UNIT ROOTS AND THE DYNAMICS OF MARKET SHARES: AN ANALYSIS USING AN ITALIAN BANKING MICRO-PANEL

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Abstract

The paper proposes the use of panel data unit-root tests to assess market-share instability in order to obtain indications of industry dynamics. The idea is to consider movements in market shares as much more than mere elements of the market structure. In fact, these movements reflect conduct that arises from that market. If shares are mean-reverting, then firm actions have only a temporary effect on shares. On the other hand, if shares are evolving, as signaled by the presence of unit roots, then any gain in shares with respect to the competitors is long term.

Keywords: turbulence, cross-section dependence.

JEL Classification: C23; D40.

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1 Introduction

A first step towards a better understanding of the dynamics of firms within an industry is to examine whether the market shares of the firms are stationary or evolving. If market shares are mean-reverting, then firm actions have only a temporary effect on market shares. If they are evolving, however, as signaled by the presence of unit roots, then any gains (or losses) in market shares with respect to competitors could be long term. In the first case, it is reasonable to infer that the industry is rather stable, or mature, and actors have reached positions that are difficult to overcome. In the second case, however, the possibility for a competitor to become permanently a leader (or to lose the leadership) could be a signal that the industry has experienced the displacement of existing technology by alternative ones and/or the displacement of existing products by new and superior substitutes. Hence, by considering the movements in market shares not as mere elements of the market structure but rather as a reflection of competitors’ conduct that arises from the market (as emphasized by Matraves and Rondi (2007); Asplund and Nocke (2006); Uchida and Cook (2005); Sutton (2007); Caves (1998)), this paper proposes unit-root tests as a way to test empirically the influence of industry characteristics on the degree of turbulence.\(^1\) To the best of my knowledge, this paper is the first applying this methodology to test banking competition.

An important characteristic of market-share models is the consistency requirement that market shares sum to unity. This relationship must be taken into account if one studies all the actors in the market.\(^2\) In addition, the fact that the market shares are bounded between 0 and 1 renders a deterministic trend model implausible. Another possibility to flexibly model market shares is to consider only the main actors in the market.

Using the latter procedure, this paper uses micro panel-data unit-root models to assess market-share instability in the Italian banking industry for a sample of firms comprised of the first five banks in each province. Assessing the competitive conditions of the Italian banking industry is of interest because the industry underwent a remarkable consolidation and deregulation process.

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\(^1\)For a discussion on the importance of turbulence on market structure dynamics see Sutton (1997) and Davies and Geroski (1997)

\(^2\)See for example Franses et al. (2001) who exploit the consistency requirement to apply the Johansen test, relying on a system-based test rather than a single equation test.
since the beginning of the nineties, which implies high degree of turbulence.

Given the well-known low power of conventional unit-root tests when applied to single short time series, panel unit-root tests can be fruitfully employed in the analysis of firms or industries that rely on micro panels, where the time dimension may be of limited length but may also be observed across several units. One of the main advantages of panel unit-root tests is that their asymptotic distribution is standard normal. This contrasts with conventional time-series unit roots, which have non-standard normal asymptotic distributions. However, these tests are not without their limitations. In particular, few tests consider the possibility of cross-sectional correlation and spillovers amongst countries, regions or provinces (Baltagi et al. (2007)). In this regard, Pesaran (2004, 2007) suggests a test for cross-sectional dependence and offers a way of eliminating it by augmenting the usual ADF regression with lagged cross-sectional mean and its first-difference to capture the cross-sectional dependence that arises through a single-factor model. Other important aspects concerning panel unit roots are related to their asymptotic behavior under the two dimensions of the panel and the requirement for a balanced panel.

The results reveal the presence of unit roots in the market shares of the first five Italian banks. The existence of dynamics in the positions of the main actors, as signalled by the unit roots, suggests that the Italian retail banking industry has experienced over time a movement towards a higher level of competition. Specifically, in the spirit of Kim et al. (2003), a dynamic in market shares could be interpreted as an indirect signal of a reduction of switching costs that makes it easier for consumers to move to different banks and, consequently, for banks to acquire new customers. As this analysis shows, the use of panel unit-root tests can offer indications of the dynamics of firms within an industry. As with any other statistical test, there is a risk of incorrect inference, but this could be minimized through proper selection of the test in relation to the main features of the dataset used.

The structure of the paper is as follows. The next section briefly introduces the data and the main features of the industry under investigation. Section 3 then presents the model for micro panels, and section 4 computes panel unit-root tests for the first five banks in every Italian province. This section also provides the Pesaran’s test of cross-section dependence. Taking into account these
results, section 5 computes the unit-root test proposed by Pesaran, which deals with cross-section dependence. The conclusions are presented in section 6.

2 Characteristics and construction of the dataset

A peculiarity of the Italian banking industry is the presence of different territorial dynamics (Guiso et al. (2006, 2004); Colombo and Turati (2004)). In particular, the retail Italian banking industry seems to be comprised of a large number of local markets corresponding to different geographical locations. In each of these submarkets, several branches of different banks compete against each other. The Italian territory is divided into 20 regions and 103 provinces (these are geographical units not unlike US counties). In accordance with the Italian Antitrust Authority, the assumption is that the province is the relevant market.

Given the widespread differences in local economic conditions and their influence on the competition process, this paper focuses on local markets by measuring market shares at the provincial level using data on branches as proxies for the market share of individual (or groups of) banks. Various motivations are behind the choice to compute market shares relying on this variable. First of all, the number of branches (or branch density) is commonly used in the empirical literature on local banking competition (see, for instance, Degryse and Ongena (2005)). Secondly, the number of branches is able to capture the dimension of banking competition that has been more heavily affected by the deregulation process. Since March 1990, the establishment of new branches has been completely liberalized. The number of branches increased steadily, raising to 32337 in 2007, the number of people served by each branch also rose, 47 per 100000 inhabitants in 2004 (compared to the EU mean of 59).\(^3\) In addition, these data are freely available, without any break, for a quite long period of time by the Italian Central Bank (Banca d’Italia).\(^4\)

Hence, the (unbalanced) dataset is composed of 103 Italian provinces. For each province I

\(^3\)Beginning in the 1980s, the Italian banking system experienced a series of reforms aimed at increasing competition in the market through liberalizing the way in which banks organized their branch and an easing of the geographical restrictions on lending. In fact, the opening of new branches had been regulated by the branch distribution plan, issued every four years. The last distribution plan was issued in 1986.

computed the market shares for the first five individual banks (or group of banks) from the year 1993 to 2006. The majority of Italian banks do not belong to any groups.

Since the unit of observation in this paper is the bank (or group of banks) in each province and year, I treat the share of the same banks (or group of banks) operating in different provinces as pertaining to a different bank. In order to consider the dynamics at a (higher) regional level, I performed tests by grouping the different provinces according to macro-regions: North, Centre and South. As Guiso et al. (2006, 2004) showed, while there is a considerable variation in the degree of banking competition across local markets, the North-Centre/South divide is a clear feature of the Italian banking industry.

Tables (1) and (2) report the summary statistics of the market share of the first five banks in the sample. A closer look at these tables seems to reveal a stable pattern over time and over the North-Centre/South divide. These patterns may indicate little, however, since there might be an intensive switching among banks’ positions and a greater variability at the local level. The challenge of the proposed methodology is to ascertain the underlying dynamics of banks at the provincial level.

3 Tests for unit roots: the model

This paper considers micro-panel data models in which the cross-section dimension is much larger than the time-series dimension. Reviews of the literature on dynamic micro panels are provided in Baltagi (2005) and Arellano (2003). For a general survey of the literature about unit-root tests, see Breitung and Pesaran (2008).

Let \( s_{it} \) be the market share of bank \( i \) in period \( t \) in each province. The model could be represented by a dynamic AR(1) panel-data model allowing for heterogeneity in the intercept but not in the autoregressive parameters.
\[ s_{i0} = \delta_0 + \delta_1 \eta_i + v_{i0} \]
\[ s_{it} = \alpha_i s_{i,t-1} + u_{it} \]
\[ u_{it} = (1 - \alpha_i) \eta_i + v_{it} \]

where \( \alpha_1 = \cdots = \alpha_N = \alpha \) for each \( i = 1 \ldots N, t = 2 \ldots T \), and where \( N \) is large and \( T \) is fixed. The series have a unit root (or are integrated of order one) if \( \alpha_i = 1 \) and are stationary if \( \alpha_i < 1 \). A test for the presence of a unit root in the panel is presented by the null hypothesis \( H_0 : \alpha = 1 \) in equation (2).

In case of independence across firms, the error term satisfies

\[ E(\eta_i) = 0, \ E(v_{it}) = 0 \] (2)

for \( i = 1, \ldots, N \) and \( t = 2, \ldots, T \) and

\[ E(v_{it}v_{is}) = 0 \] (3)

for \( i = 1, \ldots, N \) and \( t \neq s \).

In the literature, two types of panel unit-root tests can be distinguished, dependent on the alternative under consideration. The first type of test considers a homogeneous alternative (i.e. \( H_0 = \alpha_1 = \cdots = \alpha_N = \alpha < 1 \)). An example appears in Levin et al. (2002). The idea of this approach is to perform a pooled Dickey-Fuller (DF) test with the residuals. The second type of test allows for heterogeneity of all parameters. Im et al. (2003) criticize the assumption of a common root under the alternative, and require \( |\alpha_i| < 1 \) for a sufficiently large number of units. In this case, it is thus natural to perform \( N \) tests individually and to average over individual DF statistics.

In model (2) there are two sources of persistency. One is the autoregressive mechanism (which is the same for all cross-section units) and the other is the unobserved individual-specific term. The unit-root hypothesis can be considered as an extreme case in which all of the persistency is
caused by the autoregressive mechanism. In this context, the time dimension of the panel dataset is both an issue worthy of a closer look, as well as the specification of the initial value.

This paper proposes three distinct regression-based test procedures: the first is based on a simple OLS regression of market shares on their lagged values; the second test, proposed by Breitung and Meyer (1994), specifies the regression in terms of deviations from initial conditions and is therefore more powerful if the variance of individual effects is high; the third test, proposed by Harris and Tzavalis (1999), also based on the LS estimator of the autoregressive coefficient, corrects for the inconsistency arising from the inclusion of fixed effects. These simple t-tests based on least-squared estimators, which are consistent only under the unit-root null, are shown to have good size properties and at least as high power as tests based on GMM and ML estimators (Bond et al. (2005)). It is known that instrumental variable and GMM procedures provide consistent estimates of dynamic coefficients in cases where pooled least squares are inconsistent (Arellano (2003), Phillips and Sul (2007)). However, these procedures are also known to suffer bias and weak instrumentation problems when the dynamic coefficient $\alpha_i$ is close to unity.

These tests, despite their advantages, are not exempt from critics. In particular, they assume cross-section independence. Hence, Pesaran’s test for cross-section independence will be computed in this paper. The test can in fact be applied to a wide range of panel data models, including panel with short time dimension. As that test evidenced the presence of cross-section dependence, the panel unit-root test allowing for cross-section dependence, which was proposed by Pesaran, will be also computed.

3.1 OLS

As was shown in Madsen (2003); Hall and Mairesse (2002); Bond et al. (2005), the t-test based on the OLS levels estimator performs much better than other estimators (GMM, FD, WG,..) in micro panels (that is, when T is very small in comparison with N). Both simulation and asymptotic analysis have demonstrated that the OLS estimator has the highest power to reject alternatives that are close to the null hypothesis that $\alpha = 1$.

Because the number of periods is small, the properties of the initial condition are also relevant.
Madsen (2003) shows that the asymptotic power of the OLS test under the alternative differs according to the assumptions made about the initial value. In particular, the advantage of using OLS is expected to be high when the initial value is such that the time-series process become covariance stationary, even for value of $\alpha$ close to unity.\footnote{Mean stationarity (constant first moment) requires $\alpha_i < 1$ and $\delta_0 = 0$ and $\delta_1 = 1$. The covariance stationarity (constant first and second moments) also requires homoscedasticity over time of the $v_{it}$ shocks (i.e. $\text{var}(v_{it}) = \sigma^2_{v_i}$) for ($i = 1, \ldots, N$) and that $\text{var}(v_{i0}) = \sigma_{v_i}/(1 - \alpha_i)^2$.} In the other cases, when the initial values are such that the time-series becomes mean stationary and when the variation in the individual-specific terms is high, the highest power can be obtained using a t-test for the least-squares estimator in the transformed model proposed by Breitung and Meyer (1994). As has emerged from the literature, these two tests must be considered jointly.

Under the null hypothesis $H_0 : \alpha = 1$, the OLS estimator of $\alpha$ in model 2 is consistent. The t-test based on OLS estimator is

$$t_{OLS} = \frac{\hat{\alpha}_{OLS} - 1}{\sqrt{\text{Var}(\hat{\alpha}_{OLS})}}$$

where

$$\text{Var}(\hat{\alpha}_{OLS}) = (s_{-1}'s_{-1})^{-1}\left(\sum_{i} s_{i-1}'e_i e_i's_{i-1}\right)(s_{-1}'s_{-1})^{-1}$$

with $e_i = s_i - s_{i,0}\hat{\alpha}_{OLS}$, $s_i = (s_{i,2}, \ldots, s_{i,T})'$, $s_{i,-1} = (s_{i,1}, \ldots, s_{i,T-1})'$, and $s_{-1} = (s_{1,-1}', \ldots, s_{N,-1}')$.

Under the null, $\alpha = 1$, $t_{OLS}$ has an asymptotic standard normal distribution as $N \to \infty$.

Under the alternative, the OLS estimator is biased upwards, all the more so when the variance of $\eta_{it}$ is large relative to the variance of $v_{it}$. The power of this test will therefore depend on the magnitude of $\text{Var}(\eta_{i})/\text{Var}(v_{it})$ (Bond et al. (2005)).

Breitung and Meyer (1994) suggest an alternative estimation approach that involves deducting the first observation $s_{i0}$ for each firm from the right-hand side of equation (2). The estimable model becomes

$$s_{it} - s_{i0} = \alpha(s_{i,t-1} - s_{i,0}) + \epsilon_{it}$$

$$\tilde{s}_t = \tilde{s}_{t-1} + \epsilon_{it} \quad t = 3, \ldots, T$$
where \( \epsilon = v_{it} - (1 - \alpha)(s_{i0} - \eta_i) \). Again, the OLS estimator is consistent when \( \alpha = 1 \), and upward biased under the alternative. Breitung and Meyer, however, showed that the bias is \( \alpha + \frac{1 - \alpha}{2} \). That means that the power of the test, contrary to the previous case, is not affected by the individual-specific term (that is, by the term \( \frac{Var(\eta_i)}{Var(v_{it})} \)).

For long T panels, none of these could be applied, since the asymptotic distribution tends to a DF: so we should combine N DF/ADF tests as in Im et al. (2003).

### 3.2 OLS with fixed effects

Harris and Tzavalis (1999) propose a test of the unit-root hypothesis based on a bias correction of the within-group estimator under the null. Under the assumption that \( v_{it} \) is a series of independently and identically normally distributed random variables having \( E(v_{it}) = 0 \) and \( Var(v_{it} = \sigma_v^2) < \infty \), Harris and Tzavalis (1999) show that

\[
\sqrt{n}(\hat{\rho}_{WG} - 1 - B) \to N(0, C)
\]

where \( \hat{\rho}_{WG} \) is the within-group estimator and \( B \) and \( C \) are given as

\[
B = -15 \left\{ 2(T + 2) \right\}^{-1}
\]

and

\[
C = \left\{ 15(193T^2 - 728T + 1147) \right\} \left\{ 112(T + 2)^3(T - 2) \right\}^{-1}
\]

As this bias correction and variance are valid only under homoscedasticity, it is likely that the test performs poorly under heteroscedasticity (Bond et al. (2005)). Kruiniger and Tzavalis (2002) propose unit-root tests in short panels where error terms are serially correlated and heteroscedastic.

### 3.3 A test for cross-section dependence

Pesaran (2004) and Baltagi et al. (2007) show that there can be considerable size distortions in panels when the hypothesis of cross-section independence is violated and the specification exhibits, for example, spatial error correlation.
When $N$ is small and the time dimension $T$ is sufficiently large, the cross-section correlation can be modeled using seemingly unrelated regression (SURE), and traditional time-series techniques (such the Lagrange Multiplier (LM) of Breusch and Pagan) can also be applied.\(^6\) However, in cases where $N$ is large, standard techniques are not applicable. Another approach, used in the literature of spatial statistics, measures the extent of cross dependence by means of a spatial matrix.

Pesaran (2004) proposes instead a simple diagnostic test that neither requires any \textit{a priori} specification of a connection matrix nor suffers from panel-data model limitations. It is therefore applicable in a variety of contexts, including stationarity dynamic and unit-root heterogeneous panels with short $T$ and large $N$. The test, in all its various formulations, is based on simple averages of pair-wise correlation coefficients of OLS residuals from individual regressions.

\[
CD = \sqrt{\frac{2T}{N(N-1)}} \left( \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{ij} \right) \tag{11}
\]

where

\[
\hat{\rho}_{ij} = \frac{\sum_{t=1}^{T} \hat{v}_{it} \hat{v}_{jt}}{\left( \sum_{t=1}^{T} \hat{v}_{it}^2 \right)^{1/2} \left( \sum_{t=1}^{T} \hat{v}_{jt}^2 \right)^{1/2}} \tag{12}
\]

Unlike the \textit{LM} statistic, the \textit{CD} statistic has exactly mean at zero for fixed value of $T$ and $N$, under a wider range of panel-data models, and it is shown to have a standard normal distribution, assuming that the errors are symmetrically distributed ($v_{it}$ are $i.i.d.(0,1)$). In addition, it can be applied to unbalanced panels. In this last case, equation (13) can be modified by

\[
CD = \sqrt{\frac{2}{N(N-1)}} \left( \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \sqrt{T_{ij}} \hat{\rho}_{ij} \right) \tag{13}
\]

where $T_{ij} = \sum 1_{T_i \cap T_j}$ (the number of common time-series observations between units $i$ and $j$)

\(^6\)For example, Chu et al. (2007) used the panel SURADF tests to investigate Gibrat’s law of proportionate effects for 48 electronic firms in Taiwan. Panel SURADF tests handle cross-sectional dependence across firms and, at the same time, investigate a separate unit-root null hypothesis for each and every individual panel member, identifying how many and which series in the panel are stationary process.
\[
\hat{\rho}_{ij} = \frac{\sum_{t \in T_{ij}} (\hat{v}_{it} - \bar{\hat{v}}_{it})(\hat{v}_{jt} - \bar{\hat{v}}_{jt})}{\left(\frac{T}{\sum_{t=1}^{T} (\hat{v}_{it} - \bar{\hat{v}}_{it})^2}\right)^{1/2} \left(\frac{T}{\sum_{t=1}^{T} (\hat{v}_{jt} - \bar{\hat{v}}_{jt})^2}\right)^{1/2}}
\]

with \(\bar{\hat{v}}_{it} = \sum_{t \in T_{ij}} \hat{u}_{i}/T_{ij}\). Finally, in cases where the cross-section units can be ordered \textit{a priori} (as with spatial observations), the CD test can be generalized thereby also capturing the spatial pattern (Pesaran (2004)).

4 The Italian case

As previously stated, the Italian banking industry is of interest, since it experienced a deregulation process during the nineties that led, among other things, to liberalized entry and easier procedures to open new branches. Therefore, it is reasonable to expect a movement towards a higher level of competition, at both the national and the macro-regional level.

Let’s start with the simple t-tests based on OLS regressions.

Tables (3) and (4) report pooled OLS and Breitung and Meyer’ estimators respectively. The null hypothesis \(H_0 : \alpha = 1\) cannot always be rejected, and the series seem to present unit roots, especially in the market share related to the provinces in the Centre/South of Italy. These results disappear when a controlled is made for common shocks (captured by year dummies). If the hypothesis of the unit root cannot be rejected, then the positions of the main banks in the market could be displaced permanently by other actors, and there is evidence of a shift towards a higher degree of competition.

Finally, table (5) presents results for OLS regressions including fixed effects where the values of the t-statistic have been computed, correcting the bias, as suggested by Harris and Tzavalis (1999). These regressions clearly indicated the presence of the unit root at each level of aggregation.

4.1 Cross section dependence in dynamics panels

The previous section treated disturbances, as it is typically assumed in panel data models, as cross-sectionally independent. To ascertain whether the panel at hand is characterized by cross-
section dependence, I applied the CD test. Two specifications are used: one with residuals of homogeneous regression and one with residuals from \( N \) individual regressions from model (2). The tests in both cases draw also on the residuals of the specification with/without the intercept, and the observations are grouped again according to macro-regional classification (North, Centre and South).

The correlations were computed over the common set of observations for \( i \) and \( j \). As has already been noted, the OLS estimates of the constant, \( (1 - \alpha_i)\eta_i \), and the slope \( \alpha_i \) for the individual series are biased when \( T \) is small, and that bias could be substantial for values of \( \alpha \) near unity. The CD test advanced by Pesaran (2004), however, is valid for all values of \( \alpha \) in model 2, including unity. The main reason lies in the fact that despite the sample bias of the parameter estimates, the OLS have exactly mean zero even for a fixed \( T \), as long as the errors are symmetrically distributed.

The main limitation of Pesaran’s test lies in its pairwise construction, since the pairwise correlation may compensate each others, summing to zero.

While allowing for different values of \( \alpha_i \) and for cross-section correlation, we still assume that in model (2) \( v_{it} \) are serially uncorrelated with zero mean. For computational reasons, I restrict the analysis to the balanced panel comprised of 20% of the observations. Table (6) reports the results for the cross-section dependence test developed by Pesaran. In both cases, allowing or not allowing for heterogeneity, there is evidence of cross-section dependence in all of the macro-regions considered.

5 Panel unit root tests for cross-sectionally dependent panels

Overall, the outcome of the preceding tests clearly indicates the presence of cross-section dependence amongst units.

7 For this test I built a STATA command csdar.ado, relying on xtcslado as developed by De Hoyos and Sarafidis (2006).

8 Results in table (6) refer to estimation without intercept. Those with intercept are analogous and are not reported.
Pesaran (2007) builds on the assumption that the error terms \( v_{it} \) of equation (2) follow a single common-factor structure

\[ v_{it} = \lambda_i f_t + \epsilon_{it} \]  

(15)

The common factor is assumed to be stationary and to impact the cross-section by a fraction determined by the individual-specific factor loading \( \lambda_i \). Because of the common factor, cross-section dependence arises and can be approximated by the cross-section mean \( \bar{s}_t = \frac{1}{N} \sum_{i=1}^{N} s_{it} \).

As usual, the \( \epsilon_{it} \) are assumed to be i.i.d. across \( i \) and \( t \) with zero mean and variance \( \sigma_i^2 \), and \( E(\epsilon_{it})^4 < \infty \). Furthermore, \( \epsilon_{it}, f_t, \) and \( \lambda_i \) are mutually independently distributed for all \( i \).

Pesaran proposes the following augmented Dickey-Fuller regression:

\[ \Delta s_{it} = c_i + \rho_i s_{i,t-1} + \beta_i \bar{s}_{i,t-1} + \sum_{j=1}^{p} \gamma_{ij} \Delta s_{i,t-j} + \sum_{j=0}^{p} \gamma_{ij} \Delta \bar{s}_{i,t-j} + \epsilon_{it} \]  

(16)

where, as is usual in the univariate case, lagged first-differences on both \( s_i \) and \( \bar{s}_i \) are added so that account can also be taken of correlation in the error term. Either individually or in a combined fashion, the \( t \)-value of \( \rho_i \) can be used to test the presence of unit roots. In the first case, the statistic is called cross-sectionally augmented Dickey-Fuller (\( CADF_i \)), while in the second case the statistic is constructed as

\[ CIPS = \frac{1}{N} \sum_{i}^{N} CADF_i \]  

(17)

It is called CIPS, since it resembles the IPS statistic (Im et al. (2003)). In the case where \( T \) is fixed (to ensure that the \( CADF \) statistics do not depend on the nuisance parameters), Pesaran (2007) suggests applying the test to the deviations of the variable from initial cross-section mean.

Table (7) shows Pesaran’s test for the unit root computed for the Italian banking dataset. Due to the presence of the lagged level of the cross-sectional average, the limiting distribution of both the \( CADF \) statistics and the CIPS statistic do not follow a standard Dickey-Fuller distribution. However, Pesaran provides critical values based on simulations for the \( CADF \) and CIPS distributions for three cases (no intercept and no trend, intercept only, intercept and trend). As the results from this test suggests, cross-section dependence does indeed matter. When controlling for it, the
series exhibit the presence of unit roots. That means that there is a dynamic in the positions of the main competitors in the market, and the possibility exists that the main actors become displaced by competitors.

What remains to be addressed now is just which factors drive the results. It seems likely that several factors play a role. Merger and acquisition activity, the presence of scale economies, and the role of regulation all appear to have had a role. As suggested by Kim et al. (2003), movements in market shares can also be used to infer (and measure) switching costs. By making it costly for consumers to change banks, and consequently more difficult for a new bank to acquire new clients, switching costs tend to limit entry as well as shuffle in market shares. To this end, further investigation is required. However, the simple analysis in this study allows us already to infer that the Italian banking industry has experienced movement towards higher levels of competition. These results match those of Guiso et al. (2006) on local-level competition. By studying the long-term effect of the regulatory restriction, they found that after the deregulation process came a period of catching up of the areas (especially the provinces in the South) in which the banking market was less competitive during the regulation period. The presence of the unit root in the market-share data of this macro-region is thus consistent with their analysis.

6 Conclusions

In order to gain a better understanding of the competitive conditions in an industry, this paper proposed the use of unit-root tests in the setting of micro panel data sets to assess market share instability. Using an Italian banking micro panel, this study empirically tests the presence of unit roots in the series of market shares of the first five banks in each Italian province. The presence of unit roots in the market-share data could be interpreted, in fact, as a signal of an industry that has experienced the displacement of the leading bank by its competitors. On the other hand, if shares turn out to be mean reverting, then would be reasonable to conclude that the industry is rather stable and that competitors had reached positions that were difficult to overcome.

T-tests based on least-squares estimators, which are consistent only under the unit root null, have been proposed. Those tests have proven to have good size properties and are at least as high
powered as tests based on GMM and ML estimators. According to those tests, the hypothesis of unit-root tests cannot always be rejected for all of the subgroups considered in the analysis.

These tests, however, do not consider the possibility of cross-section correlation amongst units. To ascertain whether the panel at hand is characterized by cross-section dependence, I applied Pesaran’s cross-section dependence test. The Pesaran statistics clearly indicated the presence of cross-section dependence. Consequently, I applied the ADF regression proposed by Pesaran. In that case, the results strongly confirmed the presence of unit root tests.

The kind of exercises performed in this article were able to offer only indications of the dynamics of market shares in an industry. To discover which particular factors drive the results would, of course, require additional analysis. Nevertheless, as this simple application to the Italian banking case shows, panel-unit root tests are useful and versatile tools that can be used in combination with an institutional knowledge of a given industry to offer interesting insights on the competitive process of that industry.
References


Table 1: Market-share summary statistics of the first 5 banks over 103 provinces

<table>
<thead>
<tr>
<th>Year</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min.</th>
<th>Max.</th>
</tr>
</thead>
<tbody>
<tr>
<td>1993</td>
<td>0.136</td>
<td>0.11</td>
<td>0.017</td>
<td>0.707</td>
</tr>
<tr>
<td>1994</td>
<td>0.136</td>
<td>0.11</td>
<td>0.016</td>
<td>0.683</td>
</tr>
<tr>
<td>1995</td>
<td>0.138</td>
<td>0.107</td>
<td>0.016</td>
<td>0.672</td>
</tr>
<tr>
<td>1996</td>
<td>0.137</td>
<td>0.105</td>
<td>0.016</td>
<td>0.646</td>
</tr>
<tr>
<td>1997</td>
<td>0.138</td>
<td>0.106</td>
<td>0.023</td>
<td>0.643</td>
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<td>1998</td>
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<td>0.112</td>
<td>0.023</td>
<td>0.849</td>
</tr>
<tr>
<td>1999</td>
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<td>2000</td>
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<td>0.836</td>
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<tr>
<td>2001</td>
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<td>0.102</td>
<td>0.024</td>
<td>0.829</td>
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<tr>
<td>2002</td>
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<td>0.024</td>
<td>0.807</td>
</tr>
<tr>
<td>2003</td>
<td>0.137</td>
<td>0.099</td>
<td>0.024</td>
<td>0.808</td>
</tr>
<tr>
<td>2004</td>
<td>0.135</td>
<td>0.098</td>
<td>0.024</td>
<td>0.808</td>
</tr>
<tr>
<td>2005</td>
<td>0.133</td>
<td>0.095</td>
<td>0.024</td>
<td>0.807</td>
</tr>
<tr>
<td>2006</td>
<td>0.131</td>
<td>0.093</td>
<td>0.025</td>
<td>0.802</td>
</tr>
<tr>
<td>N</td>
<td>515</td>
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<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 2: Market-share summary statistics of the first 5 banks over 103 provinces

<table>
<thead>
<tr>
<th>Region</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min.</th>
<th>Max.</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>NATIONAL</td>
<td>0.138</td>
<td>0.104</td>
<td>0.016</td>
<td>0.849</td>
<td>7210</td>
</tr>
<tr>
<td>NORTH</td>
<td>0.135</td>
<td>0.092</td>
<td>0.016</td>
<td>0.525</td>
<td>2590</td>
</tr>
<tr>
<td>CENTRE</td>
<td>0.14</td>
<td>0.102</td>
<td>0.026</td>
<td>0.548</td>
<td>2100</td>
</tr>
<tr>
<td>SOUTH</td>
<td>0.138</td>
<td>0.117</td>
<td>0.024</td>
<td>0.849</td>
<td>2520</td>
</tr>
</tbody>
</table>

Table 3: OLS: Dependent variable: Firm shares

<table>
<thead>
<tr>
<th>Variable</th>
<th>NATIONAL</th>
<th>NORTH</th>
<th>CENTRE</th>
<th>SOUTH</th>
</tr>
</thead>
<tbody>
<tr>
<td>t*</td>
<td>2.91</td>
<td>3.17</td>
<td>0.65</td>
<td>1.06</td>
</tr>
<tr>
<td>p-value</td>
<td>0.004</td>
<td>0.002</td>
<td>0.517</td>
<td>0.290</td>
</tr>
</tbody>
</table>

With time dummies

| t*       | 4.8     | 6.93  | 6.2    | 4.8   |
| p-value  | 0.000   | 0.000 | 0.000  | 0.000 |

N 5758 2086 1695 1977

*Note: the t-statistic for $H_0: \beta = 1$ against $H_1: \beta < 1$

Results relying on constrained estimations - imposing restrictions on the constant being equal or greater than zero - are substantially identical.

Table 4: Breitung and Meyer 1994: Dependent variable: Firm shares

<table>
<thead>
<tr>
<th>Variable</th>
<th>NATIONAL</th>
<th>NORTH</th>
<th>CENTRE</th>
<th>SOUTH</th>
</tr>
</thead>
<tbody>
<tr>
<td>t*</td>
<td>3.19</td>
<td>2.5</td>
<td>0.31</td>
<td>2.9</td>
</tr>
<tr>
<td>p-value</td>
<td>0.001</td>
<td>0.012</td>
<td>0.750</td>
<td>0.004</td>
</tr>
</tbody>
</table>

N 5758 2086 1695 1977

*Note: the t-statistic for $H_0: \beta = 1$ against $H_1: \beta < 1$.

Table 5: Harris and Tzavalis 1999: Dependent variable: Firm shares

<table>
<thead>
<tr>
<th>Variable</th>
<th>NATIONAL</th>
<th>NORTH</th>
<th>CENTRE</th>
<th>SOUTH</th>
</tr>
</thead>
<tbody>
<tr>
<td>t*</td>
<td>-0.09</td>
<td>0.16</td>
<td>0.05</td>
<td>-0.32</td>
</tr>
<tr>
<td>p-value</td>
<td>0.103</td>
<td>0.106</td>
<td>0.101</td>
<td>0.125</td>
</tr>
</tbody>
</table>

N 5758 2086 1695 1977

*Note: the t-statistic for $H_0: \beta = 1$ against $H_1: \beta < 1$. 
Table 6: Pesaran’s Test of Cross Section Independence

<table>
<thead>
<tr>
<th></th>
<th>NATIONAL</th>
<th>NORTH</th>
<th>CENTRE</th>
<th>SOUTH</th>
</tr>
</thead>
<tbody>
<tr>
<td>Residuals from a regression*</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CD Statistic</td>
<td>6.875</td>
<td>50.370</td>
<td>44.920</td>
<td>52.694</td>
</tr>
<tr>
<td>P-value</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>Residuals from N regression*</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CD Statistic</td>
<td>5.106</td>
<td>50.228</td>
<td>44.334</td>
<td>52.864</td>
</tr>
<tr>
<td>P-value</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
</tbody>
</table>

* without intercept

Table 7: Pesaran’s Test for Unit Root

<table>
<thead>
<tr>
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<th>NATIONAL</th>
<th>NORTH</th>
<th>CENTRE</th>
<th>SOUTH</th>
</tr>
</thead>
<tbody>
<tr>
<td>CADF regression 0 lag</td>
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</tr>
<tr>
<td>t</td>
<td>-1.563</td>
<td>-2.020</td>
<td>-2.067</td>
<td>-2.086</td>
</tr>
<tr>
<td>z[t-bar]</td>
<td>1.178</td>
<td>-1.309</td>
<td>-2.067</td>
<td>-2.086</td>
</tr>
<tr>
<td>P-value</td>
<td>0.881</td>
<td>0.095</td>
<td>0.023</td>
<td>0.084</td>
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<tr>
<td>CADF regression 1 lag</td>
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<td></td>
</tr>
<tr>
<td>t</td>
<td>-1.333</td>
<td>-2.708</td>
<td>-1.590</td>
<td>-1.262</td>
</tr>
<tr>
<td>z[t-bar]</td>
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<td>-1.560</td>
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<td>1.644</td>
</tr>
<tr>
<td>P-value</td>
<td>0.999</td>
<td>0.059</td>
<td>0.772</td>
<td>0.950</td>
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</tbody>
</table>