Convergence or coalescence? Information technology and the reshaping of industry boundaries

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CONVERGENCE OR COALESCEENCE? INFORMATION TECHNOLOGY AND THE RESHAPING OF INDUSTRY BOUNDARIES

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Abstract

The impacts of the evolving information technology (IT) on organisations, markets, industries, and economies have been researched intensively. Aspects studied have included productivity, employment, business value, markets, organisation, and industry structure, to name a few. With the increasing availability of panel data spanning longer periods, it is now possible to study the relatively longer-term effects of IT and its role in industry coalescence and the reshaping of industry boundaries.

This exploratory study develops the novel and less understood concept of industry coalescence by examining the effects of IT on industry profiles and the shifting industry boundaries over the 22-year period from 1980-2002 covering three economic cycles, using both econometric and clustering techniques. Our results point to a strong tendency for several industries such as finance, communications, culture, hospitality, and wholesale and retail to coalesce into a common “service” profile while traditional industries such as agriculture, mining, and manufacturing reflect no such movement.

Keywords: IT Productivity, Industry Convergence, Coalescence.
1 INTRODUCTION AND M otivation

The effects of IT investments on business value and productivity have been well documented. After decades of IT evolution, the continuing widespread diffusion of IT in organisations appears to be having an impact on the structure and definition of industries. A few researchers have argued that the boundaries between some industries have become less distinct and have attributed this phenomenon to how organisations use IT (Hitt 1999; Baily 2000). This paper focuses on the relatively longer-term impacts of IT in reshaping the boundaries between industries. This phenomenon of industry coalescence has not been adequately understood in the past due to a combination of the non-availability of panel data over adequate time periods and the need to go beyond the traditional econometric methods for analyzing the data. This paper attempts to address both these challenges and to provide preliminary evidence for the industry coalescence effect. It also contributes to the conceptual development of the coalescence phenomenon which, we argue, has been confused with convergence concept.

A range of studies have investigated the complex relationships between IT capital investments and productivity (Brynjolfsson and Yang 1996; Dedrick et al. 2003). Some of these have explicitly recognized the significance of the industry effect (Brynjolfsson and Hitt 1996; Brynjolfsson et al. 2002). For instance, Gullickson and Harper (1999) found that the inter-industry effects can be as high as one-third of the variance of the economy-wide productivity. However, these and related studies do not address the changing nature of the industry effect and the extent to which the industries themselves are being transformed over relatively extended time periods covering multiple economic cycles. This is the challenge that we take up in this paper.

One of the more interesting issues to emerge in this context is the dual role played by IT in organisations. Apart from being a type of input capital directly used in the production process, IT can also enable changes in work systems, organisational redesign and new business processes (Bresnahan and Trajtenberg 1995). The important research question now is to understand not just how IT affects productivity, but also how it relates to the transformation of organisations and industries over time. Greenspan (2000) reported that the “new economy” is characterized by a radical transformation leading to productivity acceleration as competitive forces become increasingly intense and new technologies raise the efficiency levels. He linked this phenomenon to the rapid adoption of information technology and pointed out that such structural transformation is conceptual rather than physical. Similarly, Baily (2000) reported that the acceleration of productivity growth is heavily related to use of IT. As well, a substantial proportion of the acceleration is attributable to structural factors.

Several researchers have addressed the question of sector/industry ‘convergence’ over relatively longer time periods. According to Baumol et al. (1994), there are two distinct dimensions of convergence: homogenization and catch-up. Homogenization refers to a reduction in the dispersion (mean reversion) among some set of entities (such as countries, regions, industries, and firms) in terms of some measure of performance such as labour productivity and multifactor productivity (MFP). Catch-up refers to a narrowing of the percentage gap between leading country’s (or industry’s) performance on the variable(s) in question with that of the others in the pertinent set over time.

Bernard and Jones (1996) pointed out that technological choices, through adoption and accumulation, can contribute to convergence of relative output levels and growth rates. They examined the role of sectors in aggregate convergence for 14 OECD countries during 1970-1987 and found that manufacturing sector shows little evidence of either labour productivity or MFP convergence while other sectors, especially services, are driving the aggregate convergence. They concluded that the evolution of technology is an important driving force behind convergence in the OECD economies.

The foregoing suggests that technology in general and IT in particular are beginning to have an impact on industry profiles. An important research question is to understand how IT influences structural
factors over a longer time frame. In other words, is there a relationship between IT and industry transformation? This study of industry boundaries has profound implications for the welfare of the economy and particularly for the design of policy.

In this paper, we report on one of the first attempts to systematically analyse the effects of IT on industry boundaries, drawing on the theory of production economics. In section 2, we present the literature review. We describe our research design and data in section 3. Data description and summary statistics are provided in section 4. Section 5 discusses analyses and results. In conclusion, we evaluate our findings and suggest directions for further research.

2 LITERATURE REVIEW

To understand the dynamics of the IT-induced transformation underway, it is important to highlight both the scope and the speed of the IT revolution. Its roots are indeed very recent, beginning with the widespread introduction of large mainframe computers in the 1950s and '60s, followed by steady advances in computing power that permitted a decrease in their physical size of the computer, and the rapid development of software industries since the 1970s. More recently, the introduction and dramatic growth of inter-organisational networks, the internet, and the world wide web in the 1990s have led us to conjecture that the transformation is closely related to the diffusion of IT in organisations.

The impacts of IT have been studied in variety of ways. The most prominent one is the impact of IT investments on productivity that emerged in the 1980s when Solow (1987) and others argued that there was insufficient evidence to link the massive IT investments to productivity growth. This debate is less relevant today with the widespread consensus that by the late 1990’s, the so-called productivity paradox is not an issue any more and that the productivity gains attributable to IT are real (Brynjolfsson and Hitt 1996). One of the emerging concerns now, given the general-purpose nature and rapid diffusion of IT, has to do with how organisations and industries are being radically transformed.

More recently, there has been a growing focus on how IT can facilitate innovations in business process design resulting in entirely new models of organisation. Brynjolfsson and Hitt (1998 and 2002), Bresnahan (1999) and Drucker (1988) argued that in response to the prices of IT declines over time (for the last 30 years), organisations increased the level of investments such as flexible machinery and skilled workers to complement IT investments. IT investment has been associated with the emergence of modern work practices (Ichniowski et al. 1996), skill-related wage inequality (Autor et al. 1998; Berman et al. 1994), and flexible production (MacDuffie 1995). In the remainder of this section, we organise our discussion into three inter-related categories to analyse the IT impacts on three structural factors: organisational structure, labour market, and industry boundaries.

2.1 IT and Organisational Structure

Brynjolfsson et al. (1994) performed an industry-level study to assess the hypothesis that IT investments are partially responsible for shifting of economic activity to smaller firms. They examined industry-level data on IT capital and various measures of firm size such as number of employees per business unit and number of employees per firm and found evidence that IT investment is significantly associated with subsequent decreases in the average size of firm. They also found that the decreases in firm size are most pronounced a couple of years after the IT investment is made and that IT deployment is correlated with a decrease in the number of employees per business unit and per firm in all sectors.

Gurbaxani and Whang (1991) used the insights of transaction cost economics together with agency theory to discuss the impacts of IT on organisations and markets. They found a negative relationship between IT investments and vertical integration, and then inferred links between IT and various
components of new organisational forms such as the choice between centralized and decentralized authority within or between firms. They concluded that IT can potentially alter the cost of coordinating activity within firms (internal coordination) as well as between firms (external coordination).

Hitt (1999) not only found that IT investments produces higher stock valuations in firms but, more importantly, confirmed that IT is related to the changes to structure of the firm in the form of vertical de-integration and reduction in the size of the firm. Pinsonneault and Kraemer (2002) found IT did play a facilitating role in organisational downsizing. They found that IT was used to facilitate work redesign in a convergent change strategy and to facilitate more significant structural work redesign in strategic reorientation. Other studies looked at different combinations of IT and work practices and found that firms that couple IT investments with decentralized work practices were much more productive than those which do neither (Brynjolfsson and Hitt 1998). They also had a disproportionately positive effect on firm market value (Brynjolfsson et al. 2002).

2.2 IT and employment

Krueger (1993) found that workers who use computers on their job earned 10 to 15 percent higher wages. Autor et al. (1998) studied human capital in the form of increased level of skilled labour in the US economy. They addressed the issue of whether IT investments led to increasing wages and income dispersion by creating groups of haves and have-nots based on whether people have the skills and/or are employed in the appropriate sectors to take advantage of IT advances. They found that increasing use of computers is associated with a greater demand for human capital (such as skilled educated workers) and concluded that computers are complementary to skilled labour. Bresnahan (1999) found that the process of skill upgrading is due to organisational changes related to computerization.

A more rigorous examination revealed a more complex relationship between technology and job content. For example, Falk and Seim (2001) argued the newer machine tools require much less manual dexterity, but they demand computer literacy and perhaps some high-level programming. They found strong connection between high-skilled employment share and the level of investment in IT in the service production process and reported that firms with a higher IT investment to output ratio employ larger fraction of high-skilled workers in the service industries.

2.3 IT and Industry Boundaries

It has been shown that firms’ ability to transform is not confined to certain industries (Hitt and Snir 1999). Baily (2000) has drawn on the work of institutional economists to argue that boundaries of firms and industries are being changed by developments in IT. This arises because the lower transaction costs facilitated by the reduced costs of communication and interaction allow smaller companies to compete over narrow segments of the overall value chain forcing large companies to resort to greater downsizing and outsourcing.

Malone et al. (1987) investigated how advances in IT are affecting firm and market structures. They found that IT innovations led to reduction in coordination costs. This contributed to tighter integration of adjacent steps on the value-added chain through the development of electronic markets and hierarchies leading to flatter organisational and industry structures.

3 RESEARCH DESIGN AND METHODOLOGY

The previous conceptual development in this area has been dominated by the convergence concept, which we argue, is inadequate to understand the dynamics of industry transformation triggered by IT evolution. Homogenization and catch-up which underpin the convergence concept imply that industries adopt very similar transformation paths leading to the narrowing of the differences and
reduction in the variability over time. While this model is theoretically appealing, the evolutionary patterns typically are more chaotic and characterized by some level of homogenization as well as divergence over time (Dietzenbacher et al. 2004). It is this complex phenomenon that we refer to as ‘coalescence’, the focus of this paper.

We divide our analysis into two phases. In the first phase, we focus on the relationship between IT impacts on productivity and the changes in industry effects over three economic cycles. The goal is to observe the association between reduction of variability among industries and the level of IT impacts (in the form of elasticity) using the production function approach. The statistical evaluation of the role of IT impact is hypothesized to have association with the time path and the degree of convergence among industry level outputs. In the second phase, we extend the first phrase by focusing on industry convergence and divergence simultaneously and their relationship with IT capital investment. We investigate the transformation of industry structures overtime using a more exploratory approach, namely a type of clustering technique.

3.1 Phase 1: Convergence Analysis

3.1.1 Method (Productivity Analysis)

The production function approach has been widely used to describe the technical relationship between the inputs and outputs of a production process based on the theory of production economics. The elasticity of capital on output can be compared and tested for significance. We first establish a model to analyse economic impact of IT and the statistical significance of the industry effect over time.

\[ Y = f(K_0, K_1, L; i, c) \]

where \( Y \) represents value-added of a specific industry in a particular economic cycle\(^1\), \( c \); \( i \) represents the possible industry effects; \( K_0 \) stands for non-IT capital stock; and \( K_1 \) stands for IT capital stock; \( L \) is labour input (such as hours worked). As the starting point for this step, we estimate a standard Cobb-Douglas production in log-linear form. The general form of this function is:

\[ \ln Y = \alpha + \beta_0 \ln K_0 + \beta_1 \ln K_1 + \beta_2 \ln L + \gamma_i + \varepsilon \]

where economic cycle \( c \), subscripts are suppressed. There are two approaches to test for the statistical significance of industry effect \( (\gamma_i) \): fixed effects model and random effects model. In the fixed effects models, inference is about means and differences in means. Furthermore, fixed effects model assumes that the coefficients \( \beta \) s (i.e. constant slope) are non-varying across industries. This approach assumes “industry factor” as an explanatory variable to represent the structure of production in the regression equation where these production effects are fixed over time. In random effects models, inferences are about variances. The random effects model allows us to estimate \( \sigma_i^2 \), the variance due to the industry effects. The variance of \( \ln Y \) can be partitioned into two components as \( \sigma_i^2 = \sigma_t^2 + \sigma_c^2 \), where \( \sigma_i^2 \) is the variance due to industries and \( \sigma_c^2 \) is the variance due to error alone. Using estimates of these quantities, one can estimate the proportion of the variance in \( \ln Y \) that is accounted by the industries by calculating the intra-class correlation:

\[ PI = \frac{\sigma_i^2}{\sigma_t^2 + \sigma_c^2} \]

\(^1\) The unit of time measure is expressed in economic cycle.
Large values of $\hat{P_I}$ mean that observations in the same industry tend to be more similar relative to observations in different industries. As such, the intra-class correlation is a measure of the homogeneity of observations in classes (industries).

### 3.1.2 Convergence Hypotheses

Although many studies referred homogenization hypothesis to the reduction of dispersion of productivity level (e.g. Gouyette and Perelman 1997), Lichtenberg (1994) argued that the measures such as “the coefficient of variation” and “mean-reversion” are not sufficient conditions for convergence. Rather, he emphasized that the degree of convergence depends on the relative importance of the random disturbances in determining productivity.

The task here is to fit a separate random industry effects regression model for each economic cycle and then compare the changes of the coefficients of IT capital (i.e. $\beta_I$) and variability of industry ($PI$) for each regression. To show the variability among industries is reduced over economic cycles together with the impact of IT capital is increased over economic cycles, we need to observe:

$$PI_{i,c=1} > PI_{i,c=2} > PI_{i,c=3} \quad \text{and} \quad \beta_{I,c=1} < \beta_{I,c=2} < \beta_{I,c=3}$$

### 3.2 Phase 2: Coalescence Analysis

#### 3.2.1 Method (Cluster Analysis)

Crisp clustering has been probably the most commonly applied clustering method in real life situations. Since the introduction of fuzzy set theory fuzzy clustering concepts have gained increasing attention and have been applied successfully in many research studies. While classic crisp cluster algorithms (e.g. the c-means (Kaufman et al. 1990)) assign each object to one and only one cluster in fuzzy cluster approaches an object generally belongs to more than one cluster simultaneously. The similarity of an object to a cluster is defined by its membership degree: a membership close to ‘1’ indicates that the object is a good representative of the cluster while a membership near ‘0’ shows that the object only remotely belongs to the cluster. This concept makes fuzzy clustering very appropriate in applications with overlapping, poorly separated clusters like in many real life economic situations.

The following example is to describe the evolution from human tellers to ATM in banks. In this simple example, two kinds of investments are considered: Labour and IT investments. A bank that invests more than 50% (of total investments) on labour is assigned to the class HR-CT (Labour-centric) while a bank investing at least 50% on IT is regarded as IT-CT (IT-centric). Obviously there is a discontinuity in the memberships for a bank moving from (50.0% HR-CT & 50.0% IT-CT) to (49.9% HR-CT & 50.1% IT-CT). Although virtually equal, the first situation is fully assigned to the class HR-CT while the second is fully assigned to IT-CT in the case of crisp clustering (see Figure 1).

![Figure 1. Crisp vs. Fuzzy Classes.](image-url)
In the case of fuzzy classes, the crisp separator is replaced by continuous membership degrees. A bank with a balanced investment of 50% on HR and 50% on IT is considered as “in-between” the fuzzy classes HR-CT and IT-CT. It belongs to both classes with a membership degree of 0.5 each. A small increase in IT investment to 50.1% will result only in a small change of the membership degrees to the two classes (see Table 1).

<table>
<thead>
<tr>
<th>Investment</th>
<th>Fuzzy Memberships</th>
<th>Crisp Memberships</th>
</tr>
</thead>
<tbody>
<tr>
<td>HR</td>
<td>IT</td>
<td>HR</td>
</tr>
<tr>
<td>50.0 %</td>
<td>50.0 %</td>
<td>0.500</td>
</tr>
<tr>
<td>49.9 %</td>
<td>50.1 %</td>
<td>0.499</td>
</tr>
</tbody>
</table>

Table 1. Crisp vs. Fuzzy Memberships.

The detailed results obtained by fuzzy clustering can be “defuzzified” based on the membership level to the fuzzy classes generated by the technique. In the given example a possible defuzzification could be of that banks with a membership degree higher than 0.7 to any class are considered as full member of the class and the remaining banks are regarded as “in-between” the classes or transient banks (i.e. on the way from one class to the other). We apply fuzzy clustering analysis to for each economic cycle to observe the changes in the membership level (or membership degrees) to each fuzzy class/cluster by which transformations of industries are observed. There are two ways to analyse the results from fuzzy clustering analysis:

[Criterion 1]: A decrease or increase in the number of fuzzy clusters over time indicates homogenization (hence, a sign of convergence) or divergence.

[Criterion 2]: Changes in membership degrees between the same number of fuzzy clusters over time indicate relative structural shifts between industries. This is the situation in which there can be convergence for some but divergence for others; the phenomenon we refer to as coalescence.

4 DATA AND SUMMARY STATISTICS

<table>
<thead>
<tr>
<th>Variables</th>
<th>Computation</th>
<th>Market Sector Annual Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Value-added (Y)</td>
<td>Gross value-added expressed in constant 2000 dollars</td>
<td>$397.6billion</td>
</tr>
<tr>
<td>IT Productive Capital stock(K_i)</td>
<td>Sum of Computer and computer peripheral and Software capital expressed in constant 2000 dollars</td>
<td>$43.5billion</td>
</tr>
<tr>
<td>Non-IT Productive Capital Stock (K_o)</td>
<td>Sum of all other capital services in the market sector expressed in constant 2000 dollars</td>
<td>$1,019.8billion</td>
</tr>
<tr>
<td>Labour used (L)</td>
<td>Labour hours-worked</td>
<td>805.8million hours</td>
</tr>
<tr>
<td>Industry (I)</td>
<td><em>Good producing industries</em> include: Agricultural, Mining, Manufacturing, Utilities, and Construction. <em>Services producing industries</em> include: Wholesale, Retail, Accommodation, café &amp; restaurant, Finance &amp; insurance, Transport &amp; storage, Communications, and Cultural &amp; Recreational Services.</td>
<td>12 industries in Market Sector</td>
</tr>
</tbody>
</table>
| Economic Cycle          | Economic cycles are defined as periods between peaks in output growth. The peaks are defined as points where gaps between the actual and a trend output series turns from increasing to decreasing. We divided the dataset into periods: 1981-1987, 1988-1994 and 1995-2002 based on ABS (2003). | 1 – Period 1: 1981-1987  
2 – Period 2: 1988-1994  

Table 2. Australian National Accounts at 1-digit ANZSIC level (1981 - 2002)

We assembled annual time-series data from the National Accounts Division of the Australian Bureau of Statistics (ABS) for the period from 1981 to 2002 for 12 industries covering the full spectrum of the
Australian market sector. Industry estimates of value-added and data on productive capital stock, both expressed in constant 2000 dollars at 1-digit ANZSIC level. The definitions we use in this study for IT capital and non-IT capital are based on Australian Productivity Commission’s research (Parham et al. 2001) in which IT capital consists of only two types: (1) Computers under the category of “Other machinery and equipment”, and (2) Software (including pre-packaged, own-account, and customized). Because communication equipment is not separated from other machinery, it is included under the non-IT capital measure. Descriptions of the industry-level variables are provided in Table 2.

5 RESEARCH FINDINGS

5.1 Phase 1 Results: Convergence Analysis

<table>
<thead>
<tr>
<th></th>
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</thead>
<tbody>
<tr>
<td>lnL</td>
<td>0.446*** (.094)</td>
<td>0.209* (.113)</td>
<td>0.035*** (.078)</td>
</tr>
<tr>
<td>lnK_e</td>
<td>0.113*** (.032)</td>
<td>0.027* (.034)</td>
<td>0.194*** (.041)</td>
</tr>
<tr>
<td>lnK_f</td>
<td>0.060*** (.018)</td>
<td>0.079** (.033)</td>
<td>0.151*** (.039)</td>
</tr>
<tr>
<td>Residual Variance</td>
<td>0.004*** (.001)</td>
<td>0.006*** (.001)</td>
<td>0.008*** (.001)</td>
</tr>
<tr>
<td>Industry Variance</td>
<td>0.119** (.060)</td>
<td>0.187* (.105)</td>
<td>0.060** (.031)</td>
</tr>
<tr>
<td>N</td>
<td>84</td>
<td>84</td>
<td>96</td>
</tr>
<tr>
<td>Akaike (AIC)</td>
<td>-137.873</td>
<td>-110.387</td>
<td>-131.063</td>
</tr>
<tr>
<td>Schwarz (BIC)</td>
<td>-133.109</td>
<td>-105.623</td>
<td>-126.020</td>
</tr>
<tr>
<td>Residual Variance %</td>
<td>3.52%</td>
<td>3.22%</td>
<td>11.19%</td>
</tr>
<tr>
<td>Industry Variance %</td>
<td>96.48%</td>
<td>96.78%</td>
<td>88.81%</td>
</tr>
</tbody>
</table>

Table 3. Regressions Results – Coefficient estimates and implied gross rates of return. The numbers in parentheses are standard errors. Key: *** - p<.01, ** - p<.05, * - p<.10

The regression results for equation 2 are provided in Table 3. First, based on our results from the random effects regressions (one for each economic cycle), the impact of IT capital (β_i) increased from economic cycle 1 thru to cycle 3 (see row 4 of Table 3). The estimates are 0.060, 0.079 and 0.151 respectively and statistically significance at 0.05 levels and above. These results are consistent with recent literature of rapid increasing returns on IT investments beginning in the 2nd half of 1990s. Second, the intra-class correlations (PI) for all 3 regressions in three economic cycles (see row 11 of Table 3), they are 96.48%, 96.78% and 88.81% respectively and based on the Wald statistics, these estimates are statistically significance at 0.01 levels. These values indicate that the industry effect is virtually the same between economic cycle 1 and 2 but reduced significantly between economic cycle 2 and 3. Therefore, these findings suggest that convergence began in economic cycle 2, roughly in the early 1990s.

Furthermore, the analysis of the residuals between economic cycle 2 and cycle 3 indicates a shift in productivity variation from industry factors to factor within the industries. The AIC and BIC\(^2\) measures showed in Table 3 are the measures of goodness of fit of the models. Models with smaller values of the statistics are better. The results support our original hypothesis that the IT capital elasticity has increased (i.e. \( \beta_{t-1} < \beta_{t-2} < \beta_{t-3} \)) over the three economic cycles in the dataset. For the

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\(^2\) Various measures can be used to compare the goodness of fit of the random effects models. Models with smaller values of AIC and BIC are better. The basic measure is \(-2 \log \text{likelihood} \) or \(-2 \log \text{restricted likelihood} \), depending on whether the maximum likelihood (ML) or restricted maximum likelihood (REML) estimation is used. The most frequently used are Akaike (AIC) = \(-2l + 2d \) and Schwarz (BIC) = \(-2l + d \log(n) \), where \( l \) = log likelihood if ML, log restricted likelihood if REML and \( n \) = the number of cases if ML, number of cases minus the number of parameters if REML; and \( d \) = number of fixed-effect parameters plus number of covariance parameters if ML, number of covariance parameters if REML.
variability among industries, the three random effects regressions (i.e. equation 2) provide the preliminary measures of the variability among industries in different economic cycles (i.e. $P_{i,t=1}$, $P_{i,t=2}$ and $P_{i,t=3}$). Therefore, the results in this phase show that industry convergence began economic cycle 2 (i.e. between 1988 and 1994). However, this regression model is not sensitive enough to establish whether this effect is uniform across all industries. In other words, are there some groups of industries that may show a different effect even though the convergence evidence is present in the aggregate? We address this issue in the next phase.

5.2 Phase 2 Results: Coalescence Analysis

We performed fuzzy clustering on the same four factors ($Y$, $K_0$, $K_i$ and $L$) based on the dataset used in the previous phase. In this phase, we used factor income shares instead of productivity capital stock because factor income shares represent the proportion of income of each input capital and labour towards industry level value added. There are two distinct advantages in using factor income shares. First, since the value of each variable is expressed as percentage measures, the industry size bias is removed. Second, since the sum of all factor income shares is equal to 1 (i.e. normalised), the fuzzy clusters can be effectively formed based on the relative factor income shares.

We apply Bezdek’s (1981) fuzzy c-means (FCM) algorithm in which the fuzziness of the clusters depends on the initial parameter $m$, the so called fuzzy parameter. For $m\to 1.0$ the FCM equals the (crisp) c-means. For $m\to \infty$ we obtain $c$ identical clusters; each object has a membership degree of $1/c$ to each cluster. Without imposing a specific number of clusters to be formed, it is a commonly accepted practice to select the fuzzy parameter as $m=2.0$ to determine the optimal number of clusters based on the partition coefficient criterion (Windham 1982). The summary result is provided in Table 4 and an illustration of how industries shift between fuzzy clusters over the 3 economic cycles is shown in Figure 2.

<table>
<thead>
<tr>
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<tbody>
<tr>
<td></td>
<td>Average Membership to</td>
<td>Average Membership to</td>
</tr>
<tr>
<td></td>
<td>var*</td>
<td>var*</td>
</tr>
<tr>
<td></td>
<td>C1</td>
<td>C2</td>
</tr>
<tr>
<td>Agriculture</td>
<td>.052</td>
<td>.042</td>
</tr>
<tr>
<td>Mining</td>
<td>.051</td>
<td>.035</td>
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<tr>
<td>Manufacturing</td>
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<td>.335</td>
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<tr>
<td>Utilities</td>
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<td>.076</td>
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<tr>
<td>Constructions</td>
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<td>.090</td>
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<td>Wholesale</td>
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<td>Retail</td>
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<td>Communication</td>
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<td>.091</td>
</tr>
<tr>
<td>Counts</td>
<td>2</td>
<td>3</td>
</tr>
</tbody>
</table>

Table 4. Average membership degrees of industries to clusters: maximum membership degrees are marked bold and italics.
According to the partition coefficient criterion, the optimal number of clusters remains stable over the three cycles. In each economic cycle, the algorithm consistently finds four optimal fuzzy classes (C1-C4). Therefore, we find no preliminary evidence of convergence (or divergence) of industries based on the changes in number of fuzzy clusters between economic cycles (i.e. criterion 1). However, based on a closer examination of the membership degrees between the each industry and the four optimal fuzzy clusters, we find that certain industries display what appear to be converging tendencies while others have diverged or remained stable.

To defuzzify the results, we first identify the maximum membership degrees of the industries to the fuzzy classes in each economic cycle. We then observe the movements in term of changes (increase or decrease) of membership degrees of each industry to the clusters over the three economic cycles.

In economic cycle 1, based on the measure of maximum membership degrees, communications, cultural and hospitality belong to class 1 (labelled as C1 in Table 4); wholesale and transport industries belong to class 2 (labelled as C2 in Table 4); manufacturing, constructions, retail and finance belong to class 3 (labelled a C3 in Table 4); and agriculture, mining and utilities belong to class 4 (labelled C4 in Table 4). It has to be noted that most industries belong clearly to one fuzzy cluster (with membership degrees larger then .7). As well, there are three industries (manufacturing, finance and hospitality) that have evenly distributed membership degrees among two fuzzy classes: finance and manufacturing (C2 and C3) and hospitality (C1 and C2).

An interesting phenomenon emerged when we analyse the membership shifts of each industry between fuzzy classes from economic cycle 1 to cycle 2. First, virtually no movements are found from agriculture, mining and utilities; they maintain strong memberships in C4. Second, manufacturing and the other three industries (finance, retail and construction) in C3 have diverged into
two fuzzy classes (i.e. C2 and C3 in economic cycle 2). After the three industries (finance, retail and construction) became a separate cluster, manufacturing has become a single and strong member to C3 (with the membership degree value grew from .357 to .967) in cycle 2. Third, the industries initially belonging to C1 (communications, cultural and hospitality) and belonging to C2 (wholesale and transport) in cycle 1 seem to have coalesced into a single class (i.e. to C1 in cycle 2).

In economic cycle 3, while fuzzy classes C3 and C4 have remained steady, the newly formed fuzzy cluster C2 in economic cycle 2 has shown an increase in the number of industries particularly industries (hospitality, wholesale and transport) joining from C1 in economic cycle 2. We speculate this fuzzy cluster (C2 in cycle 3) is the evidence of industry agglomeration and the increase in memberships in this cluster is a reflection of their increasingly shared service-type profile brought about by significant increases in IT capital investment. Figure 2 illustrates industry movements between the economic cycles.

Furthermore, agriculture, mining and utilities form a stable cluster (Class C4). Manufacturing stays in the same cluster (Class C3) over the three economic cycles, and its membership degree in class 3 has actually grown stronger from cycle 1 to cycle 2. Our interpretation of these results suggests that agriculture, mining and utilities have not participated in the structural shifts, but industries (such as finance, retail and construction) with profiles initially similar to manufacturing in cycle 1 have shifted away in subsequent cycles.

Out of the remaining six industries in class C2 in cycle 3, five of them are service-producing industries (except construction), indicating significant shifts were taken place in the service industries. Not only our results are consistent with the findings of Gouyette and Perelman (1997) who investigated productivity convergence in services industries, we also found these shifts coincide with the increase in IT investments of these industries. The overall coalescence effect is manifested by the simultaneous divergence or lack of movement of some of the traditional industries such as agriculture, mining, and utilities.

6 CONCLUSION AND FUTURE RESEARCH

This paper has addressed the longer term effects of IT on industry profiles over three recent economic cycles in Australia. We employed an innovative combination of econometric methods to initially investigate the extent of homogenization and convergence followed by the application of fuzzy clustering technique to economic data over a 22-year time span. While the former demonstrated a significant level of convergence in the aggregate, the latter analysis clearly points to different clusters of industries evolving differently. Typically service-producing industries appear to coalesce into a single cluster while the more traditional industries such as agriculture, mining and utilities do not exhibit any significant movement. This coalescence effect is distinct from the more familiar concept of convergence according to which there will be homogeneity in the movement of all the industries over time.

Our research has clearly shown that the trajectories that different industries take in response to deepening IT investments and penetration are unlikely to be similar. It will be useful to investigate these trajectories for each of the industries in more detail especially for the ones which display patterns of divergence. Further research is also needed to elucidate the underlying dynamics that make seemingly disparate industries such as construction, cultural, and finance to demonstrate profile similarities. Further, similar studies at the firm level can help us understand intra-industry dynamics better. Another interesting research direction is to study the impact of outsourcing and its effects on industry convergence.
References


