pricing hypothesis

Rosse and Panzar (1977, page 15-16) erroneously claim that $H^r = 1$ in case of constant markup pricing (referred to as the Administered Pricing Hypothesis, APH). We first provide a counterexample to $H^r = 1$ under the APH, in the special case of constant marginal and average cost, or $C(q) = cq$, also using the fact that marginal cost is homogeneous of degree 1 in input prices (or we can think of a single input and constant returns, so c is the input price). Then the APH implies $R(q) = aC(q)$ for some constant $a > 1$. But in the usual case of linear pricing, $R = Pq$ where P is the output price and $q = q(P)$ with $q'(P) < 0$ (downward sloping demand). As we are showing a counterexample, it suffices to look at the case of linear pricing. Hence, under the APH, $Pq = acq$ and $P = ac$. Now

$$H^r = (c/R)\partial R/\partial c = (c/Pq)\partial R/\partial c = (c/acq)\partial R/\partial c = (1/aq)\partial R/\partial c \tag{B.1}$$

and

$$\partial R/\partial c = a(\partial C/\partial c) = a[q + c(\partial q/\partial P)\partial P/\partial c] = a[q + ca(\partial q/\partial P)]. \tag{B.2}$$

So

$$H^r = 1 + [ac/q(P)]\partial q/\partial P < 1, \tag{B.3}$$

since $a > 0$, $c > 0$, $q > 0$, and $\partial q/\partial P < 0$.

Next, we consider U-shaped average cost and prove that $H^r < 1$ under APH. Again, as we are showing a counterexample, it suffices to look at the case of log-quadratic cost (not quadratic because linear homogeneity must be satisfied). Let

$$\log C(q) = a + b \log q + (c/2)(\log q)^2 + \log w, \tag{B.4}$$

for output quantity q and a single input price w. Note that linear homogeneity in w requires the unitary coefficient on $\log w$ and forbids terms in $(\log w)^2$ and $\log q \times \log w$. This form corresponds to a standard translog cost function with a single input. The associated marginal cost is not constant unless $b = 1$ and $c = 0$. For appropriate combinations of parameter values, this function represents U-shaped average cost. APH implies $Pq = \alpha C(q)$ for some fixed $\alpha > 1$, so $P = \alpha C(q)/q$. Then

$$\log P = \log \alpha + a + b \log q + (q/2)(\log q)^2 + \log w - \log q, \tag{B.5}$$

under APH, so $\partial \log P/\partial \log w = 1$. Now under linear pricing

$$H^r = \partial \log R/\partial \log w = \partial \log(Pq)/\partial \log w. \tag{B.6}$$

Moreover, under the APH we have

$$\begin{aligned}
\partial \log(Pq)/\partial \log w &= \partial[\log P + \log q]/\partial \log w \\
&= \partial \log P/\partial \log w + \partial \log q/\partial \log w = 1 + \partial \log q/\partial \log w \\
&= 1 + (w/q)\partial q(P)/\partial w = 1 + (w/q)q'(P)\partial P/\partial w \\
&= 1 + (w/q)q'(P)(P/w)\partial \log P/\partial \log w = 1 + Pq'(P)/q.
\end{aligned}$$

Finally, we observe that $1 + Pq'(P)/q < 1$ since $P > 0$, $q > 0$, and $q'(P) < 0$. Our counterexamples for both constant and U-shaped average cost demonstrate that the result $H^r = 1$ under the APH, as claimed by Rosse and Panzar (1977), does not hold true.

Furthermore, we can show that $H^p = 1$ under the APH. We denote $P = aC(q, w)$ where $a > 1$ and w a vector of input prices and w_i the i-th input price. Since $\partial P/\partial w_i = a\partial C(q, w)/\partial w_i$, we find that

$$(w_i/P)P/\partial w_i = [aw_i/aC(q, w)]\partial C(q, w)/\partial w_i = [w_i/C(q, w)]\partial C(q, w)/\partial w_i. \tag{B.7}$$

Now $H^p = \sum_i [w_i / C(q,w)] \partial C(q,w)/\partial w_i$ by definition. Moreover, linear homogeneity of the total cost function in input prices implies

$$\sum_i [w_i / C(q,w)] \partial C(q,w)/\partial w_i = 1. \tag{B.8}$$

We can also show that $H_s^r = 1$ under the APH. We do this for the special case of constant AC. The APH implies $\mathrm{P} = \alpha c$, where c represents the constant unit cost. Linear homogeneity of the marginal cost function with respect to input prices implies that $H_s^r = \partial \log(\mathrm{TR})/\partial \log c$. Consider the log-log scaled revenue equation:

$$\log(\mathrm{TR}) = a + b \log c + c \log(\mathrm{TA}) + X\gamma + \varepsilon, \tag{B.9}$$

where X is a row vector of (log) control variables, γ the corresponding column vector of coefficients and ε the error term. Assume $\mathrm{TA} = \beta q$ (that is, total assets are proportional to output quantity q, which is roughly implied by the intermediation model of banking) and note that $\mathrm{TR} = Pq$ and $\log(\mathrm{TA}) = \log \beta + \log q$. Now Equation (B.9) can be written as:

$$\log P = [a + d \log \beta] + b \log c + (d-1) \log q + X\gamma + \varepsilon. \tag{B.10}$$

Substituting $P = \alpha c$ from the APH and rearranging terms yields another form of Equation (B.9):

$$\log c = [a + d \log \beta - \log \alpha] + b \log c + (d-1) \log q + X\gamma + \varepsilon. \tag{B.11}$$

Then $b = \partial \log c / \partial \log c = 1$. Since Equation (B.11) is equivalent to Equation (B.9), we finally obtain $H_s^r = \partial \log(\mathrm{TR})/\partial \log c = b = 1$.

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Table 1: **Summary of published empirical P-R studies**

authors	**dep.var.**	**scaling**	**period**	**region**	**continuous measure of competition**
Shaffer (1982)	log(TI)	log(TA)	1979	US (state of New York)	No
Nathan and Neave (1989)	log(TI-loan losses)	log(TA)	1982 – 1984	Canada	
Molyneux et al. (1994)	log(II/TA)	log(TA)	1986 – 1989	France, Germany,Italy, Spain and UK	
Vesala (1995)	log(II)	log(EQ), log(FA)	1985 – 1992	Finland	Yes, in some cases
Molyneux et al. (1996)	log(II)	log(TA), log(TD)	1986 – 1988	Japan	
Coccorese (1998)	log(TI)	log(TA), log(TD)	1988 – 1996	Italy	
Rime (1999)	log(II)	log(TA)	1987 – 1994	Switzerland	
Hondroyiannis et al. (1999)	log(TI/TA)	log(TA)	1993 – 1995	Greece	
Bikker and Groeneveld (2000)	log(II/TA)	log(TA)	1989 – 1996	15 EU countries	Yes
De Bandt and Davis (2000)	log(II)	log(EQ), log(FACBNEA)	1992 – 1996	France, Germany, and Italy	Yes
Gelos and Roldos (2004)	log(II)	log(TA)	1994 – 1999	8 European and Latin American countries	Yes
Bikker and Haaf (2002)	log(II/TA)	log(TA)	1988 – 1998	23 OECD countries	Yes
Coccorese (2003)	log(II), log(TI)	log(TA)	1997 – 1999	Italy	Yes
Murjan and Ruza (2002)	log(II)	log(TA), log(EQ)	1993 – 1997	Arab Middle East	
Claessens and Leaven (2004)	log(II/TA), log(TI/TA)	log(TA)	1994 – 2001	50 countries	Yes
Shaffer (2004)	log(TI)	log(TA)	1984 – 1994	US (Texas and Kentucky)	No
Mamatzakis et al. (2005)	log(II/TA), log(TI/TA)	none	1998 – 2002	South-Eastern European countries	Yes
Drakos and Konstantinou (2005)	log(TI)	log(TA)	1992 – 2000	Former Soviet Union	
Mkrtchyan (2005)	log(II/TA)	log(TA)	1998 – 2002	Armenia	
Casu and Girardone (2006)	log(TI/TA)	log(TA)	1997 – 2003	EU15	Yes
Gunalp and Celik (2006)	log(II), log(TI)	log(TA)	1990 – 2000	Turkey	No
Staikouras and Koutsomanoli-Fillipaki (2006)	log(II/TA), log(OI/TA), log(TI/TA)	none	1998 – 2002	EU10 & EU15	Yes
Matthews, Murinde, and Zhao (2007)	log(TI/TA), log(II/TA)	log(TA)	1980 – 2004	12 UK banks	Yes
Yildirim and Philippatos (2007)	log(TI/TA)	log(TA), log(EQ), log(FA), log(L)	1993 – 2000	11 Latin-American countries	Yes
Delis et al. (2008)	log(TI)	none	1993 – 2004	Greece, Spain and Latvia	Yes
Lee and Nagano (2008)	log(II/TA)	none	1993 – 2005	Korea	Yes
Gischer and Stiele (2009)	log(II)	log(EQ)	1993 – 2002	Germany	
Goddard and Wilson (2009)	log(II), log(TI)	none, log(TA)	2001 – 2007	Canada, France, Germany, Italy, Japan, the UK and the US	
Schaeck et al. (2009)	log(II/TA)	none	1980 – 2005	45 countries	Yes
Coccorese (2009)	log(TI)	log(TA)	1988 – 2005	Italy	Yes
Carbo et al. (2009)	log(TI)	log(TA)	1995 – 2001	14 EU countries	Yes

Notation: II (interest income), TA (total assets), TI (total income), EQ (equity), FA (fixed assets), TD (total deposits), FACBNEA (fixed assets, cash and due from banks, other non-earning assets), net loans (L), organic income (OI).

Table 2: **Summary of properties of the H statistic under alternative cost conditions**

		H based on		
market power	**AC function**	**unscaled rev. eq.**	**scaled rev. eq.**	**price eq.**
long-run competition	U-shaped	Rosse and Panzar (1977): $H^r = 1$	Prop. 3.2: $H_s^r = 1$	Prop. 3.2: $H^p = 1$
long-run competition	flat	Prop. 3.6: $H^r < 0$ or $0 < H^r < 1$ possible	Prop. 3.5: $H_s^r = 1$	Prop. 3.5: $H^p = 1$
short-run competition	U-shaped	Shaffer (1982a, 1983a): $H^r < 0$ possible Rosse and Panzar (1977): $0 < H^r < 1$ possible	by continuity: $H_s^r > 0$	by continuity: $H^p > 0$
monopoly	U-shaped	Rosse and Panzar (1977): $H^r < 0$	Prop. 3.1 & Cor. 3.1: $H_s^r > 0$	Prop. 3.3: $H^p > 0$
monopoly	flat	Prop. 3.4: $H^r < 0$	Prop. 3.4: $H_s^r > 0$	Prop. 3.4: $H^p > 0$
oligopoly	U-shaped	Rosse and Panzar (1977): $H^r < 0$	Prop. 3.1 & Cor. 3.1: $H_s^r > 0$	Prop. 3.1: $H^p > 0$
oligopoly	flat	Prop. 3.4: $H^r < 0$	Prop. 3.4: $H_s^r > 0$	Prop. 3.4: $H^p > 0$
monopolistic competition	U-shaped	Rosse and Panzar(1977): $0 < H^r < 1$ under conditions, but $H^r < 0$ possible	by continuity: $H_s^r > 0$	by continuity: $H^p > 0$
constant markup pricing (APH)	flat and U-shaped	Appendix B: $H^r < 1$ possible	Appendix B: $H_s^r = 1$ (assuming flat AC)	Appendix B: $H^p = 1$

Note: The case of monopolistic competition cannot arise with constant average cost, while the zero-profit constraint implies $H^p > 0$ under monopolistic competition. The result that $0 < H^r < 1$ is possible for short-run competition is based on Rosse and Panzar (1977). They show that $H^r \leq 1$ (including the region between 0 and 1) for their 'Market Equilibrium Hypothesis', which they define as firms trying to maximize profits in the presence of market forces operating to eliminate excess profits (which includes short-run competition). More generally and intuitively, if $H^r < 0$ for any profit-maximizing firm facing a fixed demand curve (as shown in Shaffer 1983a) while $H^r = 1$ for any firm in long-run competitive equilibrium, then – by continuity – there must exist a phase of partial adjustment between short-run and long-run competition for which $0 < H^r < 1$. Because H^p is positive in the polar cases of long-run competition and monopoly, it is also positive in intermediate cases, including short-run competition and monopolistic competition.

Table 3: **Sample statistics for BankScope data**

For several major countries this table reports average values of interest income, total income, total assets, proxies of lending rate, output price and input prices, and various control variables. On the aggregate (world-wide) level we report average values of the aforementioned variables, as well as 5% and 95% quantiles. Interest income, total income and total assets are in real terms and reported in millions of dollars (in year-2000 prices). The sample period covers the years 1994 – 2004.

									all countries (weighted)		
	France	**Germany**	**Italy**	**Japan**	**Spain**	**Switzerland**	**UK**	**US**	**world-wide mean**	**5% quantile**	**95% quantile**
II	676.4	81.8	163.2	126.4	551.5	110.2	1848.7	42.6	253.8	18.6	702.5
TI	865.0	96.9	207.7	149.8	675.6	171.5	2517.3	55.8	317.6	23.8	954.9
TA	12984.4	1609.1	2822.0	4172.6	8949.1	3315.0	38916.0	748.3	3975.4	160.4	14161.2
II/TA	0.062	0.061	0.061	0.023	0.057	0.038	0.059	0.062	0.096	0.050	0.224
TI/TA	0.079	0.070	0.073	0.026	0.070	0.064	0.076	0.070	0.121	0.065	0.244
IE/FUN	0.044	0.036	0.033	0.003	0.034	0.026	0.047	0.029	0.070	0.029	0.188
PE/TA	0.016	0.014	0.017	0.010	0.014	0.014	0.011	0.016	0.018	0.008	0.034
ONIE/FA	1.156	0.795	1.110	0.599	1.014	0.832	1.459	0.879	1.776	0.605	3.922
LNS/TA	0.534	0.603	0.525	0.567	0.583	0.680	0.442	0.622	0.522	0.334	0.722
ONEA/TA	0.043	0.007	0.041	0.007	0.024	0.017	0.039	0.022	0.041	0.013	0.080
DPS/F	0.318	0.436	0.433	0.474	0.407	0.406	0.352	0.489	0.412	0.298	0.477
EQ/TA	7.454	5.134	11.851	5.403	9.027	10.827	9.651	10.440	11.093	5.434	17.120

Table 4: **Estimation results for P-R models (within estimator)**

This table reports estimates of the H statistic and corresponding standard errors based on the Panzar-Rosse price and (un-)scaled revenue equation. The models denoted by 'log(II) + log(TA)' and 'log(TI) + log(TA)' refer to the revenue equation with, respectively, log(II) and log(TI) as the dependent variable and log(TA) as the scaling variable. The within estimator has been used to estimate all specifications. Clustered standard errors have been used to deal with general heteroskedasticity and cross-sectional correlation in the model errors (Arellano, 1987).

country	**# banks**	**# obs**	**log(II)**		**log(TI)**		**log(PI)**		**log(PT)**		**log(II)+log(TA)**		**log(PI)+log(TA)**	
			H^r	$\sigma(H^r)$	H^r	$\sigma(H^r)$	H^p	$\sigma(H^p)$	H^p	$\sigma(H^p)$	H_s^r	$\sigma(H_s^r)$	H_s^r	$\sigma(H_s^r)$
Argentina	107	418	0.377	0.092	0.225	0.092	0.851	0.062	0.686	0.056	0.881	0.067	0.777	0.059
Australia	33	207	0.972	0.136	1.006	0.134	0.904	0.032	0.950	0.028	0.904	0.032	0.950	0.028
Austria	194	1234	0.376	0.051	0.373	0.056	0.731	0.020	0.730	0.025	0.733	0.020	0.750	0.026
Bangladesh	33	255	1.121	0.171	1.096	0.156	0.980	0.065	0.953	0.048	0.935	0.061	0.923	0.045
Belgium	78	515	0.630	0.094	0.672	0.095	0.851	0.028	0.892	0.038	0.854	0.028	0.890	0.038
Bolivia	16	123	-0.082	0.213	-0.057	0.200	0.647	0.059	0.668	0.055	0.702	0.060	0.678	0.058
Brazil	167	859	0.466	0.059	0.521	0.055	0.705	0.035	0.761	0.027	0.703	0.035	0.757	0.027
Canada	66	432	0.212	0.092	0.201	0.090	0.761	0.032	0.747	0.031	0.752	0.033	0.735	0.032
Chile	35	202	0.209	0.183	0.199	0.142	0.824	0.141	0.798	0.055	0.817	0.148	0.845	0.056
Colombia	40	239	0.446	0.130	0.379	0.125	0.829	0.064	0.766	0.054	0.870	0.064	0.797	0.054
Costa Rica	39	150	0.213	0.085	0.243	0.087	0.811	0.039	0.841	0.036	0.760	0.044	0.808	0.042
Croatia	47	279	0.263	0.154	0.225	0.164	0.542	0.061	0.509	0.067	0.538	0.061	0.517	0.067
Czech Republic	34	197	0.578	0.129	0.516	0.134	0.828	0.075	0.750	0.091	0.812	0.075	0.729	0.091
Denmark	100	881	0.327	0.054	0.389	0.065	0.526	0.028	0.588	0.038	0.503	0.027	0.583	0.038
Dominican Republic	29	177	1.001	0.381	0.776	0.210	1.025	0.279	0.784	0.063	1.005	0.265	0.778	0.057
Ecuador	29	115	0.729	0.138	0.741	0.126	0.750	0.092	0.773	0.080	0.751	0.092	0.774	0.078
France	411	2843	0.186	0.028	0.189	0.028	0.641	0.014	0.642	0.014	0.613	0.014	0.619	0.015
Germany	2298	17260	0.373	0.018	0.400	0.018	0.716	0.005	0.742	0.006	0.719	0.005	0.739	0.006
Greece	28	152	-1.051	0.202	-1.059	0.214	0.955	0.053	0.929	0.050	0.843	0.069	0.955	0.068
Hong Kong	38	308	0.417	0.099	0.442	0.090	0.853	0.047	0.873	0.044	0.877	0.048	0.860	0.045
Hungary	26	136	-0.229	0.213	-0.290	0.206	0.710	0.085	0.647	0.067	0.694	0.096	0.636	0.076
India	75	536	0.820	0.089	0.849	0.088	0.708	0.027	0.738	0.022	0.712	0.027	0.742	0.021
Indonesia	105	572	0.203	0.067	0.288	0.070	0.748	0.032	0.830	0.038	0.749	0.034	0.826	0.041
Ireland	31	197	0.108	0.087	0.122	0.096	0.673	0.039	0.680	0.052	0.667	0.045	0.698	0.060
Israel	17	131	0.278	0.094	0.358	0.093	0.822	0.089	0.911	0.088	0.711	0.126	0.806	0.124
Italy	821	5556	0.366	0.025	0.428	0.025	0.656	0.010	0.716	0.011	0.651	0.010	0.706	0.011
Japan	620	3197	0.098	0.026	0.157	0.029	0.473	0.015	0.532	0.019	0.429	0.016	0.502	0.020
Jordan	11	100	-0.996	0.244	-1.136	0.283	0.478	0.068	0.376	0.074	0.396	0.076	0.492	0.080
Kazakhstan	24	115	-0.382	0.204	-0.424	0.197	0.663	0.064	0.612	0.045	0.638	0.071	0.604	0.049
Kenya	38	187	0.443	0.115	0.268	0.112	0.674	0.062	0.496	0.061	0.674	0.063	0.494	0.062
Latvia	29	144	-0.422	0.194	-0.188	0.180	0.698	0.107	0.825	0.097	0.713	0.121	0.858	0.110
Lebanon	59	434	0.095	0.103	0.075	0.106	0.715	0.037	0.696	0.038	0.716	0.039	0.719	0.039
Luxembourg	137	1071	0.193	0.041	0.140	0.044	0.844	0.014	0.790	0.022	0.829	0.015	0.785	0.024
Malaysia	43	335	0.591	0.068	0.620	0.070	0.874	0.025	0.901	0.030	0.866	0.026	0.896	0.031
Mexico	31	109	0.791	0.239	0.603	0.182	1.220	0.183	1.009	0.098	1.236	0.186	1.020	0.099

Table 5: **Estimation results for P-R models (within estimator continued)**

country	**# banks**	**# obs**	**log(II)**		**log(TI)**		**log(PI)**		**log(PT)**		**log(II)+log(TA)**		**log(PI)+log(TA)**	
			H^r	$\sigma(H^r)$	H^r	$\sigma(H^r)$	H^p	$\sigma(H^p)$	H^p	$\sigma(H^p)$	H^r_s	$\sigma(H^r_s)$	H^r_s	$\sigma(H^r_s)$
Monaco	14	120	0.823	0.156	0.696	0.159	0.760	0.054	0.632	0.060	0.755	0.056	0.623	0.062
Netherlands	51	330	0.179	0.106	0.064	0.104	0.901	0.038	0.779	0.043	0.922	0.040	0.776	0.046
Nigeria	64	318	0.375	0.119	0.245	0.114	0.875	0.053	0.747	0.035	0.844	0.055	0.726	0.036
Norway	64	370	0.751	0.072	0.783	0.073	0.807	0.030	0.838	0.033	0.821	0.029	0.851	0.033
Pakistan	25	178	0.769	0.119	0.622	0.120	0.651	0.080	0.503	0.084	0.664	0.080	0.518	0.083
Panama	45	134	0.535	0.122	0.460	0.135	0.881	0.045	0.806	0.053	0.889	0.048	0.847	0.055
Paraguay	26	166	-0.110	0.092	-0.058	0.119	0.856	0.044	0.946	0.071	0.866	0.059	1.128	0.091
Peru	26	165	0.401	0.135	0.239	0.167	0.789	0.051	0.661	0.087	0.793	0.052	0.693	0.087
Philippines	49	308	0.671	0.127	0.724	0.126	0.764	0.044	0.814	0.040	0.781	0.043	0.833	0.039
Poland	50	261	-0.809	0.117	-0.840	0.126	0.691	0.052	0.669	0.047	0.645	0.068	0.759	0.062
Portugal	32	227	0.344	0.113	0.596	0.141	0.771	0.047	1.022	0.094	0.777	0.049	1.049	0.097
Romania	29	138	-0.369	0.179	-0.259	0.178	0.694	0.072	0.791	0.074	0.774	0.079	0.851	0.082
Russian Federation	206	637	0.345	0.072	0.307	0.060	0.628	0.045	0.588	0.033	0.648	0.046	0.577	0.034
Slovakia	21	100	-0.415	0.230	0.221	0.262	0.538	0.107	1.183	0.177	0.764	0.124	1.323	0.217
Slovenia	20	107	-0.990	0.161	-1.041	0.154	0.785	0.062	0.732	0.062	0.735	0.092	0.612	0.091
South Africa	31	139	0.457	0.134	0.334	0.129	0.961	0.036	0.830	0.039	0.998	0.038	0.846	0.042
Spain	165	1130	0.154	0.047	0.270	0.044	0.582	0.021	0.692	0.021	0.613	0.022	0.688	0.022
Sweden	91	401	-0.016	0.055	-0.006	0.063	0.651	0.033	0.665	0.033	0.529	0.036	0.624	0.039
Switzerland	417	2425	0.107	0.033	0.019	0.035	0.559	0.020	0.470	0.022	0.559	0.021	0.475	0.024
Thailand	18	128	0.385	0.101	0.296	0.118	0.864	0.079	0.769	0.081	0.714	0.083	0.710	0.090
Turkey	51	191	0.613	0.176	0.480	0.167	0.813	0.078	0.674	0.057	0.813	0.079	0.674	0.057
Ukraine	41	184	-0.202	0.140	-0.259	0.130	0.781	0.063	0.701	0.065	0.680	0.071	0.551	0.071
United Arab Emirates	17	117	-0.520	0.196	-0.558	0.210	0.756	0.060	0.696	0.066	0.729	0.074	0.767	0.080
United Kingdom	73	403	0.467	0.074	0.535	0.075	0.735	0.030	0.805	0.026	0.735	0.030	0.810	0.027
United States	9505	55904	0.426	0.009	0.474	0.009	0.684	0.003	0.732	0.003	0.692	0.003	0.745	0.003
Uruguay	32	111	-0.333	0.133	-0.357	0.144	0.813	0.046	0.797	0.060	0.892	0.068	0.935	0.088
Venezuela	56	261	0.334	0.096	0.320	0.099	0.781	0.047	0.767	0.046	0.779	0.050	0.789	0.048
Vietnam	23	131	-0.071	0.225	-0.084	0.218	0.740	0.056	0.714	0.050	0.728	0.056	0.693	0.048
average			0.223	0.122	0.215	0.120	0.759	0.055	0.749	0.051	0.752	0.060	0.757	0.056

Table 6: **Estimation results for P-R models (pooled FGLS)**

This table reports estimates of the H statistic and corresponding standard errors based on the Panzar-Rosse price and (un-)scaled revenue equation. Pooled FGLS has been used to estimate all specifications. Clustered standard errors have been used to deal with general heteroskedasticity and cross-sectional correlation in the model errors (Arellano, 1987).

country	**log(II)**		**log(TI)**		**log(PI)**		**log(PT)**		**log(II)+log(TA)**		**log(PI)+log(TA)**	
	H^r	$\sigma(H^r)$	H^r	$\sigma(H^r)$	H^p	$\sigma(H^p)$	H^p	$\sigma(H^p)$	H^r_s	$\sigma(H^r_s)$	H^r_s	$\sigma(H^r_s)$
Argentina	-0.323	0.033	-0.419	0.031	0.705	0.004	0.673	0.007	0.752	0.005	0.697	0.005
Australia	-0.147	0.140	0.012	0.106	0.833	0.005	0.938	0.008	0.818	0.008	0.916	0.010
Austria	0.225	0.011	0.425	0.034	0.608	0.001	0.820	0.001	0.599	0.002	0.817	0.002
Bangladesh	1.362	0.078	1.435	0.077	0.989	0.008	0.988	0.016	0.981	0.013	0.994	0.014
Belgium	0.543	0.031	0.361	0.021	0.857	0.013	0.709	0.009	0.856	0.009	0.692	0.006
Bolivia	0.863	0.056	0.740	0.047	0.985	0.034	0.892	0.025	0.954	0.049	0.862	0.011
Brazil	0.548	0.018	0.630	0.018	0.731	0.003	0.794	0.001	0.714	0.003	0.787	0.002
Canada	0.335	0.083	0.299	0.092	0.741	0.006	0.710	0.006	0.740	0.005	0.718	0.003
Chile	1.608	0.110	1.548	0.117	0.939	0.021	0.826	0.007	0.952	0.013	0.809	0.006
Colombia	-1.043	0.080	-1.068	0.084	0.804	0.017	0.775	0.010	0.784	0.017	0.750	0.007
Costa Rica	-0.069	0.061	-0.030	0.051	0.750	0.010	0.789	0.005	0.741	0.011	0.787	0.005
Croatia	-1.704	0.015	-1.765	0.040	0.474	0.006	0.346	0.012	0.510	0.005	0.409	0.011
Czech Republic	0.745	0.087	0.679	0.108	0.691	0.015	0.581	0.020	0.692	0.009	0.583	0.018
Denmark	0.494	0.029	0.714	0.024	0.369	0.003	0.598	0.004	0.390	0.002	0.610	0.003
Dominican Republic	-1.322	0.136	-1.166	0.252	0.648	0.041	0.712	0.020	0.634	0.035	0.704	0.017
Ecuador	0.513	0.071	0.973	0.126	0.342	0.023	0.884	0.032	0.340	0.023	0.878	0.019
France	0.766	0.006	0.681	0.007	0.684	0.001	0.603	0.001	0.671	0.001	0.591	0.000
Germany	0.841	0.001	0.893	0.002	0.605	0.000	0.661	0.000	0.597	0.000	0.653	0.000
Greece	0.044	0.358	0.163	0.308	0.797	0.018	0.775	0.006	0.751	0.016	0.766	0.005
Hong Kong	-2.397	0.037	-2.407	0.037	0.594	0.009	0.633	0.007	0.568	0.006	0.628	0.003
Hungary	-0.584	0.027	-0.593	0.017	0.844	0.009	0.785	0.015	0.823	0.007	0.793	0.012
India	0.565	0.082	0.504	0.098	0.637	0.005	0.750	0.006	0.640	0.001	0.751	0.005
Indonesia	0.914	0.016	0.810	0.016	0.697	0.001	0.634	0.002	0.697	0.001	0.629	0.001
Ireland	1.698	0.086	1.721	0.109	0.873	0.009	0.867	0.006	0.882	0.006	0.879	0.008
Israel	-1.768	0.279	-1.809	0.268	0.818	0.019	0.690	0.018	0.802	0.021	0.702	0.013
Italy	1.676	0.007	1.814	0.005	0.589	0.000	0.727	0.001	0.576	0.000	0.722	0.001
Japan	-0.519	0.004	-0.438	0.006	0.460	0.001	0.560	0.001	0.493	0.001	0.577	0.001
Jordan	-2.635	0.192	-2.681	0.161	0.648	0.009	0.486	0.016	0.680	0.010	0.557	0.011
Kazakhstan	-0.110	0.072	-0.023	0.071	0.599	0.015	0.591	0.013	0.619	0.013	0.587	0.009
Kenya	0.220	0.111	0.317	0.113	0.586	0.017	0.616	0.014	0.593	0.020	0.608	0.007
Latvia	0.452	0.121	0.501	0.109	0.721	0.025	0.805	0.017	0.707	0.011	0.803	0.016
Lebanon	0.155	0.038	0.170	0.040	0.633	0.005	0.582	0.006	0.632	0.005	0.575	0.005
Luxembourg	0.675	0.008	0.615	0.010	0.857	0.001	0.801	0.001	0.855	0.001	0.802	0.001
Malaysia	0.811	0.031	0.781	0.019	0.879	0.005	0.862	0.007	0.875	0.004	0.870	0.007
Mexico	1.223	0.123	1.183	0.174	0.999	0.023	0.928	0.007	0.957	0.025	0.934	0.008

Table 7: **Estimation results for P-R models (pooled FGLS continued)**

country	**log(II)**		**log(TI)**		**log(PI)**		**log(PT)**		**log(II)+log(TA)**		**log(PI)+log(TA)**	
	H^r	$\sigma(H^r)$	H^r	$\sigma(H^r)$	H^p	$\sigma(H^p)$	H^p	$\sigma(H^p)$	H_s^r	$\sigma(H_s^r)$	H_s^r	$\sigma(H_s^r)$
Monaco	-0.010	0.350	0.004	0.308	0.765	0.012	0.811	0.020	0.749	0.006	0.811	0.019
Netherlands	1.169	0.034	1.160	0.035	0.833	0.003	0.849	0.005	0.821	0.003	0.841	0.007
Nigeria	0.337	0.040	0.375	0.011	0.781	0.005	0.757	0.005	0.785	0.004	0.772	0.004
Norway	1.945	0.118	2.126	0.111	0.849	0.006	0.923	0.006	0.844	0.009	0.925	0.003
Pakistan	1.219	0.130	1.081	0.081	0.637	0.022	0.511	0.012	0.672	0.012	0.501	0.014
Panama	0.289	0.076	0.362	0.079	0.634	0.015	0.644	0.020	0.630	0.014	0.644	0.020
Paraguay	-0.627	0.038	-0.579	0.029	0.659	0.006	0.770	0.019	0.702	0.007	0.775	0.016
Peru	-0.114	0.031	-0.311	0.039	0.931	0.023	0.847	0.011	0.965	0.015	0.858	0.010
Philippines	-0.068	0.136	-0.046	0.155	0.611	0.011	0.680	0.009	0.647	0.003	0.682	0.008
Poland	-0.165	0.047	-0.202	0.056	0.930	0.010	0.832	0.002	0.924	0.011	0.797	0.010
Portugal	-0.345	0.133	0.328	0.136	0.618	0.012	1.110	0.023	0.615	0.013	1.111	0.022
Romania	0.485	0.102	0.571	0.096	0.741	0.015	0.754	0.004	0.738	0.018	0.754	0.004
Russian Federation	0.507	0.007	0.566	0.009	0.555	0.005	0.611	0.002	0.557	0.002	0.619	0.003
Slovakia	0.700	0.104	0.280	0.165	0.682	0.008	0.620	0.048	0.660	0.010	0.624	0.045
Slovenia	-0.210	0.074	-0.339	0.072	0.689	0.018	0.628	0.014	0.652	0.017	0.644	0.011
South Africa	0.410	0.088	0.490	0.096	0.614	0.014	0.595	0.008	0.548	0.017	0.582	0.004
Spain	-0.045	0.021	0.113	0.017	0.454	0.003	0.575	0.001	0.452	0.003	0.579	0.001
Sweden	1.592	0.059	1.689	0.024	0.685	0.004	0.676	0.006	0.664	0.004	0.680	0.004
Switzerland	1.028	0.006	1.077	0.005	0.522	0.001	0.572	0.001	0.519	0.001	0.558	0.001
Thailand	-0.414	0.135	-0.534	0.116	0.624	0.015	0.612	0.022	0.622	0.012	0.601	0.015
Turkey	-0.196	0.058	0.070	0.065	0.592	0.016	0.693	0.008	0.579	0.013	0.693	0.008
Ukraine	0.564	0.034	0.464	0.044	0.572	0.016	0.494	0.005	0.555	0.010	0.493	0.005
United Arab Emirates	-1.685	0.138	-1.713	0.141	0.534	0.014	0.622	0.026	0.618	0.024	0.650	0.018
United Kingdom	-0.010	0.026	0.091	0.018	0.734	0.005	0.793	0.004	0.732	0.003	0.797	0.005
United States	0.210	0.000	0.314	0.000	0.522	0.000	0.631	0.000	0.527	0.000	0.628	0.000
Uruguay	1.121	0.100	0.995	0.045	0.944	0.006	0.824	0.007	0.960	0.005	0.834	0.010
Venezuela	0.699	0.033	0.781	0.059	0.681	0.011	0.723	0.005	0.696	0.008	0.721	0.001
Vietnam	0.445	0.052	0.362	0.060	0.780	0.015	0.731	0.009	0.790	0.016	0.719	0.008
average	0.214	0.076	0.240	0.077	0.701	0.011	0.719	0.010	0.700	0.010	0.720	0.008

Table 8: **Estimation results for P-R models (pooled OLS)**

This table reports estimates of the H statistic and corresponding standard errors based on the Panzar-Rosse price and (un-)scaled revenue equation. Pooled OLS has been used to estimate all specifications. Clustered standard errors have been used to deal with general heteroskedasticity and cross-sectional correlation in the model errors (Arellano, 1987).

country	**log(II)**		**log(TI)**		**log(PI)**		**log(PT)**		**log(II)+log(TA)**		**log(PI)+log(TA)**	
	H^r	$\sigma(H^r)$	H^r	$\sigma(H^r)$	H^p	$\sigma(H^p)$	H^p	$\sigma(H^p)$	H_s^r	$\sigma(H_s^r)$	H_s^r	$\sigma(H_s^r)$
Argentina	-0.350	0.214	-0.412	0.195	0.701	0.053	0.668	0.034	0.749	0.051	0.693	0.034
Australia	-0.073	0.612	0.010	0.598	0.845	0.060	0.936	0.054	0.825	0.067	0.919	0.053
Austria	0.195	0.193	0.404	0.190	0.610	0.009	0.823	0.029	0.599	0.009	0.819	0.028
Bangladesh	1.413	0.273	1.406	0.272	0.998	0.045	0.999	0.043	0.999	0.049	0.998	0.044
Belgium	0.511	0.291	0.353	0.275	0.868	0.056	0.707	0.069	0.865	0.055	0.701	0.072
Bolivia	0.896	0.257	0.744	0.247	1.009	0.053	0.858	0.068	0.986	0.052	0.846	0.062
Brazil	0.556	0.189	0.622	0.194	0.729	0.036	0.797	0.034	0.714	0.040	0.786	0.037
Canada	0.342	0.471	0.309	0.497	0.742	0.076	0.716	0.047	0.742	0.076	0.716	0.048
Chile	1.613	0.291	1.450	0.282	0.972	0.070	0.821	0.032	0.947	0.056	0.811	0.031
Colombia	-0.890	0.208	-0.929	0.214	0.811	0.050	0.763	0.064	0.779	0.048	0.747	0.057
Costa Rica	-0.071	0.290	-0.025	0.286	0.751	0.045	0.800	0.036	0.746	0.046	0.797	0.034
Croatia	-1.689	0.347	-1.749	0.358	0.480	0.052	0.360	0.086	0.523	0.040	0.414	0.077
Czech Republic	0.672	0.429	0.580	0.419	0.668	0.070	0.555	0.108	0.675	0.074	0.556	0.108
Denmark	0.487	0.458	0.712	0.434	0.371	0.041	0.607	0.039	0.388	0.042	0.614	0.038
Dominican Republic	-1.367	0.602	-1.205	0.495	0.536	0.274	0.718	0.069	0.514	0.257	0.702	0.072
Ecuador	0.447	0.364	0.957	0.351	0.343	0.056	0.863	0.063	0.344	0.053	0.853	0.059
France	0.760	0.146	0.679	0.138	0.684	0.026	0.602	0.026	0.671	0.024	0.590	0.025
Germany	0.839	0.137	0.895	0.137	0.605	0.022	0.661	0.023	0.597	0.022	0.653	0.022
Greece	0.343	0.586	0.340	0.551	0.797	0.034	0.781	0.058	0.756	0.039	0.768	0.050
Hong Kong	-2.399	0.296	-2.343	0.297	0.588	0.052	0.633	0.071	0.562	0.060	0.627	0.072
Hungary	-0.532	0.238	-0.541	0.220	0.844	0.048	0.793	0.040	0.818	0.054	0.803	0.037
India	0.631	0.478	0.735	0.449	0.645	0.055	0.747	0.051	0.642	0.055	0.751	0.053
Indonesia	0.853	0.188	0.783	0.193	0.698	0.045	0.628	0.036	0.697	0.045	0.627	0.036
Ireland	1.615	0.201	1.600	0.210	0.865	0.088	0.861	0.080	0.885	0.090	0.872	0.080
Israel	-1.804	0.667	-1.866	0.665	0.795	0.073	0.696	0.076	0.788	0.071	0.687	0.075
Italy	1.669	0.215	1.829	0.217	0.589	0.031	0.727	0.032	0.576	0.035	0.722	0.033
Japan	-0.524	0.172	-0.440	0.181	0.461	0.048	0.561	0.020	0.494	0.048	0.578	0.014
Jordan	-2.535	0.323	-2.627	0.308	0.654	0.051	0.495	0.086	0.677	0.044	0.569	0.061
Kazakhstan	0.015	0.462	0.017	0.452	0.585	0.054	0.590	0.037	0.611	0.053	0.606	0.043
Kenya	0.374	0.369	0.404	0.369	0.583	0.066	0.617	0.054	0.584	0.073	0.619	0.070
Latvia	0.391	0.241	0.477	0.258	0.725	0.071	0.802	0.076	0.721	0.070	0.803	0.076
Lebanon	0.174	0.159	0.113	0.168	0.635	0.020	0.571	0.034	0.635	0.020	0.572	0.035
Luxembourg	0.672	0.166	0.619	0.171	0.855	0.029	0.803	0.024	0.855	0.029	0.802	0.024
Malaysia	0.831	0.289	0.810	0.309	0.885	0.067	0.864	0.098	0.879	0.070	0.858	0.099
Mexico	1.249	0.262	1.176	0.322	1.013	0.127	0.933	0.058	1.005	0.123	0.935	0.056

Table 9: **Estimation results for P-R models (pooled OLS continued)**

country	**log(II)**		**log(TI)**		**log(PI)**		**log(PT)**		**log(II)+log(TA)**		**log(PI)+log(TA)**	
	H^r	$\sigma(H^r)$	H^r	$\sigma(H^r)$	H^p	$\sigma(H^p)$	H^p	$\sigma(H^p)$	H^r_s	$\sigma(H^r_s)$	H^r_s	$\sigma(H^r_s)$
Monaco	-0.091	0.375	-0.032	0.362	0.750	0.060	0.799	0.049	0.739	0.067	0.798	0.050
Netherlands	1.219	0.236	1.226	0.228	0.829	0.016	0.846	0.025	0.823	0.015	0.832	0.024
Nigeria	0.377	0.179	0.369	0.191	0.788	0.053	0.755	0.021	0.784	0.054	0.772	0.023
Norway	1.807	0.616	1.885	0.608	0.855	0.064	0.927	0.068	0.855	0.074	0.927	0.076
Pakistan	1.333	0.597	1.213	0.635	0.652	0.129	0.532	0.178	0.639	0.129	0.527	0.180
Panama	0.262	0.216	0.269	0.222	0.628	0.024	0.646	0.027	0.626	0.024	0.635	0.030
Paraguay	-0.584	0.147	-0.527	0.149	0.669	0.056	0.763	0.061	0.698	0.045	0.777	0.059
Peru	-0.107	0.224	-0.309	0.213	0.948	0.074	0.813	0.072	0.972	0.061	0.824	0.064
Philippines	-0.087	0.538	-0.032	0.563	0.608	0.068	0.675	0.072	0.640	0.050	0.682	0.060
Poland	-0.193	0.316	-0.303	0.312	0.936	0.048	0.832	0.040	0.926	0.048	0.809	0.039
Portugal	-0.223	0.420	0.324	0.432	0.621	0.112	1.115	0.116	0.619	0.109	1.111	0.112
Romania	0.478	0.270	0.518	0.256	0.738	0.054	0.765	0.043	0.749	0.052	0.763	0.041
Russian Federation	0.509	0.086	0.567	0.089	0.555	0.054	0.611	0.018	0.556	0.055	0.615	0.018
Slovakia	0.828	0.257	0.761	0.346	0.687	0.055	0.640	0.177	0.663	0.062	0.642	0.166
Slovenia	-0.341	0.766	-0.333	0.746	0.644	0.072	0.613	0.067	0.630	0.084	0.635	0.054
South Africa	0.290	0.420	0.289	0.425	0.609	0.085	0.608	0.042	0.569	0.085	0.591	0.040
Spain	-0.059	0.202	0.085	0.190	0.455	0.038	0.576	0.027	0.457	0.039	0.577	0.028
Sweden	1.689	0.214	1.715	0.221	0.682	0.064	0.687	0.059	0.664	0.063	0.686	0.058
Switzerland	1.024	0.093	1.068	0.074	0.523	0.024	0.572	0.031	0.518	0.023	0.559	0.031
Thailand	-0.364	0.210	-0.405	0.216	0.661	0.085	0.626	0.087	0.642	0.089	0.595	0.094
Turkey	0.050	0.444	0.165	0.440	0.578	0.061	0.681	0.035	0.574	0.064	0.677	0.035
Ukraine	0.522	0.195	0.449	0.187	0.566	0.062	0.493	0.043	0.559	0.068	0.487	0.052
United Arab Emirates	-1.742	0.217	-1.720	0.234	0.546	0.040	0.625	0.046	0.629	0.051	0.648	0.043
United Kingdom	0.041	0.287	0.094	0.293	0.738	0.056	0.793	0.025	0.737	0.058	0.794	0.024
United States	0.210	0.060	0.314	0.061	0.522	0.014	0.631	0.014	0.527	0.014	0.628	0.013
Uruguay	1.155	0.256	1.001	0.236	0.952	0.026	0.807	0.032	0.956	0.028	0.805	0.033
Venezuela	0.773	0.278	0.810	0.280	0.687	0.056	0.719	0.063	0.683	0.060	0.719	0.062
Vietnam	0.538	0.207	0.468	0.205	0.785	0.050	0.710	0.038	0.785	0.051	0.709	0.037
average	0.232	0.308	0.251	0.307	0.701	0.058	0.718	0.054	0.699	0.058	0.718	0.053

Table 10: **Outcomes of ROA test**

This table reports estimates of H^{ROA} and corresponding standard errors, based on the within estimator. Clustered standard errors have been used to deal with general heteroskedasticity and cross-sectional correlation in the model errors (Arellano, 1987). The last column provides the outcomes of a t-test for the null hypothesis $H_0 : H^{ROA} = 0$ versus the alternative $H^{ROA} < 0$. The value 'R' in the last column indicates that the null hypothesis of long-run structural equilibrium is rejected, whereas an 'A' indicates that the null hypothesis is not rejected.

country	H^{ROA}	$\sigma(H^{ROA})$	$H_0 : H^{ROA} = 0$
Argentina	-5.586	1.235	R
Australia	0.586	0.220	A
Austria	-0.907	0.201	R
Bangladesh	0.027	0.322	A
Belgium	-0.430	0.251	R
Bolivia	-5.197	1.031	R
Brazil	-1.480	0.402	R
Canada	-1.849	0.317	R
Chile	-1.314	0.533	R
Colombia	-11.140	2.059	R
Costa Rica	-0.247	0.269	A
Croatia	-0.349	1.004	A
Czech Republic	-1.848	0.925	R
Denmark	-1.586	0.309	R
Dominican Republic	-0.229	1.099	A
Ecuador	-0.836	1.114	A
France	-1.122	0.118	R
Germany	-0.364	0.030	R
Greece	-0.043	0.605	A
Hong Kong	-0.635	0.393	A
Hungary	-2.986	0.753	R
India	-0.425	0.289	A
Indonesia	3.830	1.226	A
Ireland	-0.052	0.124	A
Israel	0.964	1.623	A
Italy	-0.793	0.080	R
Japan	-0.516	0.108	R
Jordan	-1.766	0.515	R
Kazakhstan	1.019	0.855	A
Kenya	-2.964	2.218	A
Latvia	-2.058	1.272	A
Lebanon	-1.925	0.462	R
Luxembourg	-0.306	0.087	R
Malaysia	0.200	0.321	A
Mexico	-4.474	1.124	R
Monaco	-0.700	0.228	R
Netherlands	-0.592	0.228	R
Nigeria	-3.396	0.708	R
Norway	-0.503	0.248	R
Pakistan	-0.948	0.500	R
Panama	-1.176	0.862	A
Paraguay	-3.721	1.009	R
Peru	-1.411	0.652	R
Philippines	-0.744	0.453	A
Poland	-0.553	0.433	A
Portugal	-1.128	0.330	R
Romania	-2.660	1.404	R
Russian Federation	0.060	0.919	A
Slovakia	0.822	1.346	A
Slovenia	-0.090	0.806	A
South Africa	-3.617	1.161	R
Spain	-0.543	0.166	R
Sweden	-0.658	0.190	R
Switzerland	-1.067	0.189	R
Thailand	-1.024	2.448	A
Turkey	-2.010	1.617	A
Ukraine	-2.137	1.126	R
United Arab Emirates	-0.381	0.615	A
United Kingdom	-0.323	0.138	R
United States	-0.284	0.020	R
Uruguay	-5.059	1.077	R
Venezuela	-1.111	0.829	A
Vietnam	-0.058	0.560	A

Table 11: H **statistics in alternative model specifications**

This table reports H^r, H^p and H_s^r for different model specifications. The first part of the table reports separate H statistics for small and large banks. The second part of the table displays separate H statistics for the 1994 – 1999 and 2000 – 2004 periods. Finally, the third part of the table reports 'aggregate' H statistics for various world regions. All H statistics are based on the within estimator. Clustered standard errors have been used to allow for general heteroskedasticity and cross-sectional correlation in the model errors (Arellano, 1987).

	# banks	**# obs**	**ln(II)**		**ln(TI)**		**ln(PI)**		**ln(PT)**		**ln(II)+ln(TA)**		**ln(TI)+ln(TA)**	
			H^r	$\sigma(H^r)$	H^r	$\sigma(H^r)$	H^p	$\sigma(H^p)$	H^p	$\sigma(H^p)$	H_s^r	$\sigma(H_s^r)$	H_s^r	$\sigma(H_s^r)$
Small														
Denmark	54	449	0.113	0.070	0.106	0.093	0.203	0.040	0.196	0.068	0.189	0.038	0.187	0.068
France	223	1443	0.080	0.039	0.134	0.039	0.628	0.019	0.677	0.020	0.603	0.020	0.650	0.021
Germany	1365	8714	0.265	0.028	0.299	0.028	0.594	0.008	0.627	0.009	0.593	0.008	0.622	0.009
Italy	454	2782	0.227	0.037	0.243	0.039	0.527	0.016	0.543	0.019	0.527	0.016	0.550	0.019
Japan	355	1600	0.149	0.038	0.204	0.043	0.427	0.021	0.483	0.028	0.391	0.021	0.456	0.028
Luxembourg	75	553	0.196	0.062	0.151	0.067	0.826	0.022	0.786	0.035	0.818	0.023	0.778	0.037
Spain	101	571	-0.026	0.063	0.069	0.060	0.618	0.029	0.702	0.027	0.654	0.031	0.707	0.030
Switzerland	246	1214	0.054	0.044	-0.003	0.051	0.439	0.027	0.398	0.032	0.417	0.028	0.417	0.033
United States	5026	28022	0.463	0.010	0.495	0.011	0.709	0.005	0.741	0.005	0.724	0.005	0.764	0.005
average			0.169	0.043	0.189	0.048	0.552	0.021	0.572	0.027	0.546	0.021	0.570	0.028
Large														
Denmark	9	91	-0.372	0.240	-0.465	0.248	1.007	0.060	0.921	0.079	1.063	0.065	1.014	0.083
France	36	279	0.951	0.102	0.876	0.093	0.858	0.057	0.784	0.041	0.880	0.054	0.807	0.036
Germany	188	1688	0.619	0.054	0.683	0.054	0.849	0.018	0.912	0.021	0.852	0.019	0.913	0.022
Italy	74	557	0.407	0.096	0.435	0.093	0.850	0.025	0.874	0.028	0.852	0.025	0.862	0.028
Japan	54	315	0.097	0.092	0.146	0.091	0.768	0.056	0.818	0.051	0.826	0.066	0.899	0.059
Luxembourg	12	110	0.178	0.123	0.181	0.135	0.899	0.025	0.902	0.036	0.835	0.027	0.885	0.043
Spain	12	106	0.083	0.103	0.036	0.101	0.833	0.023	0.788	0.022	0.813	0.030	0.755	0.028
Switzerland	34	254	0.132	0.088	0.071	0.088	0.853	0.040	0.813	0.041	0.841	0.046	0.783	0.047
United States	772	5561	0.651	0.035	0.684	0.034	0.715	0.008	0.748	0.009	0.716	0.008	0.747	0.008
average			0.305	0.104	0.294	0.104	0.848	0.035	0.840	0.036	0.853	0.038	0.852	0.039
1994 – 1999														
Denmark	93	491	0.294	0.062	0.157	0.086	0.693	0.037	0.553	0.065	0.639	0.039	0.540	0.069
France	366	1609	0.295	0.036	0.231	0.036	0.789	0.018	0.720	0.019	0.771	0.019	0.694	0.020
Germany	2178	10147	0.411	0.020	0.420	0.020	0.757	0.007	0.764	0.008	0.761	0.007	0.761	0.008
Italy	699	2636	0.425	0.033	0.423	0.035	0.731	0.014	0.728	0.018	0.712	0.014	0.710	0.019
Japan	601	1195	0.051	0.053	0.131	0.056	0.650	0.041	0.731	0.045	0.555	0.047	0.647	0.052
Luxembourg	126	651	0.185	0.049	0.171	0.052	0.896	0.012	0.877	0.024	0.900	0.014	0.878	0.027
Spain	138	558	0.063	0.060	0.126	0.060	0.531	0.032	0.597	0.030	0.533	0.034	0.611	0.032
Switzerland	256	1177	0.089	0.047	0.034	0.049	0.589	0.032	0.533	0.035	0.554	0.035	0.499	0.037
United States	8716	12162	0.570	0.040	0.608	0.040	0.837	0.008	0.875	0.010	0.832	0.008	0.868	0.010
average			0.265	0.044	0.256	0.048	0.719	0.022	0.709	0.028	0.695	0.024	0.690	0.030
2000 – 2004														
Denmark	92	390	0.387	0.061	0.518	0.083	0.472	0.038	0.606	0.052	0.461	0.038	0.617	0.051
France	326	1234	0.244	0.043	0.301	0.041	0.623	0.024	0.672	0.023	0.594	0.024	0.627	0.023
Germany	1868	7113	0.435	0.027	0.427	0.028	0.750	0.009	0.743	0.011	0.744	0.009	0.739	0.011
Italy	748	2920	0.394	0.029	0.439	0.028	0.700	0.015	0.743	0.014	0.704	0.015	0.745	0.015
Japan	528	2002	0.017	0.032	0.065	0.037	0.502	0.019	0.549	0.026	0.419	0.020	0.478	0.027
Luxembourg	109	420	0.261	0.064	0.155	0.075	0.891	0.029	0.796	0.049	0.875	0.031	0.803	0.052
Spain	138	572	0.079	0.068	0.156	0.059	0.614	0.038	0.682	0.035	0.689	0.041	0.658	0.039
Switzerland	355	1248	0.219	0.044	0.111	0.044	0.618	0.029	0.518	0.032	0.647	0.033	0.505	0.036
United States	9286	43742	0.380	0.008	0.412	0.009	0.697	0.004	0.728	0.004	0.713	0.004	0.753	0.004
average			0.268	0.042	0.287	0.045	0.652	0.023	0.671	0.027	0.650	0.024	0.658	0.029
regional level														
North America	9602	56439	0.425	0.009	0.470	0.009	0.689	0.003	0.735	0.003	0.697	0.003	0.747	0.003
South and Central America	646	3114	0.381	0.034	0.349	0.032	0.795	0.019	0.761	0.015	0.821	0.019	0.787	0.015
Western Europe	4849	33947	0.216	0.009	0.237	0.009	0.680	0.003	0.700	0.004	0.676	0.004	0.699	0.004
Eastern Europe	484	2106	0.263	0.041	0.247	0.040	0.669	0.020	0.649	0.018	0.681	0.021	0.655	0.018
Asia	1029	5937	0.324	0.024	0.364	0.023	0.559	0.013	0.598	0.013	0.556	0.013	0.594	0.013
Middle East	155	973	0.148	0.056	0.116	0.056	0.717	0.025	0.682	0.023	0.711	0.027	0.690	0.025
Africa	112	601	0.477	0.077	0.342	0.074	0.818	0.036	0.683	0.027	0.799	0.037	0.668	0.028

Figure 1: **Values of the H statistic**

This figure displays H^r in increasing order for all 63 countries in the sample ('unscaled P-R'), together with the corresponding value of H_s^r ('scaled P-R'). The dashed lines around the point estimates constitute a 95% pointwise confidence interval. The estimates of the H statistic are based on the within estimator.