Business Failures, Macroeconomic Risk and the Effect of Recessions on Long-Run Growth: a Panel Cointegration Approach*

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Abstract

This paper uses panel data on Italian regions to test two competing theories of long-run productivity dynamics: the opportunity-cost model, according to which productivity-enhancing activities have a comparative advantage during recessions; and the risk-aversion model, which predicts a negative relationship between transitory disturbances and productivity growth. Panel ECM estimates suggest that macroeconomic risk factors impinge on business failures on the same direction both in the short and in the long-run, and that the adjustment to the steady-state relationship is quite slow. Thus, our findings lend support to the risk-aversion theory of productivity growth and indicate that bankruptcy risks play a significant role in the propagation of macroeconomic shocks.

JEL classification: G33, E30, C23

Keywords: Bankruptcy; Macroeconomic Instability; Panel Cointegration; Cross-Sectional Dependence

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1 Introduction

In addition to idiosyncratic factors, the likelihood of firms to survive or to fail in a competitive environment is largely governed by macroeconomic risks, with estimates of their impact on the variation of business activities ranging from 25% (Sharpe, 1981) to 75% (Schankerman, 2002). In this paper we use data on 20 administrative regions over the period 1985-2002 to empirically assess the nature and properties of the nexus between business failures and macroeconomic shocks in Italy. In particular, we employ panel cointegration techniques to disentangle the short and long run co-movements between sources of systematic (i.e., non-diversifiable) risks for business units and corporate failure rates. This allows us to directly test two competing theories of the interaction between the business cycle and productivity growth.

A large body of literature has highlighted that adverse macroeconomic conditions significantly affect companies' profitability and gearing, forcing financially fragile firms to fail (Ballantine *et al.*, 1993; Machin and Van-Reenen, 1993; Geroski *et al.*, 1997). Therefore, in the short-run bankruptcies are unambiguously countercyclical, as recessions create financial distress by narrowing the margin between cash flow and debt service. From a theoretical viewpoint, however, the systemic long-run outcome following from temporary aggregate shocks causing a bunch of concurrent bankruptcies is undetermined.

On the one hand, the bankruptcy of a company can be good news for survivors due to reduced competition (Iqbal, 2002). Moreover, the *opportunity cost* (OC) theory of productivity growth suggests that transitory aggregate disturbances may have long-run positive effects on economic growth, as activities aimed at improving productivity have a comparative advantage during recessions (Caballero and Hammour, 1994; Aghion and Saint-Paul, 1998). If we interpret the number of business liquidations as a manifest expression of economy-wide efforts to perform resource reallocation, the OC theory has immediate testable implications as regards the relationship between business failure rates and economic activity.

On the other hand, Bernanke (1981) suggests that the economy-wide level of bankruptcy risk can play a structural role in the propagation of recessions. Since bankruptcies are costly, the onset of a recession forces firms to retain sufficient liquidity to meet their fixed financial obligations. This reduces the demand for durable (i.e., illiquid) assets, which leads to further income reduction. New durable assets, in turn, are the most common way to introduce technological progress into firms (Greenwood *et al.*, 1997). As a result, during a downturn risk-averse firms will postpone productivity-enhancing capital expenditures, thus negatively affecting their future growth opportunities. Such a scenario could be made even worst under rather general conditions, as trade credit and commercial inter-linkages might contribute to spread failures over large sectors of the economy due to contagion effects occurring along supplier-customer relationships (Greenwald and Stiglitz, 2003). We will refer to this story as the *risk aversion* (RA) theory of productivity growth.

The two theoretical accounts share one common prediction for the short-run, but they imply two competing predictions on the long-run relationships emerging from the transmission of aggregate shocks *via* the bankruptcy mechanism. In fact, both theories imply that in the short-run causality should run from shocks to macroeconomic risk factors towards business failures. Moving to the long-run, however, the OC theory predicts that the short-run impact of adverse disturbances is reversed, as prices fully adjust. Conversely, the RA theory states that the relationship between business failures and aggregate activity is confirmed if not amplified as the economy moves towards its steady-state.

Moving from a simple theoretical framework highlighting some key relationships between the business bankruptcy rate and macroeconomic conditions, the empirical analysis consists of three steps. First, panel unit root tests are used to assess the presence of stochastic non-stationarity in a set of variables comprising regional business failure rates, value added, vertical interest rate spreads, a measure of surprise inflation, real wages and new business formation rates. Second, the existence of a cointegration relationship between the rate of business failure and other integrated aggregate variables is investigated. The long-run relationship in terms of a cointegration vector is determined recurring to several alternative estimators. Third, the results from the previous step are used in estimating a panel error-correction model. This last step allows us to distinguish between short-run and long-run influences, and to pursue a comparative approach.

We present three main results. First, we find strong evidence for a cointegration relationship among the business failure rate, trend output (with negative sign), the vertical interest spread and a measure of surprise inflation (both with positive sign). Weaker evidence emerges as we introduce into the cointegration equation the rate of new business formation and the real wage. Our findings suggest that the bankruptcy rate moves closely together over time with clearly identifiable macroeconomic variables. The identification of such a long-run proportional relationship has relevant implications for academics - as bankruptcies cannot be easily accommodated by complete-markets general equilibrium models (see e.g. Kehoe and Levine, 2001) -, as well as for practitioners interested in the determinants of credit risk, and regulators involved in systemic risk management. Second, we find evidence of causality running from real macroeconomic variables to bankruptcies, but not the other way round. Furthermore, short-run impacts of aggregate shocks on the bankruptcy rate display the same sign as the long-run ones. Combining these two findings, we conclude that business failures are likely to respond to impulses from macroeconomic risk factors, as predicted by both theories, and that the bankruptcy transmission mechanism in Italy during the 1985-2002 period has been consistent with the long run predictions of the RA theory of productivity growth. Third, if we postulate that money is long-run neutral - a reasonable assumption indeed, according to the literature (see e.g. Bullard, 1999) - the cointegration relationship found in the data can be immediately interpreted as a test of monetary superneutrality (Bullard and Keating, 1995). In particular our findings suggest that money is not superneutral, as permanent inflation shocks are associated - in addition to corporate failures - with permanent movements in trend output and real interest rates.

The remainder of the paper is laid out as follows: Section 2 sketches a theoretical framework that constitutes the backbone for our empirical analysis, and briefly reviews the main findings of previous studies in this area; Section 3 describes the data employed in the study; Section 4 reviews the econometric methodology; results are presented in Section 5; Section 6 concludes.

2 Theoretical Framework and Empirical Literature

To motivate our empirical specification, we put forward a simple reduced-form model which builds on the analytical frameworks developed by Wadhwani (1986) and Greenwald and Stiglitz (1993). The key idea is that firms' financial structure matters for their production decisions and, due to uninsurable idiosyncratic random disturbances, for their probability of bankruptcy.

Let A_{jt} denote the net worth of firm j at time period t. Nominal profits Π_{jt} are given by:

$$\Pi_{jt} = R_{jt} - W_{jt} - i_t K_{jt}, \tag{1}$$

where R_{jt} is the nominal revenue, W_{jt} is the wage bill, while $i_t K_{jt}$ represents nominal income payments due to the owners of the capital stock. Note that this assumes that the balance sheet identity $A_{jt} + B_{jt} = K_{jt}$ holds true, where B_{jt} are total liabilities, and that the return here proxied by the nominal interest rate is identical for either internal and external funds.

The j^{th} firm is assumed to go bankrupt whenever it has no positive real net worth (Platt, 1985). Using lower case letters to denote real variables, the bankruptcy condition reads as:

$$a_{jt+1} = a_{jt} + \pi_{jt} < 0. \tag{2}$$

which, after taking into account the profit function in real terms obtained from (1) through deflation, becomes:

$$a_{jt} + r_{jt} - w_{jt} - i_t k_{jt} < 0. \tag{3}$$

In words, bankruptcy occurs when real losses are so large that they wipe out all the company's net worth accumulated up to that point.

Real revenues are modeled as a function of a number of determinants, including: real aggregate economic activity, expressed as deviations from a long-run trend (y); inflation, both actual ($\dot{p}$) and expected ($\dot{p}^e$); a random idiosyncratic shock (u_{jt}) with cumulative distribution function $G(\cdot)$, aimed at capturing all other unsystematic factors affecting r_{jt}, like the effectiveness of management or shocks to productivity. If, for the sake of simplicity, we assume a linear relationship:

$$r_{jt} = \phi_1 y_t - \phi_2(\dot{p}^e - \dot{p}) + u_{jt}, \tag{4}$$

combining (3) and (4) it follows that bankruptcy occurs if the random term u_{jt} is lower than a critical threshold given by:

$$\overline{u}_{jt} = w_{jt} - i_t(a_{jt} + b_{jt}) - a_{jt} - \phi_1 y_t + \phi_2(\dot{p}^e - \dot{p}). \tag{5}$$

Thus, the probability of bankruptcy of firm j can be expressed as:

$$BP_{jt} = G\left(w_{jt}, i_t, b_{jt}, a_{jt}, y_t, (\dot{p}^e - \dot{p})\right). \tag{6}$$

In other terms, the probability to go bankrupt borne by firm j is an increasing function of interest payments (both because of a higher nominal interest rate and of a higher stock of real debt), of the wage bill and of errors in predicting inflation; and it is decreasing in the level of real equity and in aggregate economic activity. As we aggregate across all firms, the total bankruptcy rate across the economy can be expressed by:

$$BR_t = H\left(w_t, i_t, b_t, a_t, y_t, (\dot{p}^e - \dot{p})\right), \tag{7}$$

where we assume that the expected signs in $H(\cdot)$ are the same as in $G(\cdot)$.

BR_t represents the aggregate probability of bankruptcy. It depends on four typical macroeconomic variables - the real wage rate, the real interest rate, real output, and surprise inflation - and two typical balance-sheet variables, that is real liabilities and real net worth. It must be stressed, however, that in the latter case it is the distribution of the variables that really matters.

Several studies have employed econometric specifications inspired to equation (7). Altman (1983) sets the stage for subsequent empirical studies on the macroeconomic determinants of corporate failures, exploiting quarterly data for the U.S. over the 1951-1978 period. He makes use of a first-differenced distributed-lag model to show that business failures are negatively related to aggregate activity (measured by the real GNP), money market conditions (M2) and investors' expectations (proxied by the S&P index). New business formation, in turn, seems to lead the failure rate. The latter result follows from a well-known fact in industrial demography, namely that young firms are more likely to fail than older ones. Platt and Platt (1994) extend the analysis for the U.S., by means of a cross-sectionally correlated autoregressive model supplied with annual data over 1969-1982 for 48 states plus the District of Columbia. They give evidence of a negative relationship between business failures and economic activity (employment and corporate profits), while costs (real wage) and the business formation rate enter with a positive sign. Furthermore, Platt and Platt identify four subgroups of U.S. continental states with homogeneous experiences. U.K. is the country for which research on how macroeconomic determinants affect corporate failures has been more extensive. Bhattacharjee et al. (2005) provide a noteworthy contribution in the strand of literature aimed at assessing the impact of non-diversifiable risk on the rate of failure. The authors observe that firms can disappear through the mutually precluding events of failure and acquisition and, by employing a competing-risk hazard model, identify a number of macroeconomic factors affecting the probability of exit of UK firms over the business cycle. A further list of papers with a focus on short-run dynamic relationships includes Wadhwani (1986), Hudson (1986), Davis (1992), Young (1995) and Cuthbertson and Hudson (1996). They all employ time-series techniques to find that aggregate economic activity, real costs, monetary and credit conditions, and the birth rate of firms contribute to explain the business failure rate with the expected sign. Starting from these premises, Vlieghe (2001) and Liu (2004) explicitly address the issue of disentangling short-run and long-run responses of corporate failures relating with respect to macroeconomic variables, by means of time-series cointegration and error correction models. A long-run relationship emerges between business rate of failure, economic activity, corporate lending and real interest rate. The case of Israel has been addressed by Sharabany (2004). He argues that, besides other well known variables, unexpected inflation is an important determinant of corporate failures. He also shows that macroeconomic variables affect the financial distress of small and large companies differently. Finally, Fabling and Grimes (2005) employ regional data for New Zealand to assess the scope of regional variation in insolvency by means of a SUR model. Furthermore, they stress the importance of property prices - a variable considered also in Vlieghe (2001) - as personal houses are a common form of collateral when raising debt finance.

The analysis contained in what follows adds to the previous literature in three ways. First, as discussed e.g. in Claessen and Klapper (2002), at an international level insolvency regimes are largely affected by country-specific factors, like the legal and regulatory framework, the judicial system and formal bankruptcy procedures. Given that the literature has so far focussed only on countries with an *Anglo-Saxon* legal framework (La Porta *et al.*, 1998), it seems interesting to provide additional evidence on the relationship between business failures and macroeconomic risk factors for a country - like Italy - with a civil law origin. Second, we exploit results from the young but burgeoning literature on non-stationary panel analysis with cross-sectional dependence, in order to conduct a rigorous decomposition between short-run and long-run relationships. The low power of pure time series-based tests for unit root and cointegration in small sample is well-known. As a matter of fact, the power of traditional unit root tests is mainly affected by the span of the data and not on the frequency of the observations. This problem could seriously affect the cointegration analysis put forth in previous studies. Panel data circumvent the low power problem of standard unit root tests by increasing the number of observations. Finally, we use our empirical results to assess the merits of alternative theories addressing the relationships between recessions, bankruptcies and long-run aggregate activity.

3 Data Description

We employ annual data for 20 Italian regions over the period 1985-2002. We build from original sources several of the variables used in our final specification, as no available panel dataset had the characteristics necessary to pursue our objective. The rate of company liquidations (FR) is computed as the ratio between the number of compulsory and voluntary liquidations registered by local courts (Source: Ministry of Justice) and the total number of operating firms registered in each region (Source: Movimprese). Following Bernanke and Gertler (1996), the variable selected to capture the effect determined by credit availability is the vertical spread between the average regional interest rate applied to lending activities and the one applied to deposits and current accounts (Source: Bank of Italy) ($Spread$). Aggregate activity is proxied by regional real GDP series (Source: Istat). The "inflation surprise" variable ($Price$) has been computed as the difference between the expected regional inflation and the realized PPI inflation (Source: ISTAT). Series on expected inflation are not available on a regional basis. In order to overcome the lack of data we follow a simple methodology, based on the Fisher parity equation for the ex-ante nominal interest rate:[1]

$$i = r^* + E(\pi),$$

where i is the nominal interest rate, r^* is the equilibrium real interest rate at the moment in which a debt contract is signed, while $E(\pi)$ is the one year-ahead inflation expectation. Obviously, the ex-post real interest rate is given by

$$r = i - \pi,$$

from which we get:

$$E(\pi) - \pi = r - r^*,$$

i.e., the spread between expected and actual inflation is given by the real interest rate spread. It is evident that we can expect that a positive spread (over estimated inflation) implies a cost shock for leveraged firms. We determine r^* as the time average of regional GDP rates of growth. In order to take into appropriate account the publicly announced - hence, predictable - disinflation pursued by the monetary authority over the period considered, we detrend this variable through a of fixed effects panel regression on a common trend. Real wage (RW) is computed by taking the ratio between regional (hourly) nominal wage (Source: OECD) and the relative CPI. Nominal wage data are only available in aggregate (national) terms: regional variables are built by taking into consideration the dispersion of per-capita labour income within each region (Source: ISTAT). Finally, in line with the previous literature, we use an ancillary variable, aimed at capturing an industrial demography effect - i.e., the rate of new business formation (BR) - calculated as the ratio between new registrations and the total number of registrations (Source: Movimprese).

[1] We have alternatively constructed inflation expectations at the regional level by fitting an AR model for regional inflation. This strategy has a major shortcoming. As the period under scrutiny is characterized by a substantial and expected disinflation, using backward looking predictors leads to a systematic over-estimation of the actual rate of inflation.

4 Econometric Setting

As discussed above, the distinction between the short-run and long-run empirical association of business failures to macroeconomic risk factors has important implications for theoretical models of business cycles and productivity growth. While the OC theory predicts asymmetric short-run and long-run relations between restructuring activities and productivity growth, the RA theory suggests that the long-run effect has the same sign, and a possibly higher magnitude (in absolute terms) than the short-run one.

From an econometric viewpoint, the analysis follows three familiar steps: (i) firstly, we need to investigate the stochastic properties of the variables employed in the analysis by means of panel unit root tests; (ii) the second step consists of testing for cointegration among a restricted set of variables, to assess for the presence of a long-run relationship; (iii) thirdly, we use the residuals from the cointegrating regression as an error correction term within a panel VECM framework. A short description of the methodologies we implement follows. Breitung and Pesaran (2005) provide a useful overwiex of the available tools to test for unit roots and conitegration in panels.

4.1 Panel Unit Root Tests

To test for the presence of stochastic trends in our dataset, we employ a battery of panel unit root tests designed to explicitly address the assumption of cross-sectional dependence.[2] Panel unit root tests are expected to be much more powerful than tests for individual time series, as they exploit bi-dimensional information from time series as well as from cross-sectional data. The reason for using several panel tests is to check for the robustness of our results as the testing strategy varies. In all cases, the null hypothesis is that the variable being analyzed has a unit root.

The first two tests implement a factor structure.[3] We employ the testing strategy developed by Bai and Ng (2004) (BNG), and the statistics based on an error component model proposed by Choi (2006). In both cases, the intuition consists in splitting the data into two unobserved components: the first component is assumed to be strongly cross-sectionally correlated, while the second one is largely unit specific. The testing procedure is then articulated in two main steps: in the first step, data are de-factored, while in the second one panel unit root test statistics based on de-factored data and/or common factors are computed. The third panel unit root test is based on the one-factor model with heterogeneous loading factors for residuals proposed by Pesaran (2005), whose key idea is to augment standard ADF regressions with the cross section average of lagged levels and first-differences of the individual series. The fourth test is proposed by Chang (2002), who models cross-sectional dependencies by imposing few or none restrictions on the residuals' covariance matrix. As in this case standard statistics come from complicated combinations of nuisance parameters defining correlations among units, Chang resorts to instrumental variable estimators. Finally, we use the robust standard-error version of the OLS t-statistic suggested by Breitung and Das (2005). The main advantage of this test is that it displays a good power when both N and T are small, as in our case.

[2] Cross-sectional dependence often arises in presence of unobserved common factors, omitted, although detected, common factors, spatial spill over effects, or general interdependence that can be present even when observed and unobserved common effects have been properly taken into account.

[3] The econometric specification of these tests is reported in the Appendix.

4.2 Panel Cointegration Tests and Estimation of the Cointegrating Vector

In line with the comparative approach explained above, we rely on a substantial number of different panel cointegration tests.

(a) Firstly, we consider the seven cointegration tests proposed by Pedroni (1999, 2000, 2004). These tests are based on the null hypothesis of no cointegration, and heterogeneity is allowed under the alternative hypothesis. The main purpose of panel cointegration techniques is to pool information on common long run relationships but, at the same time, allow for short-run dynamics and fixed effects to be heterogeneous across the different members of the panel. The following cointegrating system is considered:

$$\begin{aligned} y_{it} &= \alpha_{it} + x'_{it}\beta + \varepsilon_{it}, \\ x_{it} &= \sigma_i x_{it-1} + \epsilon_{it}, \\ i &= 1, ..., N \qquad t = 1, ..., T. \end{aligned} \tag{8}$$

The system is estimated via FMOLS. Notice that the vector $\delta_{it} = \begin{bmatrix}\varepsilon_{it} & \epsilon'_{it}\end{bmatrix}$ is stationary and has covariance matrix denoted by $\mathbf{\Omega}_i$. The estimator has the following form:

$$\widehat{\beta}_{FM} - \beta = \left(\sum_{i=1}^{N} \widehat{\mathbf{\Omega}}_{i22}^{-2} \sum_{t=1}^{T} (x_{it} - \overline{x})^2\right)^{-1} \sum_{i=1}^{N} \widehat{\mathbf{\Omega}}_{i11}^{-1} \widehat{\mathbf{\Omega}}_{i22}^{-1} \left(\sum_{t=1}^{T} (x_{it} - \overline{x})\varepsilon^*_{it} - T\widehat{\gamma}_{it}\right),$$

where

$$\begin{aligned} \varepsilon^*_{it} &= \varepsilon_{it} - \widehat{\mathbf{\Omega}}_{i22}^{-1} \widehat{\mathbf{\Omega}}_{i21}, \\ \widehat{\gamma}_{it} &= \widehat{\mathbf{\Gamma}}_{i21} + \widehat{\mathbf{\Omega}}_{i21}^{0} - \widehat{\mathbf{\Omega}}_{i22}^{-1} \widehat{\mathbf{\Omega}}_{i21} (\widehat{\mathbf{\Gamma}}_{i22} + \widehat{\mathbf{\Omega}}_{i22}^{0}). \end{aligned}$$

Implicitly, the covariance matrix has been decomposed as $\mathbf{\Omega}_i = \mathbf{\Omega}_i^0 + \mathbf{\Gamma}_i$, where $\mathbf{\Omega}_i$ is the contemporaneous covariance matrix and $\mathbf{\Gamma}_i$ is the weighted sum of autocovariances.

Among the seven Pedroni's tests, four are based on the within dimension (panel cointegration tests) and three on the between dimension (group mean panel cointegration tests). Both categories of tests are based on the null hypothesis of no cointegration, hence : $\sigma_i = 1\ \forall i$, σ_i being the autoregressive coefficient on estimated residuals under the alternative hypothesis.

The panel cointegration and group-mean panel cointegration tests differ as regards the specification of the alternative hypothesis: for the panel cointegration statistics, the alternative hypothesis is given by $\sigma_i = \sigma < 1\ \forall i$, while for the group-mean panel cointegration statistics, the alternative hypothesis is given by $\sigma_i < 1\ \forall i$. Hence, a crucial characteristic of the group-mean tests is represented by their generality, given that that they allow for heterogeneous coefficients under the alternative hypothesis, a valuable advantage in our case.

(b) A second technique employed draws on the work by Mark and Sul (2003), who elaborate an extension of the single equation dynamic ordinary least squares (DOLS) method of Saikkonen (1991) and Stock and Watson (1993) for estimating and testing hypotheses about a cointegrating vector to panel data: they regard this fully parametric method as the estimator panel DOLS. Mark and Sul (2003) discuss its limit distribution and apply it to estimate the long-run money demand function using a panel data set of 19 countries with annual observations spanning from 1957 to 1996. We present two limit distributions for panel DOLS. The first limit distribution is obtained for a fixed number of cross-sectional units N, letting $T \to 1$. In this case, panel DOLS converges in distribution to a function of Brownian motions and the Wald statistic for testing a set of s linear constraints has a limiting $\chi^2(s)$ distribution. This limit theory seems well suited for many applied macroeconomic or international problems. Here, researchers often have available panel data sets of moderate N but much larger T. Consider the following regression:

$$y_{it} = \delta^i d_{it} + x'_{it}\beta + \varepsilon_{it}, \tag{9}$$

where $\delta^i d_{it}$ represents the deterministic component and x'_{it} terms are assumed $I(1)$ and not cointegrated. Innovations in x'_{it}, denoted with $u_{it} = \Delta x_{it} - E(\Delta x_{it})$, are assumed to be correlated with ε_{it}. The estimator is based on the error decomposition

$$u_{it} = \sum_{k=-\infty}^{\infty} \gamma_k^{'} \Delta x_{it+k} + v_{it}. \tag{10}$$

where v_{it} is orthogonal to all leads and lags of Δx_{it}. Inserting (10) in the regression (9) yields:

$$y_{it} = \beta^{'} x_{it} + \sum_{k=-\infty}^{\infty} \gamma_k^{'} \Delta x_{it+k} + v_{it}. \tag{11}$$

In practice, the infinite sums are truncated at some small numbers of leads and lags.

(c) Finally, to account for the impact of cross-sectional dependence in the cointegrating relationship, we resort to the methodology proposed by Breitung (2005), who derives a two-step estimator which relies on the fact that the Fisher information is block-diagonal with respect to the short and long-run parameters. The two-step estimator allows us to estimate the individual-specific coefficients in the first step, whereas in the second step the long-run parameters are retrieved from a pooled least-squares regression. Monte Carlo simulations show that this parametric approach is more effective in reducing small sample bias than the FMOLS of Pedroni (2000) amd Phillips and Moon (1999). The estimated standard errors, which are shown to be more reliable than those obtained from semi-parametric estimation procedures, are adjusted to account for both heteroskedasticity and contemporaneous correlation in the errors.[4]

Accordingly, an asymptotically efficient estimator can be constructed by estimating the short- and long-run parameters in separate steps. Suppose that the $n \times r$ matrix of cointegrating vectors is 'normalized' as $\beta = (\mathbf{I}_r, \mathbf{B})$ where $\mathbf{I}_r$ is the identity matrix of order r and $\mathbf{B}$ is the $(n-r) \times r$ matrix of unknown coefficients.13 Then β is exactly identified and the Gaussian ML estimator of $\mathbf{B}$ is equivalent to the OLS estimator of $\mathbf{B}$ in:

$$\mathbf{z}_{it}^{*}= \mathbf{B}\mathbf{z}_{it}^{(2)}+\mathbf{v}_{it}. \tag{12}$$

where $\mathbf{z}_{it}^{(2)}$ is the $r \times 1$ vector defined by $\mathbf{z}_{it} = \left[\mathbf{z}_{it}^{(1)^{'}}, \mathbf{z}_{it}^{(2)^{'}}\right]^{'}$ and:

$$\mathbf{z}_{it}^{*} = \left(\alpha_i^{'}\Sigma_i^{-1}\alpha_i\right)^{-1} \alpha_i^{'}\Sigma_i^{-1}\Delta\mathbf{z}_{it} - \mathbf{z}_{it-1}^{(1)}.$$

[4] Breitung (2005) applies a SUR procedure to the second step of the two-step estimator. An alternative approach is followed by Bai and Kao (2004), who consider a factor structure in the errors and pursue a FMOLS two-step methodology, whereby common factors are retrieved from the residuals of an initial FMOLS estimation.

The matrices α_i and Σ_i can be replaced by $\sqrt{T}$-consistent estimates without affecting the limiting distribution. Accordingly, these matrices can be estimated for each panel unit separately, e.g., by using Johansen's (1991) ML estimator. To obtain the same normalization as in (12) the estimator for α_i is multiplied with the $r \times r$ upper block of the ML estimator of β. Breitung (2005) showed that the limiting distribution of the OLS estimator of $\mathbf{B}$ is asymptotically normal. Therefore, tests of restrictions on the cointegration parameters have the standard limiting distributions (i.e. a χ^2 distribution for the usual Wald tests).

5 Empirical Results

Table 1 reports the results of the five panel unit root tests for the six variables described in Section 3. In all cases, at least three testing methodologies suggest that the null hypothesis of a unit root cannot be rejected. There is strong evidence of stochastic trends for log(*FR)* and *Spread*. The three tests by Choi (2002) point towards a non-acceptance of the null for four variables, namely log(*GDP)*, log(*BR)*, log(*RW)* and *Price*. As shown by means of bootstrapping exercises in Gutierrez (2006), however, Choi's tests are largely oversized in small samples. By combining these results with the ones obtained from the BD test - which is known to be particularly suitable for small samples - it emerges that the inference on the presence of a stochastic trend remains problematic just for log(*BR*) and *Price*. In this latter case, in particular, the Pesaran (2005) test suggests that the non-stationarity hypothesis cannot be non rejected at standard critical levels only for a lag length equal to 3. It is well known that in panel data contexts the rejection of the unit root null hypothesis can depend on large negative values of some individual time series tests. As suggested by Karlsson and Löthgren (2000), we supplement the results from panel unit root testing with unit root tests for individual time series.[5] We find that in all cases the hypothesis of nonstationarity cannot be rejected, so that we proceed on the assumption that all the variables possess a stochastic trend.

Once *GDP* has been shown to be difference-stationary, we decompose regional series for aggregate activity into a trend component (*LRGDP*) and a cyclical component (*SRGDP*) by means of the Hodrick-Prescott filter. Recall that one of the key testable implications we are dealing with consists in the dynamic relationship between the steady-state growth rate of productivity and short-run restructuring activities. For this reason, we prefer to consider separately cyclical effects from relationships involving potential output, and in what follows we employ *LRGDP* when dealing with the long-run, and *SRGDP* when dealing with short-run dynamics.

The next step is to control for cointegration among non-stationary variables. The first column of Table 2 reports the panel cointegration estimation results from Pedroni's methodology as we test for cointegration among all the six variables in our dataset.[6] The test statistics are distributed as a standardized Gaussian density. Four out of seven testing statistics significantly reject the null of no cointegration. FMOLS panel estimation results for the corresponding cointegration vector are reported in the first row of Table 3. All parameters are significant at standard critical values, and all signs are as expected from theoretical reasoning. These findings suggest that the rate of failure moves along a long-run relationship with key macroeconomic variables. Steady-state elasticities with respect to the trend output, the new business formation rate and the real wage are equal to -0.02, 0.1 and 0.03, respectively, while the semi-elasticity with respect to the vertical spread and

[5] Individual test statistics, available upon request from the authors, are not reported for reasons of space.

[6] Tetsts have been alternatively performed with BR_t and, along the lines suggested by the literature, with BR_{t-1}.

surprise inflation are equal to 0.06 and 0.05.

The time-series and cross-section structure of the panel we employ should call for some caution in accepting these results with no further investigation. When the number of time-series observations is small - as in our case - it is well-known that the semi-parametric FMOLS estimator may be seriously biased. Hence, we re-estimate the cointegration vector by applying the fully parametric method proposed by Breitung (2005), which has been shown to outperform the FMOLS estimator for short samples via Montecarlo simulations. More importantly, it allows us to control for contemporaneous correlation in the error terms. Results are presented in the second row of Table 3. Estimates are sign-consistent with the ones obtained by FMOLS for the Spread, GDP and Price variables, although only Spread turns out to be statistically significant. Estimates for BR_{t-1} and RW, on the contrary, come with an inverted sign. As a result, the inference we advance is that the right cointegration vector - if it exists - is likely to contain the variables FR, Spread, LRGDP and Price. If some relationship with BR_{t-1} and WR holds true, it is at best confined to the short-run.

In Table 4 we report estimates for the conjectured four-variable cointegration vector. We compare the results obtained by means of FMOLS with the parametric method proposed by Breitung and, for further control, with the PDOLS estimator by Mark and Sul (2003). The corresponding seven statistics proposed by Pedroni for testing cointegration among non-stationary variables are reported in the second column of Table 2. Our findings seem to be particularly robust. As we control across the different estimation techniques the parameters in the cointegration vector are all highly significant, with the same - and expected - sign, and of the same order of magnitude. We interpret the significant rejection of the null for four out of seven test statistics for the Pedroni's cointegration test as a confirmation of the soundness of our modelling choice.

Next, we estimate four panel ECM models with the twofold aim of separating long-run and short-run dynamics, as well as of addressing the issue of causality. In fact, the presence of cointegration is consistent with (Granger-)causality running just in one (for example, from macroeconomic risk factors to business failures) or in all possible directions. Since both theories on the interaction between business cycle and long-run productivity growth move from the working assumption that macroeconomic shocks should determine business failures, any information about actual causuality is particularly useful. As shown in Canning and Pedroni (1999), the Granger Representation Theorem (GRT) - according to which a system of cointegrated variables can be represented in the form of a dynamic ECM model - can be safely applied to panel data. Thus, we estimate four ECM panel models, one for each variable of interest, according to:

$$\begin{aligned} \Delta x_{it}^{j} &= c^{j} + \lambda^{j}\widehat{\varepsilon}_{t-1} + \sum_{h=1}^{p}\beta_{1,h}^{j}\Delta x_{i,t-1}^{j} + \sum_{h=1}^{p}\boldsymbol{\beta}_{2,h}\Delta\mathbf{z}_{i,t-h}^{j} + u_{it}^{j}, \\ \text{for } j &= \ln(FR), Spread, Price, \ln(GDP), \end{aligned}$$

where x is the dependent variable, $\mathbf{z}$ is a vector of exogenous variables, $\widehat{\varepsilon}_{t-1}$ (i.e the residual from the cointegration relationship, stationary by construction) represents the *disequilibrium* term, while the λ^{j} parameters determine the pace of adjustment to long-run steady-state conditions once short-run displacements have occurred. The GRT implies that at least one of the λ^{j} parameters is expected to be significant if a long-run relationship between the variables is to hold. Results from estimates with FGLS are reported in Table 5. The number of lags p is always set to one. Two types of causality tests can be performed. First, for each of the variables in the ECM relationships we test whether the lagged changes of the other variables and the error correction adjustment term are jointly equal to zero. This restriction amounts to test the hypothesis that none effect, both in the short and in the long-run, runs from the explanatory variables towards the dependent one. As shown in Table 5, all $\chi^2(6)$ Wald tests reject the null hypothesis that the six coefficients are jointly zero. In other words, we can reject the hypothesis that one or more variables in the estimated panels evolve entirely exogenously from the others. Conversely, our estimates suggest complicated two-way feedbacks among the business failure rate and macroeconomic risk factors.

To determine whether these feedbacks are relevant just in the short run, we also test for the adjustment term λ^j to be equal to zero in each ECM panel model. The results can be obtained by simply inspecting the t-value for such a parameter in each estimated equation (Table 5). The null hypothesis of no long-run effect from macroeconomic variables on the business failure rate is consistently rejected, while the opposite is not true at standard significance level. We conclude that macroeconomic risk factors are weakly-exogenous with respect to corporate bankruptcies as far as the long run is concerned. This result lends support to the hypothesis that in Italy the proper long-run causality direction has gone from macroeconomic risk factors to business failures, but not the other way round.

An assessment of which theoretical framework - the OC theory or the RA one - is more likely to explain how macroeconomic shocks relate to long-run productivity can be obtained by combining the results presented in Table 4 and the north-west panel of Table 5, where we report estimates for the ECM model with business failures as the dependent variable. The two risk factors cointegrated with the business failure rate - GDP and Spread - also exert an influence along a similar direction in the short-run. This finding lends support to the hypothesis that in Italy firms tend to respond to a deterioration of macroeconomic conditions in a risk-averse manner. Far from being an opportunity to implement restructuring activities which could yield a higher long-run average rate of productivity growth, recessions are likely to induce firms to postpone productivity-enhancing investments. If this rationalization is correct, downturns are bad both in the short and in the long run, and this latter effect should have a higher probability to be observed the higher is the fraction of financially constrained firms. In order to check for the robustness of our findings, for instance, it could be interesting to extend the analysis put forward in this paper to countries where - at odds with the bank-centered Italian financial system - firms use extensively the market for commercial papers to fund their investment activities. Going back to the results in Table 5, we find that surprise inflation, while positively related to business failures in the long-run, does not seem to play any substantial role during the process of dynamic adjustment. Finally two variables, namely BR_{t-1} and RW, matter only in the short-run. The adjustment to the long-run relationship after a macroeconomic shock is quite slow, at about 10% per annum.

As a final remark, notice that under the assumption that money is long-run neutral - an assumption we cannot test in this setting, however - the cointegration vectors reported in Table 4 can be used to make inference on the issue of long-run monetary superneutrality. In fact, our estimates suggest that permanent shocks to inflation are positively related to permanent variations of the trend output, and negatively related to permanent variations in the vertical interest rate spread. It seems interesting to notice that these findings are in line with the evidence on 14 OECD countries obtained by Rapach (2003). As suggested by Ahmed and Rogers (2000), a positive correlation between permanent inflation shocks and permanently higher levels of real output on the one hand, and a negative relationship between a permanent increase in inflation and permanently lower real interest rates on the other hand, are largely inconsistent with the predictions of many monetary theories.

6 Concluding Remarks

The relationship between business failures and macroeconomic risk factors has been an issue of concern for academics, practitioners and policy-makers for long time. All studies have been so far conducted for countries with a common law origin. Since bankruptcy procedures and their relationship with macroeconomic factors are likely to depend on the institutional structure and the legal framework in which firms operate, it seems interesting to extend the analysis to countries with a civil law tradition. In this paper we study the case of Italy on the basis of panel-based unit root and cointegration estimation procedures. These techniques avoid power distortions of standard tests in small samples and thus misguided conclusions.

Three points emerge from the empirical analysis. (*i*) Our estimates lend support to the hypothesis that a long-run relationship exists between business failures, trend output, a vertical interest spread and a measure of surprise inflation. Furthermore, we find evidence of long-run effects running from macroeconomic risk factors to bankruptcies, but not the other way round. Finally, evidence is found for the effect of real wages and the rate of new business formation during the transition to the steady-state. From a policy perspective, our results suggest that fiscal and monetary policy arrangements could affect business bankruptcies differently over the short and the long-run. In the short-run, for example, standard countercyclical policies aimed at targeting cyclical fluctuations of real GDP (i.e., demand-side policies) are likely be less effective than policies aimed at helping firms to mitigate their variable (labor) and/or fixed (interest payments) costs.

(*ii*) Some macroeconomic risk factors - in particular the GDP and a measure of the tightiness on the credit market - that cause the business failure rate in the short-run are also cointegrated with it and, mostly important, the signs of their long and the short-run relationships remain the same. We interpret these results as an empirical rejection of the opportunity-cost theory of productivity growth - i.e. productivity-improving activities become more important during recessions due to intertemporal substitution between these activities and directly productive activities - in favor of a risk-aversion model, according to which recessions are bad for long-run growth as risk-averse firms reduce productivity-improving investments in fixed capital whenever macroeconomic conditions deteriorate.

(*iii*) Assuming that money is neutral in the long-run, our findings suggest that money is not long-run superneutral with respect to trend output and real interest rates, in addition to the bankruptcy rate. The signs reported in the cointegration vector indicate that permanent positive inflationary shocks are associated with permanently higher levels of real output, and with permanently lower real interest rates.

Appendix

In this appendix we briefly review all five families of tests for unit root employed in the paper.

(i) **Bai and Ng (2004)**. The technique employed in this class of panel unit root tests consists in decomposing a series y_{it} as the sum of three components: a deterministic one, a common component expressed as a factor structure and an idiosyncratic error. The process followed by y_{it} is non-stationary if one or more of the common factors are non-stationary, or the idiosyncratic error is non-stationary, or both. Instead of testing for the presence of a unit root directly in y_{it}, BNG propose to test the common factors and the idiosyncratic components separately. Thus, it is possible to infer whether the non-stationarity comes from a pervasive or an idiosyncratic source. This is the main difference with respect to other testing procedures based on factor structure, which generally test the unit root only in the de-factored data. BNG use a decomposition method which proves to be robust to the degree of integration of the common or idiosyncratic components. In others words, the common variations is extracted without appealing to any stationarity assumptions and/or cointegration restrictions: factors are first estimated on first-differenced data, and subsequently cumulated. Let us consider the following model with individual effects and no time trend:

$$y_{it} = \alpha_i + \rho_i^{'} F_t + \varepsilon_{it},$$

where F_t is a vector $(r \times 1)$ of common factors and λ_i is a vector of factor loadings. Among the r common factors, BNG allow r_0 stationary factors and r_1 stochastic common trends with $r_0 + r_1 = r$. The corresponding model in first differences is:

$$\Delta y_{it} = \alpha_i + \rho_i^{'} f_t + z_{it},$$

where $z_{it} = \Delta\varepsilon_{it}$ and $f_t = \Delta F_t$ with $E(f_t) = 0$. The common factors in Δy_{it} are estimated by the principal component method. Then, the 'differencing and re-cumulating' estimation procedure is based on the cumulated variables defined as:

$$\widehat{F}_{mt} = \sum_{s=2}^{t} \widehat{f}_{ms} \qquad \widehat{\varepsilon}_{it} = \sum_{s=2}^{t} \widehat{z}_{is}.$$

BNG test the unit root hypothesis in the idiosyncratic component and in the common factors with the estimated variables $\widehat{F}_{mt}$ and $\widehat{\varepsilon}_{it}$. To test for the non stationarity of the idiosyncratic component, they propose to use pooled tests based on Fisher's type statistics for the de-factored estimated components, which consists in combining the p-values from individual ADF tests, $p_{\widehat{\varepsilon}}(i)$. Two test statistics are considered:

$$Z_{\widehat{\varepsilon}} = \frac{-\sum_{i=1}^{N} \log p_{\widehat{\varepsilon}}(i) - N}{\sqrt{N}} \rightarrow \mathrm{N}(0,1) \text{ as } T, N \rightarrow \infty$$

and

$$P_{\widehat{\varepsilon}} = -2 \sum_{i=1}^{N} \log p_{\widehat{\varepsilon}}(i) \rightarrow \chi^2(2N) \text{ as } T \rightarrow \infty.$$

In order to test the non-stationarity of the common factors, BNG distinguish two cases. When there is only one common factor among the N variables ($r = 1$), they rely on a standard ADF test in a model with an intercept. If there are more than one common factors ($r > 1$), a test for the number of common independent stochastic trends for each common factor, denoted r_1, is available. Naturally, the null $r_1 = 0$ implies that there are N cointegrating vectors for N common factors, and that all factors are $I(0)$. Individually testing each of the factors for the presence of a unit root generally leads to a problem of overstatement of the number of common trends. To avoid this downside, BNG propose two statistics based on the r demeaned estimated factors $\widehat{F}_{mt}$ similar to those proposed by Stock and Watson (1988). The idea is to test for the equality between the number of common trends and the estimated number of common factors, i.e. $r_1 = r$. The first test, MQ_f, imposes that the non-stationary components are finite order vector-autoregressive precesses. A second test, MQ_c, allows the unit root processes to possess more general dynamics.

(ii) **Choi (2006)**. Choi (2006) opts for an error-component model to detect cross-sectional correlations. His testing procedure is similar to those developed in BNG, with a major difference characterizing the method[7] employed to eliminate non-stochastic trend components and cross-sectional correlations:

$$\begin{aligned} y_{it} &= \alpha_i + f_t + \varepsilon_{it}, \\ v_{it} &= \sum_{j=1}^{q_i} d_i v_{it-j} + u_{it}, \end{aligned}$$

where ε_{it} are i.i.d.$(0, \sigma_{\varepsilon i})$, and assumed to be cross-sectional independent, while α_i and f_t denote the unobservable individual effect and the unobservable time effect, respectively. In this model, the null hypothesis corresponds to the presence of a unit root in the remaining random component, v_{it}. Hence:

$$H_0 : \sum_{j=1}^{q_i} d_i = 1 \qquad H_1 : \sum_{j=1}^{q_i} d_i < 1 \quad \text{for some } i.$$

The test is built by first demeaning the data by GLS as in the Elliott, Rothenberg and Stock's (1996) unit root test (ERS). The following step consists in testing for unit roots the cross-sectionally independent variables: the relevant statistic, called Dickey-Fuller-GLS statistic, has the Dickey-Fuller distribution as T and N tend to infinity. Based on these individual tests, Choi proposes three Fisher's type statistics: under the null hypothesis, each of them has a standard normal distribution as $N \to \infty$ and $T \to \infty$:

$$P_m = -\frac{1}{\sqrt{N}} \sum_{i=1}^{N} \log\left(p_i + 1\right),$$

$$Z = \frac{1}{\sqrt{N}} \sum_{i=1}^{N} \Phi^{-1}\left(p_i\right),$$

$$L^* = \frac{1}{\sqrt{\frac{\pi^2 N}{3}}} \sum_{i=1}^{N} \log\left(\frac{p_i}{1-p_i}\right).$$

[7] In particular, the cross-sectional correlations and deterministic components are eliminated by Elliott, Rothenberg and Stock's (1996) GLS-based de-trending and conventional cross-sectional demeaning for panel data.

(iii) **Pesaran (2005)**. In order to tackle the problem of cross-sectional dependence, Pesaran (2005) suggests to augment the standard ADF regression with the cross-section averages of lagged levels and first-differences of the individual series. If the residual are not serially correlated, the regression used for the i-th cross-section unit is defined as:

$$\Delta y_t = \alpha + b_i \mathbf{y}_{i,t-1} + c_i \overline{y}_{t-1} + d_i \Delta \overline{y}_{t-1} + e_{it},$$

where:

$$\overline{y}_{t-1} = N^{-1} \sum y_{i,t-1},$$
$$\Delta \overline{y}_t = N^{-1} \sum \Delta y_{it}.$$

Let $t_i\,(N,T)$ be the t-statistic of the OLS estimate of b_i. The panel unit root tests are then based on the average of individual cross-sectionally augmented ADF statistics (CADF) $t_i\,(N,T)$, denoted with CIPS:

$$CIPS = \frac{1}{N} \sum_{i=1}^{N} t_i\,(N,T)\,.$$

Pesaran also presents a truncated version of the test ($CIPS^*$), aimed at avoiding influences of extreme outcomes that could emerge from small samples in the time dimension.

(iv) **Chang (2002)**. In Chang (2002), the issue of dependency among innovations is taken into account by recurring to an instrumental variable (IV) approach. For each cross-sectional unit, Chang proposes to estimate the autoregressive coefficients from the usual ADF regression using as instruments a set of ancillary variables generated *via* an integrable, non-linear transformation of the lagged values of the endogenous variable. N individual t-statistics, Z_i, each one based on non-linear IV estimators, are then obtained. The non-linearity of the regularly integrable function generating instruments from the endogenous variable assures that the individual t-ratios Z_i converge asymptotically to standard normal distributions independent across cross-sectional units. This allows Chang to propose a panel unit root test based on the cross-sectional average of individual t-ratios:

$$S_N = \frac{1}{\sqrt{N}} \sum_{i=1}^{N} Z_i.$$

(v) **Breitung and Das (2005)**. Finally, we resort to the approach based on panel corrected standard errors (PCSE) developed by Breitung and Das (2005). According to them, the general cross-sectional error dependence can be specified as follows:

$$\begin{aligned} \Delta y_{it} &= -\mu_i \alpha_i + \rho_i y_{it-1} + \varepsilon_{it}, \\ \varepsilon_{it} &= \theta_i^{'} \mathbf{f}_t + \xi_{it}, \quad i = 1, ..., N. \end{aligned}$$

where $\mathbf{f}_t$ is a vector of serially uncorrelated unobserved common factors and ξ_{it} is a serially uncorrelated error term with zero mean and positive definite covariance matrix, while $\theta_i^{'}$ denotes the factor loading term. Furthermore, it is assumed that $\boldsymbol{\xi}_t$ and $\mathbf{f}_t$ are independently distributed. Let's refer now to a simple model featuring weak cross-sectional dependence:

$$\boldsymbol{\Delta}\mathbf{y}_t = \boldsymbol{\gamma} + \rho \mathbf{y}_{t-1} + \boldsymbol{\varepsilon}_t,$$

where $\gamma_i = -\mu\alpha_i$. The cross-sectional correlation is the given by:

$$\mathbf{\Omega}_t = E\left(\boldsymbol{\varepsilon}_t\boldsymbol{\varepsilon}_t^{'}\right),$$

with bounded eigenvalues. For the model without constant BD work out the t-statistic for the null $\mu = 0$ and find that it is asymptotically distributed as $N(0, \sigma_\Omega)$, where:

$$\sigma_\Omega = \lim_{N\to\infty} \frac{tr(\mathbf{\Omega}_t^2/N)}{tr(\mathbf{\Omega}_t/N)^2}.$$

It turns out that σ_Ω converges to a constant greater than one and this provides and intuition for why a positive bias is introduced when testing without considering cross-correlation of error terms.

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Table 1: Unit Root Tests.

	BNG			Choi			Pesaran			Chang	BD
Variables	r	$Z_{\widehat{\varepsilon}}$	$P_{\widehat{\varepsilon}}$	P_m	Z	L^*	p^*	$CIPS$	$CIPS^*$	S_N	r_{pse}
$\log(\mathbf{FR})$	3	0.477 (0.317)	44.266 (0.296)	1.191 (0.117)	-0.222 (0.412)	-0.645 (0.259)	1	-2.423 (0.010)	-2.423 (0.010)	0.8425 (0.800)	-0.925 (0.177)
							2	-1.732 (0.480)			
							3	-1.092 (0.985)			
$\log(\mathbf{BR})$	4	-0.339 (0.633)	36.966 (0.608)	14.916 (0.000)	-8.886 (0.000)	-10.444 (0.000)	1	-2.014 (-0.175)	-2.014 (-0.175)	0.977 (0.836)	-3.373 (0.000)
							2	-1.625 (0.620)			
							3	-1.085 (0.985)			
$\log(\mathbf{GDP})$	3	1.894 (0.029)	56.940 (0.04)	2.375 (0.001)	-2.998 (0.001)	-2.836 (0.002)	1	-2.350 (0.02)	-2.350 (0.02)	-0.712 (0.382)	-0.452 (0.326)
							2	-1.914 (0.265)			
							3	-1.461 (0.800)			
$\log(\mathbf{RW})$	3	1.258 (0.104)	51.252 (0.110)	7.762 (0.000)	-6.291 (0.000)	-6.420 (0.000)	1	-1.799 (0.400)	-1.799 (0.400)	2.623 (0.996)	-0.589 (0.278)
							2	-2.118 (0.100)			
							3	-1.564 (0.695)			
Spread	3	2.019 (0.022)	58.063 (0.032)	-0.361 (0.641)	-0.863 (0.194)	-0.782 (0.217)	1	-2.087 (0.120)	-2.087 (0.120)	0.654 (0.743)	-0.732 (0.232)
							2	-2.279 (0.030)			
							3	-1.924 (0.255)			
Price	3	6.202 (0.000)	95.472 (0.000)	12.221 (0.000)	-7.910 (0.000)	-8.896 (0.000)	1	-2.576 (0.010)	-2.576 (0.010)	0.852 (0.803)	-2.934 (0.002)
							2	-2.574 (0.010)			
							3	-1.095 (0.960)			
Notes: P-values in Parentheses											

Table 2: Panel Cointegration Tests.

	A	**B**
Panelv	-0.593	0.958
Panelrho	1.982***	-0.171
Panelpp	-6.498***	-5.061***
Paneladf	-2.959***	-3.663***
Grouprho	3.865***	1.757***
Grouppp	-7.757***	-5.669***
Groupadf	-1.512	-3.804***

A. Regressors: Full Dataset

B. Regressors: FR, Spread, Price, LRGDP

Table 3: Cointegration Vector-Overall Dataset.

	Spread	ln(**LRGDP**)	**Price**	ln(**BR**)$_{t-1}$	ln(**RW**)
FMOLS	0.060***	-0.020***	0.050***	0.100***	0.030***
	(0.001)	(0.002)	(0.006)	(0.024)	(0.012)
Breitung	0.094***	-0.012	0.055	-0.066	-0.273
	(0.009)	(0.020)	(0.090)	(0.048)	(0.464)

Standard Errors in Parentheses

Table 4: Panel Cointegration Tests.

	Spread	ln(**LRGDP**)	**Price**
PDOLS	0.070***	-0.020***	0.090***
	(0.007)	(0.001)	(0.005)
Breitung	0.102***	-0.016***	0.029***
	(0.011)	(0.003)	(0.010)
PDOLS(1)	0.084***	-0.034***	0.081***
	(0.016)	(0.003)	(0.029)
PDOLS(2)	0.130***	-0.026***	0.095***
	(0.019)	(0.003)	(0.031)

Standard Errors in Parentheses.

PDOLS(1): Ordinary; PDOLS(2): Common Time Effects

Table 5: FGLS Regression for Panel ECM Models.

DV: $\Delta\ln(FR)_t$			**DV:** $\Delta(Spread)_t$		
Regressors	**Coeff.**	**S.E.**	**Regressors**	**Coeff.**	**S.E.**
$\Delta\ln(FR)_{t-1}$	-0.108***	0.043	$\Delta(Spread)_{t-1}$	0.017	0.049
$\Delta\ln(BR)_{t-1}$	0.054***	0.018	$\Delta\ln(BR)_{t-1}$	-0.206***	0.050
$\Delta\ln(RW)_{t-1}$	0.033***	0.003	$\Delta\ln(RW)_{t-1}$	0.050***	0.008
$\Delta(Price)_{t-1}$	0.002	0.003	$\Delta(Price)_{t-1}$	0.083***	0.017
$\Delta(Spread)_{t-1}$	0.028***	0.005	$\Delta\ln(FR)_{t-1}$	0.392***	0.049
$\Delta\ln(SRGDP)_{t-1}$	-0.008***	0.003	$\Delta\ln(SRGDP)_{t-1}$	0.009	0.010
Ecm_{t-1}	-0.098***	0.015	Ecm_{t-1}	0.037**	0.021
$Constant$	-0.040***	0.007	$Constant$	-0.043	0.110
Wald Test	199.630		Wald Test	175.110	
P-value	(0.000)		P-value	(0.000)	
DV: $\Delta(Price)_t$			**DV:** $\Delta\ln(LRGDP)_t$		
Regressors	**Coeff.**	**S.E.**	**Regressors**	**Coeff.**	**S.E.**
$\Delta(Price)_{t-1}$	-0.105***	0.048	$\Delta\ln(LRGDP)_{t-1}$	-0.147***	0.051
$\Delta\ln(BR)_{t-1}$	-0.647***	0.093	$\Delta\ln(BR)_{t-1}$	0.716***	0.168
$\Delta\ln(RW)_{t-1}$	0.042***	0.012	$\Delta\ln(RW)_{t-1}$	0.023	0.028
$\Delta\ln(FR)_{t-1}$	0.558***	0.071	$\Delta(Price)_{t-1}$	0.197***	0.046
$\Delta(Spread)_{t-1}$	0.198***	0.041	$\Delta(Spread)_{t-1}$	-0.068	0.065
$\Delta\ln(SRGDP)_{t-1}$	-0.126***	0.018	$\Delta\ln(FR)_{t-1}$	-1.355***	0.149
Ecm_{t-1}	0.055	0.054	Ecm_{t-1}	-0.062	0.080
$Constant$	0.116***	0.048	$Constant$	-0.007	0.077
Wald Test	192.65		Wald Test	130.25	
P-value	(0.000)		P-value	(0.000)	

Notes: DV denotes the dependent variable in the panel ECM.