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Regional Financialisation and Financial Systems Convergence: Evidence from Italy

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Abstract:

The term 'financialisation' has now entered the lexicon of academics and policy makers, though there is still no agreement on its meaning and significance. One of the earlier definitions was offered by Epstein (2005; see also Krippner, 2005), who referred to the growing weight of financial motives, financial actors and markets in the operation of modern economies, both at the national and international level, from the early 1980s until today. Building on this definition, this paper sheds further light on the implications of spatial financialisation, which has been associated with the over and under-extension of credit across and within countries and evolving financial instability. The paper's primary contribution is to extend in a robust manner a powerful panel data convergence testing methodology to analyse the spatial scale and temporal evolution of Italian regional lending conditions. The paper concludes that financial divergence has broadly increased in Italian regions. Furthermore, we are able to link regional financialisation to the growing north-south divide in a significant and meaningful way. As a result the ability of southern regions in Italy to absorb adverse macroeconomic and financial shocks has been weakened. Relevant regional financial policies have thereby become very important.

Keywords: Italy; regional; financialisation; financial systems convergence

1. Introduction[1]

The term 'financialisation' has now entered the lexicon of academics and policymakers (e.g. Palley, 2013 and Turner, 2010, respectively), though there is still no agreement on its meaning and significance. One of the earlier definitions was offered by Epstein (2005; see also Krippner, 2005), who referred to the growing weight of financial motives, financial actors and markets in the operation of modern economies, both at the national and international level, from the early 1980s until today. More recently, Van der Zwan (2014) has reviewed the origins of the term and its various definitions and highlights three features of the structural changes in modern societies that go under the label of financialisation; namely (1) a regime of accumulation dominated by financial motives and financial actors; (2) the ascendency of 'shareholder value' as a mode of business governance; and (3) the culture of individualism and market competition associated with it that dominates everyday life from housing, to pensions and utilities. This paper's contribution focuses on regional financialisation and financial systems convergence in the context of Italian bank lending conditions. In doing so it draws on the first feature of financialisation as above, namely the dominance of the financial sector.

According to neoclassical theory, the convergence process does not depend on the regional financial sector, above and beyond its role in facilitating the efficient intermediation of finance and growth as part of the catching-up process (Moore and Nagurney, 1989). The mainstream literature provides advancement by accounting for financial frictions, imperfections and market segmentation due to the underlying principal-agent problem (Stiglitz and Greenwald, 2003). In particular, credit-rationing arises endogenously across the business cycle within New Keynesian dynamic stochastic general equilibrium (DSGE) models and works to amplify macroeconomic and financial shocks due to the 'financial accelerator' (Bernanke et al., 1996). The distribution of wealth affects the equilibrating process in a non-trivial way; however an important implication of the mainstream micro-foundations is that during crises regions may experience temporary deviations from equilibrium in the form of uneven access to credit, differences in lending spreads and loan-deposit premia.

Post-Keynesians do not dispute the imperfections and constraints embedded within mainstream (New Keynesian) models; however they view regional credit supply and demand as interdependent and influenced by banking sector development and liquidity preference (Dow and Rodriguez-Fuentes, 1997). Because there is a tendency for high savings and low expenditure in regions with under-developed banking sectors, the initial assumption in the heterodox literature is of divergence rather than convergence (Chick and Dow, 1998). According to Post-Keynesian liquidity preference theory, capital may flow from less developed regions to more prosperous, liquid and financialised regions, in a self-reinforcing mechanism, which manifests itself in the development of centralised financial hubs and spatial clustering of credit conditions (Dow 1992, 1999). This has led some to conclude that uneven financial sector growth may increase income inequalities and make financial crises more likely to re-appear in the future (see, for example, Lapavitsas, 2009; Stockhammer, 2012; Dow et al., 2012).

Italy is a particularly interesting case because of its longstanding north-south divide in terms of economic characteristics and financial structure (see, for example, D'Amico et al., 1990; Faini et al., 1993; Dunford, 2002). Despite the implementation of various policies designed to promote financial liberalisation and convergence, the economic and financial disparities have become more pronounced over recent years and the prospect of convergence seems even further out of sight (Kitson et al., 2011). Moreover, the view emerging from the empirical literature is that spatial financialisation, in terms of uneven regional financial sector development and accumulation, may be linked to the growing north-south divide. See, for example, Martin and Minns (1995) for the United Kingdom; Rodriguez-Fuentes (1998) for Spain; Dow et al. (2012) for Italy; Crocco et al. (2014) for Brazil.[2] In particular, this process may be beneficial for certain agents, namely those located in centralised financial hubs; however, it may disadvantage agents in more remote, periphery regions.

This paper's contributions relative to the literature are as follows. First, the vast majority of studies conduct analysis at an international level, which may mask considerable intra-national heterogeneity (Corrado et al., 2005). Studies investigating convergence of lending conditions have been constrained by regional financial data quality and availability. Importantly, this paper makes use of greater availability of harmonised NUTS-2 level data on bank lending growth, lending spreads and loan-deposit premia, thus facilitating a more extensive empirical investigation for the Italian case.[3] Second, the (non-mainstream) approaches discussed above, while empirically grounded, are also theoretical. However, they involve much more than imperfections and financial frictions (i.e. constraints on the mainstream convergence model), while at the same time not purporting to predict the exact spatial scale of convergence (or divergence) because these processes operate within a system, which is open and evolving. In this sense, the use of the flexible, data-driven clustering methodology of Phillips and Sul (2007) may be preferred to one where the convergence process is assumed to be fixed across time and space. Third, this paper's application of econometric techniques enables identification, testing and further explanation of the dynamics of convergence over a particularly interesting period, which extends beyond the global economic and financial crisis. In this latter sense our approach, which utilises the Phillips and Sul (op. cit.) method, provides some originality in that it has not been used to analyse changes in the speed of convergence to our knowledge so far.[4,5] The application is particularly useful due to the lack of power when conducting standard unit root and cointegration tests in small or moderate samples.

The empirical strategy proposed in this paper proves insightful since it identifies situations where lending conditions are converging in certain regions even if divergence is detected at the aggregated level. First, application of Phillip and Sul's (2007) clustering algorithm permits identification of a cluster of convergent regions, which are more central geographically than regions in the divergent cluster. Second, the estimated speed of divergence is higher in southern Italian regions than northern regions and it has increased notably since the onset of the global economic and financial crisis. Third, most of the evolving north-south divergence may be related to regional financialisation, liquidity preference and the distribution of income. Our findings suggest that the evolution of financial behaviour has become an important factor related to the growing north-south divide.

This paper is structured as follows. Section 2 sets out the convergence testing methodology and corresponding hypotheses. Section 3 provides background and describes the data. Section 4 presents the main empirical results. Section 5 provides further discussion and explanation. Section 6 summarizes and concludes.

2. Methodology

2.1 Introduction

Investigating the convergence of regional lending conditions is a complex task. Sigma convergence tests do not permit individual regions to be transitionally divergent, whereas beta convergence tests in the spirit of Barro and Sala-i-Martin (1992) can yield biased and inconsistent estimates of the speed of convergence (Phillips and Sul, 2009). Therefore, negative estimates cannot be directly interpreted as evidence of convergence. Instead, this paper extends Phillips and Sul's (2007) panel convergence test, which may be used to assess whether regional lending conditions are bound by a long-term equilibrium relationship, while incorporating evolving regional heterogeneity. Their log-t test more effectively detects the presence of convergence than standard unit root and cointegration tests, whereby the underlying hypothesis of long-run equilibrium may be rejected in short-panel contexts due to data limitations.[6] For example, in small or moderate samples, cointegration in lending conditions may not be detected if the speed of convergence is very gradual and insufficient to reflect cointegrated behaviour, even when the variables of interest are actually converging. Furthermore, the log-t convergence test is straightforward to implement in practice and incorporates a broad range of convergence possibilities without necessitating any specific assumptions about the stationarity of variables (Rughoo and Sarantis, 2014).[7]

2.2 Testable Hypotheses

To motivate the Phillips and Sul (2007) convergence test consider first equation (1), which provides a simple theoretical time-varying factor representation of lending market conditions, measured by $x_{i,t}$, for Italian region i in period t:

$$x_{i,t} = g_{i,t} + a_{i,t} = \frac{(g_{i,t} + a_{i,t})}{\mu_t} = \delta_{i,t}\mu_t \quad \text{for all i and t.} \tag{1}$$

As it is typically assumed in the literature (see, for example, Matousek et al., 2015), macroeconomic and financial panel data, including data on bank lending, may be decomposed into systematic component, $g_{i,t}$, and transitory component, $a_{i,t}$. Furthermore, $x_{i,t}$ may be expressed in terms of a common trend component, μ_t, and time-varying idiosyncratic component, $\delta_{i,t}$, which measures the economic distance between the trend component μ_t and $x_{i,t}$, as in equation (1). Equation (2), then, provides the expression for $h_{i,t}$, the so-called relative transition coefficient, which effectively measures $\delta_{i,t}$ in relation to the cross-section at time t, thus providing a measure of the transition of region i relative to all Italian regions:

$$h_{i,t} = \frac{x_{i,t}}{\frac{1}{N}\sum_{i=1}^{N} x_{i,t}} = \frac{\delta_{i,t}\mu_t}{\frac{1}{N}\sum_{i=1}^{N}\delta_{i,t}\mu_t} = \frac{\delta_{i,t}}{\frac{1}{N}\sum_{i=1}^{N}\delta_{i,t}} \tag{2}$$

If regional transition coefficients $\delta_{i,t}$ converge to some fixed point δ, this implies that the relative transition coefficient of equation (2) converges to unity. According to Phillips and Sul's (2007) model of transition, the rate at which the cross-sectional variation decays to zero, defined as α, must be non-negative for regional convergence.[8] The general point is that, under convergence, the influence of common shocks prevails, whereas the influence of region-specific shocks decays, thus enabling transition to equilibrium. The higher the rate of decay, the faster is the transition to equilibrium. In equilibrium $\delta_i = \delta_j$ for $i \neq j$, which implies $\delta_i = \delta$, thereby enabling a statement of the null hypothesis of convergence as in equation (3).

$$\mathrm{H}_0 : \delta_{i,t} = \delta, \quad \alpha \geq 0 \tag{3}$$

Even under the null hypothesis in equation (3), the model allows for transitional periods in which $\delta_{i,t} \neq \delta_{j,t}$ for i ≠ j, thereby incorporating possible transitional heterogeneity across regions in the short and medium-term. However, the long-run implication of equation (3) is that, while short-run deviations from equilibrium may occur, long-term trends bind regions together through a cointegrating vector.

Equations (4) and (5) present the alternative hypotheses, which incorporate two possibilities. In the first case, $\delta_i \neq \delta$ and regions i diverge with a negative speed of convergence, $\alpha < 0$, which implies that region-specific shocks predominate over time in terms of their influence on lending conditions. However, transitional divergence does not eliminate the possibility of sub-panel convergence. In the second case, $\delta_{i,t}$ converges to δ_k, for some regions with a non-negative speed of convergence, $\alpha \geq 0$. For K such groupings, G = $[G_1, G_2, \ldots, G_K]$, where $\delta_{i,t}$ converges to δ_k, the number of regions across all groups sums to N.

$$\mathrm{H}_A : \delta_{i,t} \neq \delta, \quad \alpha < 0 \tag{4}$$

$$\mathrm{H}_A : \delta_{i,t} = \begin{cases} \delta_1, & \alpha \geq 0 \quad \text{if} \quad i \in G_1 \\ \delta_2, & \alpha \geq 0 \quad \text{if} \quad i \in G_2 \\ & \vdots \\ \delta_K, & \alpha \geq 0 \quad \text{if} \quad i \in G_K \end{cases} \tag{5}$$

Together with the null hypothesis in equation (3), the dual alternative hypotheses set out in equations (4) and (5) provide an appealing flexibility with respect to the underlying theoretical framework and account for various possibilities, including i) convergence of all regions, ii) divergence of all regions and, iii) convergence of only certain regions. While the first outcome is more in line with traditional convergence predictions, the second and third outcomes permit divergence or sub-panel convergence; whereby certain regions may be converging over time even if divergence is apparent. Thus, we allow for the interesting possibility of divergence and 'club convergence' in the form of spatial clustering of lending conditions, which may arise, for example, under heterodox theories of Chick and Dow (1998) and Dow (1992, 1999).

The details of empirical implementation and estimation of the crucial speed of convergence parameter α are set out below.

2.3 Log-t Panel Convergence Test

The first step in implementing our empirical investigation is the extraction of the (non-cyclical) trend component of the data, which enables more powerful inference of the long-run convergence properties in lending conditions (Phillips and Sul, 2007). Following other contributions, the Hodrick and Prescott (1997) filter is used to filter out the cyclical component of bank lending data (see, for example, Matousek et al., 2015). The indicators of lending market conditions, introduced and discussed below in section 3, are then computed based on the trend components and in turn these are used to calculate the filtered transition coefficients $h_{i,t}$ and mean square transition differential:[9]

$$H_t = \frac{1}{N}\sum_{i=1}^{N}(h_{i,t}-1)^2 \quad \text{for } t = [rT, \ldots, T] \tag{6}$$

The dataset is trimmed to validate the regression equation in terms of the asymptotic characteristics of transition and to ensure test consistency in convergence applications. The trimmed proportion, r, is set to 0.3, which is satisfactory according to Phillips and Sul (2007) on the basis of Monte Carlo experiments. After trimming the data, the following regression model is estimated:

$$\log\left(\frac{H_1}{H_t}\right) - 2L(t) = \phi_0 + \phi_1 \log t + \varepsilon_t \tag{7}$$

The inclusion on the left-side of equation (7) of the slow-moving function of time, L(t), improves test performance under the alternative hypothesis advanced above. We follow the recommendation of Phillips and Sul (2007) by setting $L(t) = \log(t+1)$. Estimation is conducted on the trimmed sample starting at $t = [rT]$.

Phillips and Sul (2007) show that, under the null hypothesis of convergence, the normalised cross-sectional variance ratio H_1/H_t tends to positive infinity and to negative infinity under the alternative hypothesis of sub-panel convergence. While parameter ϕ_0 conveys no information about the speed of convergence, parameter ϕ_1 corresponds to the scaled speed of convergence parameter, 2α. The implication of the underlying model of transition is that the higher the estimate of ϕ_1, the greater is the speed of convergence. Under the baseline log-t model, the convergence test proceeds as a one-sided t-test of $a \geq 0$. The null hypothesis of convergence is rejected if the normally-distributed test statistic lies below the relevant critical value for a one-sided test.

To address sample heterogeneity and instability arising within the sample of study the baseline ordinary least squares estimation (LS) approach is combined with the iteratively re-weighted least squares technique (IRLS) of Huber (1964). The IRLS model assigns a higher weight to observations, which are deemed better behaved and may be useful in addressing outlier observations and extreme observations associated with departures from non-normality arising during periods of crises. The use of LS and IRLS estimators enhances the robustness of the empirical strategy, although we also consider augmentations of the baseline log-t regression model to account for changes in the empirical association across the sample, which includes periods of substantial economic and financial instability.

As discussed by Phillips and Sul (2009), the speed of convergence can change over time as regions shift from one economic regime to another; this cannot be ruled out given the structural and policy changes arising in our sample, particularly in response to the crisis. This may also be motivated by the concept of regime-sensitive cointegration, due to Siklos and

Granger (1997), which is applicable to both large and small sample-sizes. To that end, the baseline model in equation (7) may provide limited insight into the time-variance of the convergence process. A related issue is that, in a short-panel context, a degrees-of-freedom problem may arise under sub-sample estimation. Therefore, the baseline regression model in equation (7) is augmented with yearly intercept dummy variables and slope dummy variable interaction terms for the natural log of time index t. The interaction specification in equation (8), as below, permits investigation of whether and how the speed of convergence has changed over time.

$$\log\left(\frac{H_1}{H_t}\right) - 2L(t) = \phi_0 + \sum_\tau \pi_{0,\tau} D_t + \phi_1 \log t + \sum_\tau \pi_{1,\tau} D_t . \log t + \varepsilon_t \tag{8}$$

In equation (8) the dependent variable is unchanged, although dummy variable terms are now included as additional regressors. Specifically, dummy variables, D_t, are used to identify temporal marginal effects on the intercept and slope respectively over yearly intervals. For the latter, interaction terms are included in the regression model, based on the product of the natural log of the time index and dummy variables, $D_t . \log t$.[10] Therefore, $\pi_{0,\tau}$ and $\pi_{1,\tau}$ are a collection of temporal marginal intercept and slope effects over yearly intervals. This enables inference of the temporal speed of convergence across individual years of the trimmed sample and importantly it helps overcome in a short-panel context the restriction that the convergence process is fixed across time. The estimate $\phi_1 + \pi_{1,\tau}$ corresponds to the scaled speed of convergence parameter, 2α. Under the augmented log-t model, the convergence test proceeds as a one-sided t-test of $a \geq 0$; therefore, convergence may be inferred in any given year τ in equation (8) by testing whether $\phi_1 + \pi_{1,\tau} \geq 0$. The null hypothesis of convergence is rejected if the normally-distributed test statistic lies below the relevant critical value of -1.645 for a one-sided test.

2.4 Log-t Sub-Panel Convergence

Under the alternative hypothesis it is not possible to reject the possibility of sub-panel or cluster convergence; therefore, to identify regional groupings with similar convergence characteristics, we apply the clustering algorithm developed and detailed by Phillips and Sul (2007, 2009). This algorithm consists of the following steps.

Step 1: The $x_{i,t}$ series are ordered according to the last observation, $x_{i,T}$, and an initial regional grouping is formed by selecting the first k highest individuals to form the subgroup G_k for some $2 \leq k < N$, where N is the total number of Italian regions. The log-t regression is then run and the convergence test statistic $t_b(k)$ computed for this grouping. The initial grouping of size k* is identified by maximising the convergence test statistic according to the criterion $\min\{t_b(k)\} > -1.645$, where -1.645 is the lower critical value of the normal distribution corresponding to the 5% significance level.

Step 2: Once the initial grouping of Italian regions is formed, each remaining region is added separately to this grouping. If the corresponding test statistic is greater than the chosen critical value, c, then the region is also included and forms the first cluster.[11]

Step 3: In the final step, the log-t test is conducted on the regions not selected; if $t_b(k)\}$ > -1.645 then convergence is detected and the second cluster is formed. In the case of rejection, this process is repeated from the start for the remaining regions. If no other convergence clusters are identified, then what remains is a divergent cluster comprising the remaining regions.

3. Background and Data Description

Italy is a country with longstanding regional inequalities and differences in productivity, employment and demographic growth (see, for example, Dunford, 2002). There are highly developed areas in terms of productive and banking structures, such as regions in the north-east and north-west, and also poorer, under-developed regions, which rely on more traditional banking systems. Northern and southern Italian regions can also be related to the core-periphery concept, insofar as the 'core' northern regions are more affluent and developed. The 'periphery' southern regions are generally poorer with under-developed banking sectors, which are characterised by higher perceived customer risk, regional power structures that inhibit competitiveness and limited physical access to banks prevail (see, for example, Faini et al., 1993). Southern regions are also more reliant on the primary sector and industries with lower technological content, whereas northern regions are oriented more to financial services and exposed to associated innovations.

When investigating convergence of regional lending conditions, this paper considers several relevant indicators, including the growth in retail bank lending, the lending spread, and loan-deposit premium to non-bank customers. Interest rate and lending growth data correspond to non-bank customers and consumer households respectively. Short and long-term nominal interest rate data are used to construct the lending spread; under this indicator, high demand for loans relative to supply in any region is reflected in high long-term interest rates relative to short-term rates.[12] The difference between nominal lending and deposit rates is used to measure the loan-deposit premium, whereby tighter credit conditions in any region are indicated by high nominal lending interest rates relative to deposit rates.[13] Using data on regional bank lending growth in addition to spread and premium indicators, it is possible to analyse more comprehensively Italian regional lending conditions.

There are issues when undertaking empirical research concerning the seasonality of bank lending data. First, it is possible that seasonal unit roots may occur, particularly given the use of quarterly data. However, seasonality may present itself as a common trend across all regions, or a trend that is specific only to certain regions, in which case the underlying hypotheses of convergence versus sub-panel convergence or divergence, as set out in equations (3)-(5), remain relevant. Furthermore, for robustness, we conduct Hylleberg et al.'s

(1990) test, which suggests that seasonal unit roots are not a characteristic of our bank lending data.[14] Second, aside from the unit root issue, seasonal factors may generate intra-annual variation in bank lending data, above and beyond other influential factors, including possible 'outlier' observations. In particular, the trend component of bank lending data may be distorted unless seasonal variation removed. However, after conducting a battery of seasonality tests, we find no conclusive evidence, with the exception of Sicilia for the premium measure. Even then, seasonality does not seem very influential.[15] Therefore, we proceed using the seasonally-unadjusted data.

The indicators of lending conditions are scaled in annualised percentage points and taken from quarterly regional reports published by the Bank of Italy's Statistical Bulletin.[16] Data are available from 1999Q1-2014Q2 for 20 NUTS-2 Italian regions: Piemonte, Valle d'Aosta, Lombardia, Liguria, Trentino-Alto Adige, Veneto, Friuli-Venezia Giulia, Emilia-Romagna (Northern); Toscana, Umbria, Marche, Lazio (Central); Abruzzo, Molise, Campania, Puglia, Basilicata, Calabria, Sicilia, Sardegna (Southern). For each of the 20 regions there are 62 quarterly observations.

Table 1. Summary Statistics

	Lending Growth				Lending Spread				Loan-Deposit Premium			
	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max
Full Sample	8.53	3.46	6.48	10.41	-1.84	0.58	-3.24	-0.71	5.52	0.40	3.87	7.65
Northern	9.01	4.12	8.08	10.41	-1.45	0.52	-2.13	-0.71	4.83	0.36	3.87	5.85
Central	8.80	3.39	8.40	9.67	-1.63	0.56	-1.97	-1.37	5.04	0.50	4.77	5.65
Southern	7.91	2.83	6.48	9.51	-2.32	0.64	-3.24	-1.62	6.45	0.39	5.65	7.65
Cluster 1	8.69	3.43	6.48	10.41	-1.88	0.59	-3.24	-0.71	5.33	0.38	4.42	6.73
Northern	9.38	4.24	8.44	10.41	-1.47	0.52	-2.13	-0.71	5.14	0.34	4.42	5.85
Central	8.80	3.39	8.40	9.67	-1.63	0.56	-1.97	-1.37	5.13	0.56	4.78	5.65
Southern	8.05	2.78	6.48	9.51	-2.42	0.67	-3.24	-1.64	6.65	0.47	5.90	6.73
Cluster 2	8.04	3.23	7.31	8.92	-1.49	0.57	-1.62	-1.36	5.16	0.38	3.87	7.65
Northern	8.41	3.93	8.08	8.92	-1.36	0.52	-1.36	-1.36	4.73	0.37	3.87	5.85
Central	-	-	-	-	-	-	-	-	4.77	0.31	4.77	4.77
Southern	7.50	2.97	7.31	7.70	-1.62	0.44	-1.62	-1.62	6.65	0.47	5.65	7.65

Source: Authors' own computation using the Gauss code of Phillips and Sul (2007) and data sourced from the Bank of Italy's Statistical Bulletin.

Note: Mean, Min and Max corresponds to the sample mean, minimum and maximum values based on the cross-sectional averages for the full sample, for regions in clusters 1 and 2, and northern, central and southern regions SD stands for standard deviation, which is computed across time for individual regions and then averaged across regions as it is indicated in the table.

Differences in lending conditions are apparent across Italy (see Table 1).[17] Northern regions exhibit higher consumer lending growth, less negative lending spreads and smaller loan-deposit premia than other regions. Southern regions exhibit much lower lending growth, more negative lending spreads and higher loan-deposit premia. Furthermore, the lending spread is higher in northern Italy, which suggests that the cost of short-term borrowing is relatively low and that demand for loans associated with longer-term projects is relatively high in northern regions. Constraints and mark-ups, which are part of the loan-deposit premia, are higher in southern Italy, which is indicative of the lower levels of banking sector efficiency, competitiveness and higher perceived risk in these regions.

The sample standard deviations and range of conditions even within northern, central and southern regions are indicative of considerable sample heterogeneity across time and space. When all quarters and regions are considered, lending growth rates range from as low as 0.73% in southern Italy to as high as 22.6% in northern Italy; lending spreads range from -4% in southern Italy to 0.8% in southern Italy; loan-deposit premia range from 3.1% in northern Italy to 8.8% in southern Italy.

4. Empirical Analysis

4.1 Aggregated Estimation

The first part of the convergence analysis concerns lending conditions across all Italian regions. For comparison, the output for lending growth, lending spread and the loan-deposit premium under both pooled and panel estimation, are all presented in Table 2. The pooled approach involves estimating the log-t model for each region vis-à-vis the Italian national counterparts for lending growth, spread and premium indicators. Regional estimates for the crucial parameter ϕ_1 of equation (7), which conveys information about the speed of convergence, are then averaged to obtain the pooled estimates. Under the panel approach, the log-t model is estimated once for all 20 regions. Both approaches can be used to examine convergence. Table 2 summarises the estimation output, which is based on various estimators, including least squares, iteratively re-weighted least squares and dummy variable interaction augmentations of both.

Table 2. Log-t Convergence Test – Various Estimators

	LS		IRLS		LSDV(1)		LSDV(2)	
	Pooled	Panel	Pooled	Panel	Pooled	Panel	Pooled	Panel
Lending Growth								
ϕ_1	-2.69**	-2.92***	-2.53***	-2.37***	-2.73***	-3.18***	-2.73***	-2.42***
	(1.21)	(0.24)	(0.50)	(0.14)	(1.11)	(0.19)	(0.71)	(0.13)
Lending Spread								
ϕ_1	-1.29**	-1.86***	-1.91***	-1.87***	-1.21**	-1.87***	-1.21***	-1.88***
	(0.58)	(0.01)	(0.32)	(0.03)	(0.53)	(0.04)	(0.38)	(0.01)
Loan-Deposit Premium								
ϕ_1	-1.52***	-1.93***	-1.78***	-1.92***	-1.54***	-1.94***	-1.54***	-1.94***
	(0.45)	(0.01)	(0.26)	(0.01)	(0.40)	(0.01)	(0.23)	(0.01)

Source: See source in Table 1.
Note: Parameter ϕ_1 corresponds to equation (7). LS, IRLS, LSDV(1), LSDV(2) correspond to estimation using least squares, iteratively re-weighted least squares, and dummy variable interaction augmentations of both. Dummy variable terms account for changes in the intercept and slope during 2008-2010. Estimates corresponding to dummy variable terms are not reported for brevity, but are available from the authors upon request. Newey-West heteroscedasticity and autocorrelation robust standard errors are reported (in parentheses). ***, ** and * indicate rejection of the null hypothesis of convergence at 1%, 5% and 10% significance levels respectively.

Reported in Table 2 are the point estimates for parameter ϕ_1 and corresponding standard errors (in parentheses). Point estimates, which are twice the scaled speed of convergence, 2α, are significantly less than zero indicating overall to divergence of lending growth rates, spreads and risk premia across Italian regions. Point estimates are quite similar under the various estimators and from both pooled and panel estimation, although estimates obtained under panel estimation are much more precise. The relative size of the point estimates implies that the rate of divergence of lending growth has sometimes been more than double that of the lending spread and loan-deposit premium, which are more comparable. Similar estimates are obtained for different non-bank lending markets – lending to consumer households, non-financial firms and producer households – where the latter includes proprietors and sole entrepreneurs (see Table 3). There is clear evidence at an aggregated level of divergence in Italian regional lending markets.

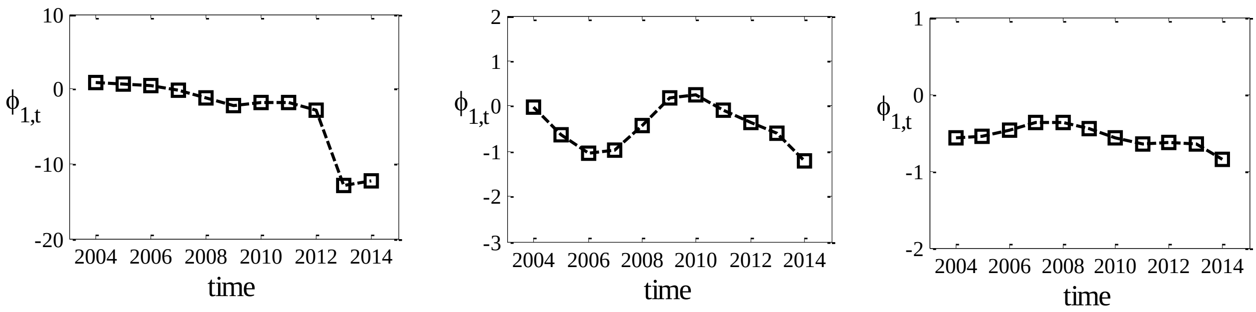
Table 3. Log-t Convergence Test for Lending Growth - Various Estimators

	LS		IRLS		LSDV(1)		LSDV(2)	
	Pooled	Panel	Pooled	Panel	Pooled	Panel	Pooled	Panel
Consumer Households								
ϕ_1	-2.69**	-2.92***	-2.53***	-2.37***	-2.73***	-3.18***	-2.73***	-2.42***
	(1.21)	(0.24)	(0.50)	(0.14)	(1.11)	(0.19)	(0.71)	(0.13)
Non-Financial Firms								
ϕ_1	-3.08***	-3.11***	-3.18***	-3.08***	-3.22***	-3.35***	-3.32***	-3.36***
	(1.16)	(0.07)	(0.53)	(0.17)	(1.03)	(0.23)	(0.27)	(0.12)
Proprietors								
ϕ_1	-2.76***	-2.90***	-3.20***	-2.85***	-2.68***	-3.09***	-2.86***	-3.12***
	(0.93)	(0.04)	(0.40)	(0.12)	(0.85)	(0.13)	(0.25)	(0.08)

Source: See source in Table 1.
Note: See note in Table 2.

These findings are not unexpected since Italy is a country with longstanding differences in terms of economic characteristics and regional financial structure. However, regarding the temporal evolution of the speed of convergence, estimation of equation (8) provides evidence of changes across the trimmed sample.[18] The temporal estimate, $\phi_{1,t}$, which is indicated in any given period τ by the estimate of $\phi_1 + \pi_{1,\tau}$, and is negative for most periods, with no favourable trends emerging over time (see Figures 1-3 below). The speed of convergence for consumer bank lending growth becomes significantly negative from 2007; this downward trend has been reinforced in subsequent years. Therefore, the relative divergence indicated previously may reflect trends in bank lending growth arising across the sample and especially around the onset of the global economic and financial crisis.[19]

Figures 1-3. Temporal evolution of the speed of convergence for all regions for bank lending growth (left), non-bank lending spread (centre) and loan-deposit premium (right).



Source: See source in Table 1.

The economic implication is that Italian lending conditions are not broadly bound together across regions through a cointegrating relationship at the NUTS-2 level. The global economic and financial crisis has clearly exacerbated the divergence in lending conditions in a generalised way, thus corroborating and extending the finding of Rodriguez-Fuentes (1998). This finding may also be related to Dow et al. (2012), who find evidence of unit root processes for lending spreads and loan-deposit premia vis-à-vis national counterparts. Both the Dow et al. (op. cit.) study and our study suggest that macroeconomic and financial shocks have persisted to the extent that, all regions considered, lending conditions have not returned to an equilibrium position. Therefore, the divergence appears more persistent rather than transient. However, under the alternative hypothesis of this paper, certain regions may be converging over time even if divergence is apparent in aggregate. The next task is to investigate whether there are particular clusters of regions with convergence characteristics and to identify any divergent regions.

4.2 Disaggregated Estimation

This section presents and discusses findings from the panel convergence clustering algorithm, which helps separate the hypothesis of panel divergence from that of sub-panel convergence.

4.2.1 Initial Application and Testing

A first application of the convergence clustering algorithm yields an initial set of results. However, one consequence of setting c = 0 is that it tends to raise the chance of finding more clusters than the true number (Phillips and Sul, 2009). Therefore, and for robustness, log-t tests are conducted across the originally identified clusters to assess whether they may be merged into larger clusters. If clusters can be merged into a single cluster, which is sufficiently homogenous in terms of convergence characteristics, then the final and initial cluster classifications will differ in terms of membership.[20]

Table 4. Sub-Panel Log-t Convergence Tests for Lending Growth

Initial Classification		Tests of Clusters Merging			Final Classification	
Cluster 1 [8]	0.88	Cluster 1 + 2	Cluster 1 + 3	Cluster 1 + 4	Cluster 1 [15]	-0.39
	(0.42)	-0.39	-0.31**	-1.42***		(0.37)
		(0.37)	(0.17)	(0.35)		

Cluster 2 [7]	0.01 (0.12)	Cluster 2 + 3 -0.62*** (0.13)	Cluster 2 + 4 -2.10*** (0.17)	Cluster 2 [5]	-3.36*** (0.18)
Cluster 3 [2]	-1.74* (1.33)		Cluster 3 + 4 -3.36*** (0.17)		
Cluster 4 [3]	-2.84*** (0.27)				

Source: See source in Table 1.
Note: The number of regions in each cluster is indicated in square brackets []. Point estimates for ϕ_1 from equation (7) are reported along with Newey-West heteroscedasticity and autocorrelation robust standard errors (in parentheses). ***,** and * indicate rejection of the null hypothesis of convergence at 1%, 5% and 10% significance levels respectively.

Table 5. Sub-Panel Log-t Convergence Tests for Lending Spread

Initial Classification		Tests of Cluster Merging	Final Classification	
Cluster 1 [18]	0.07 (0.02)	Cluster 1 + 2 -0.43*** (0.01)	Cluster 1 [18]	0.07 (0.02)
Cluster 2 [2]	-2.30*** (0.46)		Cluster 2 [2]	-2.30*** (0.46)

Source: See source in Table 1.
Note: See note in Table 4.

Table 6. Sub-Panel Log-t Convergence Tests for Loan-Deposit Premium

Initial Classification		Tests of Cluster Merging		Final Classification	
Cluster 1 [6]	0.89 (0.05)	Cluster 1 + 2 0.36 (0.04)	Cluster 1 + 3 -0.57*** (0.01)	Cluster 1 [11]	0.38 (0.05)
Cluster 2 [5]	0.05 (0.03)		Cluster 2 + 3 -0.60*** (0.02)	Cluster 2 [9]	-0.67*** (0.01)
Cluster 3 [9]	-0.67*** (0.01)				

Source: See source in Table 1.
Note: See note in Table 4.

Tables 4-6 contain three panels. The left panel contains the initial cluster classifications following a first application of the clustering algorithm. The first column lists the clusters identified with the number of regions in square brackets; the second column provides for each cluster the estimates for ϕ_1, from which the speed of convergence may be inferred. The middle panel contains the outcomes from tests of clusters merging. That is, clusters are merged sequentially and the log-t test is conducted for each of the merged clusters. There are in total three K x (K-1)/2 unique cluster combinations, where K is the number of clusters originally identified. Final cluster classifications are determined from the outcomes of these tests.[21]

For lending growth there are four initial clusters (see Table 4). The combination of clusters 1 and 2 is only weakly convergent because the negative point estimate is not significantly less than zero. The null of convergence is rejected for all other cluster combinations. Therefore, clusters 1 and 2 are merged into a final (weakly) convergent cluster, whereas clusters 3 and 4 are combined to form a single divergent cluster. For the lending spread there are only two original clusters, which form a divergent cluster when merged; therefore, original and final classifications are unchanged (see Table 5). For the loan-deposit premium there are three original clusters (see Table 6). It is not possible to reject the null of convergence when clusters 1 and 2 are merged; however, the null is rejected when the other clusters are merged, resulting in two final clusters.

4.2.2 Discussion of Final Cluster Classifications

The results point to the presence of a single convergent cluster and a single divergent cluster for lending growth, lending spreads and loan-deposit premia. Therefore, the null hypothesis of panel convergence may be rejected in favour of the alternative hypothesis of sub-panel convergence. Our conclusions, which are based on speed of convergence estimates reported in Tables 4-6, are unchanged if instead we apply robust IRLS estimation or control for the crisis effect using dummy variables.[22] The final cluster memberships are summarised in Table A5 (as in the Appendix).

Final cluster membership is drawn from across Italy. Membership of the convergent cluster for lending growth, lending spreads and loan-deposit premia contains northern and southern regions, and all regions from the central regions, except Lazio for the premium indicator. There is a series of neighbouring regions that is always classified as convergent: Emilia-Romagna, Toscana, Umbria, Marche, Abruzzo, Molise, Campania, Puglia, Basilicata and Sicilia. Contrarily, membership of the divergent clusters is drawn almost entirely from non-central regions. Interestingly, regions at the Italian periphery tend to be associated with divergence to a greater extent than those geographically more central regions. The divergent lending growth cluster includes Piemonte, Valle d'Aosta, Trentino-Alto Adige, Calabria and Sardegna.[23] The divergent lending spread cluster includes Friuli-Venezia Giulia and Sardegna. The divergent loan-deposit premium cluster includes regions with borders to France, Switzerland, Austria and Slovenia, as well as the regions Lazio, Calabria and Sardegna. Therefore, our results suggest that a region's remoteness with respect to the Italian centre-space may be a crucial factor related to divergence. Spatial clustering of cluster membership is confirmed formally by Geary's c spatial autocorrelation test statistics, which are equal to 0.385 (p-value = 0.001), 0.134 (p-value = 0.006) and 0.632 (p-value of 0.003) for bank lending growth, lending spread, and the loan-deposit premia memberships.[24] Thus, the null hypothesis of no spatial autocorrelation in final cluster membership is rejected in all cases at the 1% level of significance.

Description within clusters is broadly in line with statistics at a national level and reported in Table 1. Our interpretation is that regions in the convergent cluster are gradually moving towards an environment of moderate lending growth, availability of loans, and loan-deposit premia, as it is evident from the corresponding cross-sectional standard deviations for these measures (see Figures A1-A3 in the Appendix). The declining loan-deposit premia points to a moderation in risk premia and lending mark-ups. The existence of a single convergent cluster is suggestive of conditional sigma convergence in lending conditions in the sense that the convergence process involves some regions and not others. This evidence for sub-panel convergence corroborates the earlier findings on Italian credit markets by Dow et al. (2012). These findings are more in line with heterodox theories than conventional neoclassical predictions, whereby capital flows should enable more remote, less developed regions to catch-up with more affluent regions.

4.2.3 Temporal Evolution of the Speed of Convergence

This sub-section extends on the previous analysis by using the final cluster classifications to estimate the temporal speed of convergence across the sample for different centre and periphery combinations. In this case, ‘centre-space’ refers to those regions in the convergent cluster, which are geographically more central, whereas ‘periphery’ refers to the divergent regions, which are spatial located in more remote parts of northern and southern Italy. To proceed, we add sequentially to the convergent clusters the divergent northern and southern regions, thus enabling estimation of the temporal speed of divergence of periphery regions with respect to convergent regions.

Two different approaches are considered when classifying regions in the centre-space. First, the average lending growth, lending spread and loan-deposit premium is computed across convergent regions according to cluster 1 membership. Under this approach, the corresponding log-t estimation is based on the normalised cross-sectional variance ratio of the average conditions in the centre-space and in periphery regions as it is indicated in Table 7. The corresponding speed of convergence estimates for lending growth, lending spread and loan-deposit premium indicators are summarised in columns (1), (3) and (5). Second, because there is variation within the Italian centre-space, log-t estimation is based on the normalised cross-sectional variance ratio of conditions in all cluster 1 regions and periphery regions. The corresponding speed of convergence estimates under the second approach are reported in columns (2), (4) and (6) of Table 7. The key difference is that we treat the centre-space as a single region under the first approach and as a set of regions under the second approach.

Table 7 Centre-Space and Periphery Convergence Tests

	Lending Growth		Lending Spread		Loan-Deposit Premium	
Centre-Space and Periphery Combinations	(1)	(2)	(3)	(4)	(5)	(6)
Centre and Periphery [Northern + Southern]	-3.66***	-1.49***	-5.73***	-0.43***	-0.73***	-0.49***
	(0.13)	(0.25)	(0.10)	(0.01)	(0.01)	(0.01)
Centre and Periphery [Northern]	-3.78***	-1.04***	-4.97***	-0.17***	-0.50***	-0.36***
	(0.20)	(0.12)	(0.10)	(0.02)	(0.04)	(0.01)
Centre and Periphery [Southern]	-4.41***	-1.06***	-8.43***	-0.25***	-1.47***	-0.21***
	(0.27)	(0.43)	(0.70)	(0.01)	(0.02)	(0.01)
ϕ_1_Southern/ϕ_1_Northern	1.16	1.02	1.70	1.47	2.94	0.58

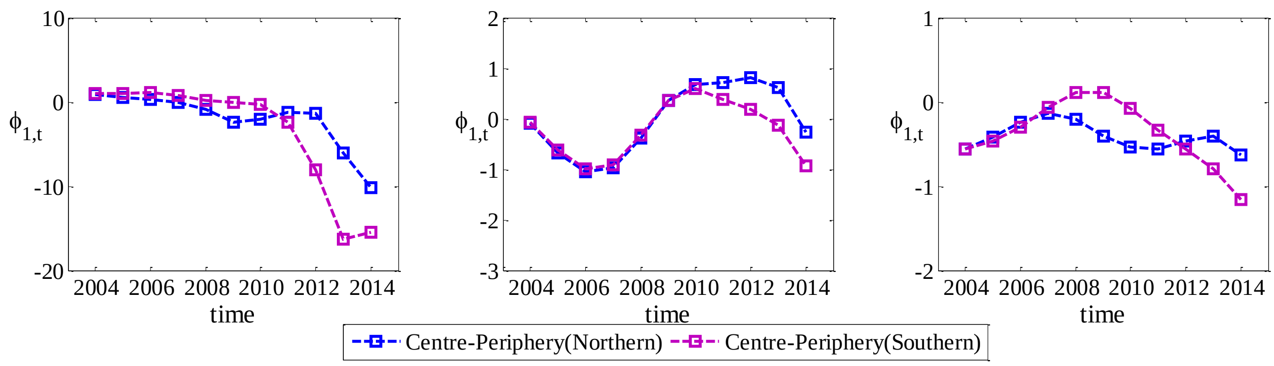
Source: See source in Table 1.

Note: Estimates and standard errors (in parentheses) correspond to parameter ϕ_1 in equation (7) upon the enlargement of the convergent cluster to include the periphery regions. Newey-West heteroscedasticity and autocorrelation robust standard errors are reported in parentheses. *** indicates rejection of the null hypothesis of convergence at the 1% significance level.

Estimates and standard errors (in parentheses) in Table 7 correspond to parameter ϕ_1 in equation (7) upon the enlargement of the convergent cluster to include the periphery regions. For lending growth the periphery regions are Piemonte, Valle d'Aosta, Trentino-Alto Adige (Northern), Calabria and Sardegna (Southern); for the lending spread the periphery regions are Friuli-Venezia Giulia (Northern) and Sardegna (Southern); for the loan-deposit premium the periphery regions are Piemonte, Lombardia, Liguria, Trentino-Alto Adige, Veneto, Friuli-Venezia Giulia (Northern), Calabria and Sardegna (Southern). Centre-space regions are members of cluster 1 for lending growth, spread and premium. As expected the estimates of the speed of convergence are negative for all centre-periphery combinations, which is indicative of divergence in lending conditions of periphery regions with respect to the Italian centre-space. This is the case for all the indicators and under both approaches to classifying the Italian centre-space.[25] However, the point estimates for the centre-southern periphery combination tend to be more negative than for the centre-northern periphery combination, which suggests an asymmetry in the divergence process. The ratio of the speed of convergence for southern and northern periphery regions, $\phi_{1\_South}/\phi_{1\_North}$, in most cases exceeds unity and suggests that the speed of divergence in the south may be up to three times faster than in the north.

As a further step in the analysis, equation (8) is estimated for various centre-periphery combinations to investigate changes in the speed of convergence across the trimmed sample.[26] These findings are not dissimilar to those presented in Figures 1-3 for all Italian regions; the speed of convergence is negative for most periods, and there is a downward trend over recent years (see Figures 4-6). Following the onset of the global economic and financial crisis, the speed of divergence with respect to the Italian centre-space has been greater for southern periphery regions and notably so for bank lending growth. The speed of convergence for lending growth has become significantly negative from 2008 for the centre-northern periphery combination and from 2009 for the centre-southern periphery combination.

Figures 4-6. Temporal evolution of the speed of convergence for centre-space and periphery (northern/southern) combinations for bank lending growth (left), lending spread (centre) and loan-deposit premium (right).



Source: See source in Table 1.

5. Discussion

To synthesise understanding of convergence in a robust way, probit and logit estimations are conducted using a binary dependent variable, which takes a value of unity if any two regions are always in the convergent cluster for lending growth, spread and premium, or zero otherwise. Various geographic, financial, economic, demographic and policy explanatory variables are drawn from the literature. The results from this exercise are summarised in Table A6 (as in the Appendix).

In terms of geography, we consider the great-circle distance between regions in kilometres and a binary variable, which indicates whether regions are part of the Italian extrema or not. The extrema are defined as those regions with borders to neighbouring countries (Valle d'Aosta, Piemonte, Liguria, Trentino-Alto Adige Fruili-Venezia Giulia, Veneto and Lombardia), the southernmost regions (Calabria, Basilicata and Puglia) and islands (Sardegna and Sicilia). Evidently, distance and geographic remoteness from the Italian centre-space are both negatively and significantly related to the probability of convergence. This may also be related to the productivity puzzle, in that proximity to economic activities – financial sector or otherwise – may reduce costs associated with gathering information about new technologies, markets and competitors (Faini et al., 1993 p. 167).

Differences in liquidity preference of banks seem to matter more than differences in physical access to bank branches. The latter are insignificant, whereas the difference in bank liquidity preference – measured in terms of the pre-crisis (2007) current account deposits divided by total consumer lending – is always highly significant and negatively related to the probability of convergence. This may be related to Post-Keynesian liquidity preference theory, as in Dow (1992, 1999), and empirical findings elsewhere. For example, both the Crocco et al. (2014) study and our study point to a differentiation of banking strategy, whereby banks in more developed regions tend to lend less to agents in more remote, under-developed regions. This may reflect a preference for liquidity arising from economic uncertainty and perceived customer risk; thus, the 'financially-defensive behaviour' of banks may be an important part of the over and under-extension of regional credit (Dow, 1992 p. 662).

Interestingly the coefficients on the sum of the pre-crisis (2007) regional GDP-per-capita and its square indicate that regions with very low or very high pre-crisis income levels are less likely to be convergent across our sample, which may reflect underlying differences in the risk-profile of agents (D'Amico et al., 1990). Additionally, coefficients on the sum of pre-crisis (2007) regional lending-to-GDP and its square indicate that regional-pairs with moderate levels of financialisation, at least in terms of consumer lending relative to income, are more likely to be convergent. Thus, the growing north-south divergence may reflect regional financialisation and within that the tendency towards relatively low (high) saving and high (low) expenditure in more (less) economically and financially-developed regions.

This may be reinforced by interregional financial flows and higher expectations about economic and financial prospects in northern regions (Chick and Dow, 1988).

Accumulation of years of credit-driven growth, reinforced by monetary balance sheet and credit channels, may explain why certain Italian regions, namely those in the north, have generally fared much better following the onset of the crisis in terms of economic fundamentals (see, Kitson et al., 2011, their Figure 6, p. 295). As expected, the income inequality gap, as measured by the absolute difference in regional Gini indices, is negatively related to the probability of convergence. The suggestion here is that agents in the more prosperous regions have been better positioned during the crisis in terms of cash, collateral and income, while they have not faced financing constraints associated with spatial financialisation, inequality and exclusion, which is more prevalent in less developed regions.

Regarding demographic characteristics, there is limited evidence that differences in population growth rates affect regional convergence, as the correctly signed estimate is insignificant. Finally, a dummy variable is included, which takes a value of unity if at least one of the regions has access to European Union (EU) cohesion funds for convergence during 2007-2013 or zero otherwise.[27] The marginal effect of the relevant estimates indicates that funding access increases the probability of convergence by approximately 0.2. Therefore, other factors aside, there is some evidence here that cohesion policy has helped promote financial sector convergence over our sample.

6. Summary and Conclusions

Against the backdrop of theoretical ambiguities and growing concerns of policymakers about macroeconomic and financial instability in an era of financialisation, this paper analyses convergence of Italian bank lending conditions. In this contribution we compile and employ a relatively extensive NUTS-2 level dataset to investigate convergence in regional bank lending growth, lending spreads and loan-deposit premia over the period 1999 to 2014. The case of Italy is particularly interesting because over more recent years the prospect of convergence seems even further out of sight, despite the implementation of various policies designed to reduce the longstanding north-south divide. This paper extends the methodology of Phillips and Sul (2007), which permits powerful modelling of long-run equilibria within a heterogeneous panel data context, to investigate further both the spatial scale and temporal evolution of convergence.

This paper's empirical strategy proves insightful since it identifies situations where lending conditions are converging across certain regions even if divergence is detected overall, thus corroborating previous findings of Dow et al. (2012). Furthermore, this paper identifies a convergent cluster of regions, which are more central geographically than regions in the divergent cluster, while the speed of divergence has increased notably for southern regions since the onset of the global economic and financial crisis. We are also able to link convergence with proximity to the Italian centre-space, regional financialisation, bank liquidity preference, the distribution of income and access to EU cohesion funds. In this respect, our study goes above and beyond the previous literature by providing new results, which suggest that the evolution of regional financial behaviour has become an important factor related to the growing Italian north-south divide.

In conclusion this paper finds a significant relationship between regional financialisation and financial systems convergence. If financial flows within Italy cannot be relied upon by themselves to promote interregional convergence, and if instead they have exacerbated longstanding disparities in Italy, then some rebalancing is required in the policy response. Our findings suggest that policymakers should continue reducing informational problems in the south and associated inefficiencies, while putting in place structures to more effectively moderate lending behaviour and promoting further cohesion across and within countries.

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Appendix

Table A1. Temporal Speed of Convergence

	Lending Growth			Lending Spread			Loan-Deposit Premium		
Year	θ	SE(θ)	p-value	θ	SE(θ)	p-value	θ	SE(θ)	p-value
ϕ_1	0.95	(0.02)	[1.00]	-0.09	(0.03)	[0.00]	-0.57	(0.01)	[0.00]
$\pi_{1,2005}$	-0.34	(0.02)	[1.00]	-0.56	(0.05)	[0.00]	0.01	(0.01)	[0.00]
$\pi_{1,2006}$	-0.58	(0.03)	[1.00]	-0.95	(0.03)	[0.00]	0.09	(0.01)	[0.00]
$\pi_{1,2007}$	-1.21	(0.05)	[0.00]	-0.88	(0.03)	[0.00]	0.19	(0.01)	[0.00]
$\pi_{1,2008}$	-2.20	(0.06)	[0.00]	-0.34	(0.05)	[0.00]	0.20	(0.01)	[0.00]
$\pi_{1,2009}$	-3.14	(0.02)	[0.00]	0.28	(0.04)	[1.00]	0.12	(0.01)	[0.00]
$\pi_{1,2010}$	-2.75	(0.03)	[0.00]	0.35	(0.03)	[1.00]	0.01	(0.01)	[0.00]
$\pi_{1,2011}$	-2.70	(0.03)	[0.00]	0.01	(0.04)	[0.00]	-0.07	(0.01)	[0.00]
$\pi_{1,2012}$	-3.74	(0.25)	[0.00]	-0.25	(0.03)	[0.00]	-0.06	(0.01)	[0.00]
$\pi_{1,2013}$	-13.81	(0.47)	[0.00]	-0.50	(0.04)	[0.00]	-0.08	(0.02)	[0.00]
$\pi_{1,2014}$	-13.32	(0.35)	[0.00]	-1.13	(0.05)	[0.00]	-0.28	(0.02)	[0.00]

Source: See source in Table 1.

Note: Parameter θ for year 2004 corresponds to parameter ϕ_1 in equation (8), estimated using ordinary least squares. Parameters θ for years 2005-2014 correspond to the dummy variable interaction terms $\pi_{1,\tau}$. Newey-West heteroscedasticity and autocorrelation robust standard errors are reported (in parentheses). The p-value is reported in square brackets [] for a one-tailed t-test with a null hypothesis of convergence.

Table A2. Temporal Speed of Convergence of Centre-Space and Periphery Combinations – Lending Growth

	Centre and Periphery			Centre and Periphery(North)			Centre and Periphery(South)		
Year	θ	SE(θ)	p-value	θ	SE(θ)	p-value	θ	SE(θ)	p-value
ϕ_1	0.95	(0.02)	[1.00]	0.83	(0.02)	[1.00]	0.99	(0.01)	[1.00]
$\pi_{1,2005}$	-0.34	(0.02)	[1.00]	-0.31	(0.02)	[1.00]	0.03	(0.01)	[1.00]
$\pi_{1,2006}$	-0.58	(0.03)	[1.00]	-0.51	(0.02)	[1.00]	0.17	(0.01)	[1.00]
$\pi_{1,2007}$	-1.21	(0.05)	[0.00]	-0.87	(0.04)	[0.10]	-0.27	(0.04)	[1.00]
$\pi_{1,2008}$	-2.20	(0.06)	[0.00]	-1.76	(0.07)	[0.00]	-0.84	(0.02)	[1.00]
$\pi_{1,2009}$	-3.14	(0.02)	[0.00]	-3.21	(0.03)	[0.00]	-1.02	(0.01)	[0.00]
$\pi_{1,2010}$	-2.75	(0.03)	[0.00]	-2.84	(0.04)	[0.00]	-1.34	(0.05)	[0.00]
$\pi_{1,2011}$	-2.70	(0.03)	[0.00]	-2.12	(0.03)	[0.00]	-3.46	(0.17)	[0.00]
$\pi_{1,2012}$	-3.74	(0.25)	[0.00]	-2.24	(0.09)	[0.00]	-8.99	(0.39)	[0.00]
$\pi_{1,2013}$	-13.81	(0.47)	[0.00]	-6.85	(0.40)	[0.00]	-17.25	(0.32)	[0.00]
$\pi_{1,2014}$	-13.32	(0.35)	[0.00]	-11.03	(0.16)	[0.00]	-16.41	(0.46)	[0.00]

Source: See source in Table 1.

Note: See note in Table A1.

Table A3. Temporal Speed of Convergence of Centre-Space and Periphery Combinations – Lending Spread

	Centre and Periphery			Centre and Periphery(North)			Centre and Periphery(South)		
Year	θ	SE(θ)	p-value	θ	SE(θ)	p-value	θ	SE(θ)	p-value
ϕ_1	-0.09	(0.03)	[0.00]	-0.09	(0.03)	[0.00]	-0.07	(0.03)	[0.00]
$\pi_{1,2005}$	-0.56	(0.05)	[0.00]	-0.58	(0.05)	[0.00]	-0.54	(0.04)	[0.00]
$\pi_{1,2006}$	-0.95	(0.03)	[0.00]	-0.95	(0.03)	[0.00]	-0.92	(0.03)	[0.00]
$\pi_{1,2007}$	-0.88	(0.03)	[0.00]	-0.88	(0.03)	[0.00]	-0.84	(0.03)	[0.00]
$\pi_{1,2008}$	-0.34	(0.05)	[0.00]	-0.29	(0.05)	[0.00]	-0.25	(0.05)	[0.00]
$\pi_{1,2009}$	0.28	(0.04)	[1.00]	0.45	(0.05)	[1.00]	0.44	(0.04)	[1.00]
$\pi_{1,2010}$	0.35	(0.03)	[1.00]	0.76	(0.03)	[1.00]	0.66	(0.03)	[1.00]
$\pi_{1,2011}$	0.01	(0.04)	[0.00]	0.80	(0.03)	[1.00]	0.46	(0.03)	[1.00]
$\pi_{1,2012}$	-0.25	(0.03)	[0.00]	0.91	(0.05)	[1.00]	0.26	(0.03)	[1.00]
$\pi_{1,2013}$	-0.50	(0.04)	[0.00]	0.70	(0.05)	[1.00]	-0.06	(0.04)	[0.00]

$\pi_{1,2014}$	-1.13	(0.05)	[0.00]	-0.18	(0.06)	[0.00]	-0.86	(0.05)	[0.00]

Source: See source in Table 1.
Note: See note in Table A1

Table A4. Temporal Speed of Convergence of Centre-Space and Periphery Combinations – Loan-Deposit Premium

	Centre and Periphery			Centre and Periphery(North)			Centre and Periphery(South)		
Year	θ	SE(θ)	p-value	θ	SE(θ)	p-value	θ	SE(θ)	p-value
ϕ_1	-0.61	(0.00)	[0.00]	-0.56	(0.01)	[0.00]	-0.56	(0.00)	[0.00]
$\pi_{1,2005}$	0.04	(0.00)	[0.00]	0.14	(0.01)	[0.00]	0.09	(0.01)	[0.00]
$\pi_{1,2006}$	0.15	(0.01)	[0.00]	0.32	(0.01)	[0.00]	0.26	(0.02)	[0.00]
$\pi_{1,2007}$	0.27	(0.00)	[0.00]	0.43	(0.00)	[0.00]	0.49	(0.00)	[0.00]
$\pi_{1,2008}$	0.28	(0.01)	[0.00]	0.36	(0.01)	[0.00]	0.67	(0.01)	[1.00]
$\pi_{1,2009}$	0.16	(0.01)	[0.00]	0.15	(0.01)	[0.00]	0.67	(0.01)	[1.00]
$\pi_{1,2010}$	0.05	(0.01)	[0.00]	0.02	(0.01)	[0.00]	0.48	(0.02)	[0.00]
$\pi_{1,2011}$	-0.00	(0.01)	[0.00]	-0.00	(0.01)	[0.00]	0.23	(0.02)	[0.00]
$\pi_{1,2012}$	0.01	(0.00)	[0.00]	0.10	(0.01)	[0.00]	-0.00	(0.01)	[0.00]
$\pi_{1,2013}$	-0.04	(0.01)	[0.00]	0.15	(0.01)	[0.00]	-0.23	(0.02)	[0.00]
$\pi_{1,2014}$	-0.27	(0.01)	[0.00]	-0.07	(0.01)	[0.00]	-0.60	(0.01)	[0.00]

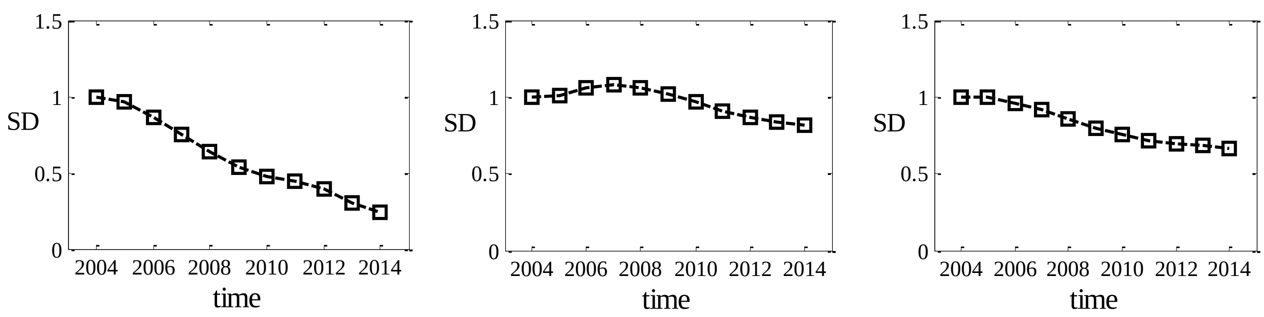
Source: See source in Table 1.
Note: See note in Table A1.

Table A5. Final Cluster Membership

Cluster Membership	Conclusion
Lending Growth	
Cluster 1: Lombardia, Liguria, Veneto, Friuli-Venezia, Emilia-Romagna, Toscana, Umbria, Marche, Lazio, Abruzzo, Molise, Campania, Puglia, Basilicata, Sicilia	Convergent
Cluster 2: Piemonte, Valle d'Aosta, Trentino-Alto, Calabria, Sardegna	Divergent
Lending Spread	
Cluster 1: Piemonte, Valle d'Aosta, Lombardia, Liguria, Trentino-Alto, Veneto, Emilia-Romagna, Toscana, Umbria, Marche, Lazio, Abruzzo, Molise, Campania, Puglia, Basilicata, Calabria, Sicilia	Convergent
Cluster 2: Friuli-Venezia, Sardegna	Divergent
Loan-Deposit Premium	
Cluster 1: Valle d'Aosta, Emilia-Romagna, Toscana, Umbria, Marche, Abruzzo, Molise, Campania, Puglia, Basilicata, Sicilia	Convergent
Cluster 2: Piemonte, Lombardia, Liguria, Trentino-Alto Veneto, Friuli-Venezia, Lazio, Calabria, Sardegna	Divergent

Source: See source in Table 1.

Figures A1-A3. Normalised standard deviations (SD) of convergent clusters for lending growth, lending spread and loan-deposit premium. Standard deviations are normalised by the first observation in the trimmed sample.



Source: See source in Table 1.

Table A6. Convergent Cluster Membership – Evidence from Probit and Logit Estimations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Distance	-0.002**	-0.003**	-0.002*	-0.003*	-0.002**	-0.005**	-0.004***	-0.007***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)
Extrema	-1.195***	-2.201***	-1.272***	-2.309***	-1.137***	-2.083***	-1.346***	-2.444***
	(0.314)	(0.635)	(0.357)	(0.712)	(0.357)	(0.698)	(0.477)	(0.919)
Difference in Branches			0.463	0.997	1.777*	3.341*	0.947	1.567
			(0.651)	(1.150)	(0.982)	(1.717)	(1.482)	(2.848)
Difference in Liquidity Preference			-2.415***	-4.095***	-2.288***	-3.865***	-2.330***	-4.004***
			(0.499)	(0.895)	(0.518)	(0.910)	(0.778)	(1.411)
Loans/GDP (%)			-0.069***	-0.121***	0.325*	0.597*	0.442**	0.790**
			(0.025)	(0.044)	(0.181)	(0.308)	(0.203)	(0.351)
Loans/GDP x Loans/GDP (%)					-0.005**	-0.008**	-0.005**	-0.008**
					(0.002)	(0.004)	(0.002)	(0.004)
GDP-per-capita (PPS)							0.817***	1.454**
							(0.307)	(0.571)
GDP-per-capita x GDP-per-capita (PPS)							-0.009***	-0.015***
							(0.003)	(0.006)
Difference in GINI Index							-0.235**	-0.426**
							(0.116)	(0.211)
Difference in Population Growth (%)							-0.043	-0.081
							(0.045)	(0.080)
Cohesion Funds							1.446***	2.628**
							(0.522)	(1.048)
Pseudo R^2	0.161	0.161	0.306	0.307	0.324	0.327	0.516	0.512
Pseudo LL	-87.259	-87.259	-72.148	-72.131	-70.27	-70.037	-50.361	-50.716
Model p-value	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
N	190	190	190	190	190	190	190	190

Source: Authors' own computation. Data on the number of bank branches, household loans, current account deposits are from Statistical Bulletin; nominal GDP, GDP-per-capita PPS (purchasing power standards) and population growth data are from Eurostat; GINI index data are from ISTAT. The difference in bank branches, liquidity preference, nominal loans/GDP, nominal GDP, GDP-per-capita, difference in GINI indices is based on pre-crisis data for the year 2007. The population growth differential is computed over the period 2004-2014.

Notes: Probit estimates are reported in columns (1), (3), (5) and (7); logit estimates are reported in columns (2), (4), (6) and (8). The pseudo R-squared (Pseudo R^2), pseudo log-likelihood (Pseudo LL), p-value from a joint test of significance of the slope parameters in square brackets [] and sample-size for estimation (N) are reported. The constant term is included in all regressions, but not presented for brevity. Heteroscedasticity-robust standard errors are reported (in parentheses). ***,** and * indicate statistical significance at 1%, 5% and 10% significance levels respectively.

Endnotes

[1] The authors are grateful to three anonymous referees for their useful comments, which have helped to improve the paper. Any remaining errors are the sole responsibility of the authors.

[2] For example, Martin and Minns (1995) find that UK pension funds are mainly channelled into investments via institutions headed in London and surrounding areas; however, little of the money trickles down to the other regions to finance capital investment or promote business expansion. Rodriguez-Fuentes (1998) analyses the relationship between Spanish regional credit growth and GDP-per-capita over the period 1985-1993; the negative association is indicative of a catching-up process, i.e. less developed regions experience higher lending growth, although the relationship reverses during crises. However, the relationship is assumed to be constant within subsamples, regions and across sectors. Crocco et al. (2014) conduct another aggregated analysis and show over the period 1999-2008 that Brazilian regional credit availability depends on the distance from centralised financial markets, the distribution of income, physical access to banks and measures of liquidity preference, although their contribution focuses on credit access rather than convergence. Dow et al. (2012) apply unit root tests to investigate stationarity of Italian regional interest rate spreads over the period 1998-2008. The empirical evidence uncovered in this study confirms the proposition that "overcentralisation of the financial system disadvantages peripheral regions, and, second, a local financial infrastructure characterised by local and regional-based banks is better for those regions" (p. 894).

[3] In the Nomenclature of Territorial Units for Statistics (NUTS), there are three levels for Italy; these correspond to regional groupings (NUTS-1), regions (NUTS-2) and provinces (NUTS-3). Italy is divided into twenty NUTS-2 regions, which represent the first-level administrative divisions of the country.

[4] Faini et al. (1993), and relevant literature therein, also argue, and provide relevant empirical evidence, for financial policies in view of the productivity puzzle (which is due to the financial sector's problems that are different and more severe from the rest of Italy's regions); in effect finance in the South of Italy is inefficient in comparison to the rest of the country. Also informational asymmetries, which "may result in too much money being invested in high risk projects and too little in safe projects" (Faini et al., op. cit., p. 187) are highlighted in the case of the less developed regions in Italy. In addition, government failure is also held responsible for the poor performance of southern Italy. In general terms, Faini et al. (op. cit.) suggest that "financial intermediaries' operating costs are higher in the South, while productivity, profits and own capital are lower" (p. 197). In effect the Faini et al. (op. cit.) contribution is from the point of view of 'financial liberalisation' rather than from 'regional financialisation', the focus of our contribution.

[5] Rughoo and Sarantis (2014) and Matousek et al. (2015) employ the Phillips and Sul (2007) methodology to investigate international financial convergence between 2003-2011 and 2005-2012 respectively. However, the focus of these studies is on banking integration and efficiency at a country level, rather than on regional financial-sector accumulation. As to why the Phillips Sul (op. cit.) method has not been utilised so far in the financialisation literature, this is an interesting question. The reason may very well be that the method is a relatively recent development, but more importantly it may be that the focus of the relevant literature is such that this method has not been helpful. We would argue, though, as we do in the main text of this contribution that the Phillips Sul (op. cit.) method focuses on the speed of convergence, which can change over time; this is clearly, and in our view, an important consideration in the case of Italy.

[6] Simulations indicate that the log-t test works well even for moderately small sample-sizes that are common in applied work (Phillips and Sul, 2007 p. 1812).

[7] A battery of panel unit root tests suggests that over the sample period bank lending conditions considered in this paper are either trend stationary (lending growth) or stochastic nonstationary processes (lending spread and premium). However, the log-t test does not rely on any particular assumptions about trend stationarity or stochastic nonstationary (Phillips and Sul, 2007 p. 1773).

[8] Phillips and Sul (2007) model the regional transition coefficients as follows:

$$\delta_{\mathrm{i,t}} = \delta_{\mathrm{i}} + \frac{\sigma_{\mathrm{i}}\xi_{\mathrm{i,t}}}{\mathrm{L(t)t}^{\alpha}}$$

where δ_i is a constant; L(t) is a slowly-moving function of time, t; stochastic term $\xi_{i,t}$ is iid(0,1), scaled by parameter σ_i, and may be weakly dependent over time. Parameter, α, governs the rate at which the cross-sectional variation decays to zero over time. The inclusion of L(t) ensures over time that $\delta_{i,t} = \delta_i$ even if $\alpha = 0$.

[9] We set the value of lambda to 1,600, which is the standard calibration for quarterly data.

[10] There are as many dummy variable interaction terms as there are years in the trimmed sample less one to avoid the dummy-variables trap.

[11] Phillips and Sul (2007) suggest setting c = 0 when T is small to ensure that it is highly conservative.

[12] The short-term lending rate is based on loans with duration of up to one year and the long-term rate is based on loans with duration of more than one year.

[13] The deposit rate is payable on current accounts. The lending rate corresponds to matched and revocable loans.

[14] For each variable of interest and region we reject the null hypothesis of a seasonal unit root at 5% and 10 % significance levels. These results are not reported to conserve space, but are available from the authors upon request.

[15] For instance, using the popular X12-ARIMA algorithm and the seasonality F-tests therein, we obtain a correlation between the unadjusted and seasonally-adjusted series of 0.98. Furthermore, convergence test outcomes are almost identical if adjusted data for Sicilia are used instead; importantly, our main conclusions are unchanged.

[16] Bank lending data are distributed by customer location (region) and segment of economic activity. For further details about the construction and reporting of data see the Methodological Appendix of the Bank of Italy's Statistical Bulletin, which is available at: http://www.bancaditalia.it/pubblicazioni/bollettino-statistico/.

[17] Cluster statistics reported in the table correspond to results obtained from the clustering algorithm of Phillips and Sul (2007), and discussed in section 4.2.2.

[18] See Table A1 in the Appendix for estimation output corresponding to the temporal speed of convergence parameters.

[19] The downward trend in convergence for consumer lending growth is also apparent for non-financial firms and proprietors, especially during the final years in the sample. However, the divergence over these years is relatively severe for consumer lending growth. Speed of convergence estimates for non-financial firms become statistically less than zero from 2009; for proprietors, the speed of convergence is statistically less than zero for all but one year in the sample. These results are not illustrated graphically for brevity, but all results referred to in this contribution are available from the authors upon request.

[20] The clustering algorithm of Phillips and Sul (2007) is based on least squares estimation; however, we also verify the conclusions reached using iteratively re-weighted least squares and dummy variables interaction estimations.

[21] For example, three clusters are initially identified for the loan-deposit premium. To test merging of clusters, cluster 1 and 2 are first combined; if the resulting merged cluster exhibits convergence, i.e. $\varphi_1 \geq 0$, then the merged cluster may be classified as a convergent cluster. We then try merging the other original clusters and re-test for convergence. Since only clusters 1 and 2 can be combined to form a convergent cluster, we have two final clusters from cluster 1 + cluster 2. What remains is cluster 3, which is classified as the divergent cluster.

[22] The speed of convergence is never (always) significantly less than zero for those regions classified as convergent (divergent). These results are not reported for brevity. All results referred to in the main text are available from the authors upon request.

[23] If the regional consumer price index is used to deflate the nominal bank lending data, a measure of real lending growth may be constructed, for which we obtain similar results, albeit with minor changes to cluster membership.

[24] The inverse spatial-weighting matrix is constructed using a binary indicator for whether regions share a border.

[25] We note that the speed of divergence is greater when the centre-space is measured as the regional average of cluster 1 members; this may reflect the greater weight of divergent periphery regions in the relative transition coefficient.

[26] See Table A2-A4 in the Appendix for estimation output corresponding to the temporal speed of convergence parameters.

[27] Our focus is on the main beneficiaries of EU cohesion funds, which are the regions with low historic convergence, i.e. Campania, Puglia, Calabria, Sicilia and Basilicata. The convergence objective concerns regions characterised by low levels of GDP and employment, where GDP-per-capita is less than 75% of the EU average between 2000 and 2002, as detailed at http://ec.europa.eu/regional_policy/sources/docgener/informat/country2009/it_en.pdf.