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Multi-Industry Labour Force Skills: Structure and Dynamics

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Abstract
This paper proposes a taxonomic exercise of industrial sectors by looking at the repertoires of skills that are embedded in the occupational structures. Using original data from the United States the empirical analysis presented here fleshes out structural and longitudinal aspects of industry-specific knowledge organization. Our results point to a novel dynamic classification that goes beyond the traditional taxonomy of ?sectoral types? and is based on the types of transformative processes that industrial sectors undergo over time.

Jelcodes:O33,J24

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Keywords: Industry dynamics; Skills; Taxonomy

JEL Code: C38; L0; J24; O33

1. Introduction

The field of innovation studies contributes significantly to our understanding of the extent to which knowledge drives economic development. The main tenet contemplates three articulations: the multiplicity of forms of knowledge that are generated within evolving economic systems; the variety of processes by which knowledge is organized and diffused; and, the contexts in which different kinds of knowledge are put to use. Ample empirical evidence demonstrates that the most salient mark of knowledge growth is persistent diversity at various levels of aggregation including firms (Bottazzi, et al 2002; Bottazzi and Secchi, 2003; Dosi et al, 2008), industries and sectors (Pavitt, 1984; Mowery and Nelson, 1999; Malerba, 2002), regional (Cooke et al, 1997) and national systems of innovation (Nelson, 1993; Carlsson et al, 2002). The causes of this diversity cannot be reduced to a single factor but, rather, are ascribed to complementary transformations in the knowledge base, the networks of actors and institutional infrastructures (Nelson, 1994; Malerba, 2005). In turn these changes trigger a selection of organizational problem-solving routines that, eventually, accentuates the particular pattern of resource commitment within the innovation system (Amable, 2003; Hall and Soskice, 2001; Whitley, 2007). All the above contributes to the view of cross-industry heterogeneity as autocatalytic engine of capitalistic development (Metcalfe, 2003).

Existing empirical studies on the subject matter take an indirect route to the analysis of knowledge dynamics, and focus on how particular organizational forms associate to “output” such as e.g. productivity, number of patents, profits growth rates, et cetera. This paper proposes an alternative perspective on cross-industry heterogeneity by using a “throughput” measure of knowledge organization, namely the skills that are embodied in the labour force. Drawing on Richardson’s (1972) view of industry as a collection of activities we propose that occupations are institutional vehicles for the coordination of knowledge, and that the configuration of industry-specific knowledge is determined by a mutual adaptation of the workforce’s skills and tasks. Akin to a DNA code, the mapping of knowledge structures is useful to the effect of detecting specificities and commonalities across industrial sectors. This framework is probed empirically by analysing data on 290 industrial sectors in the United States (US) over the period 2002-2011 to address two specific questions:

(1) How do skill configurations associate to industry groups?
(2) What is the dynamic behaviour within and across industry groups over time?

The present paper contributes various streams of scholarly research. First, using workforce structure as an indicator of the organization of industry-specific knowledge draws attention to a hitherto underdeveloped theme, at least within innovation studies, namely the relation between labour and technical change. Our paper takes steps in that direction by, first, identifying specific categories of practical know-how that resonate with recent works on skills (Giuri et al, 2010; Neffke and Henning, 2013) and, subsequently, by exploring empirical associations with industry agglomerates. Another contribution of the paper is the focus on cross-industry differences that adds an important nuance to the prevalently macro approach to the dynamics of occupations (e.g. Howell and Wolff, 1992; Autor et al, 2003) by yielding a novel landscape of industry groups based on skill. Lastly, the paper builds on and moves forward previous exercises of industry classification (e.g. Pavitt, 1984; Castellacci, 2008; Peneder, 2010) by offering a dynamic view that goes beyond the traditional taxonomy of 'sectoral types' and that is instead based on the types of transformative processes that industrial sectors undergo over time.

The paper is structured as follows. Section 2 prepares the ground by connecting industry dynamics with occupational structures as vehicles to apply specific knowledge. The empirical analysis of Section 3 uncovers the association between skill structures and industry types. Section 4 concludes and summarizes.

2. Conceptual and empirical issues at stake

The first subsection highlights synthetically the gap within the literature on innovation and technological change that motivates the present study. The second elucidates the logic underpinning the choice of skills as units of analysis.

2.1 – Industry dynamics and the meso perspective

The relation between industry characteristics and the dynamics of technological change is a pillar in the tenet of innovation studies. Rooted in the logic of evolutionary economics, the dynamics of industry is understood as a struggle among different modes of organization competing for survival in the restless capitalistic contest (Metcalfe, 2001). Enterprise-based economies, the argument goes, undergo continual transformations triggered by changes in the relative importance of economic activities. The thrust of this perpetual motion is the emergence and replenishment of pathways that, by stimulating the conditions for the accumulation of and access to relevant knowledge, provide coherence to naturally unpredictable and diverse ensembles of micro-behaviors (Nelson, 1990). The developmental consequences of these coordinated behaviours can be observed at various levels: at micro-level, say a firm, economic evolution consists of changes in the composition of traits (characteristics), in the trait-carriers (agents) and the structure of interactions across them; at macro-level evolution entails the adaptation of coordination rules amongst micro-behaviors. The evolutionary framework has been recently enriched by the addition of an intermediate lens of analysis, the meso-level, intended as a bridge between the micro- and the macro-dimensions (Dopfer et al, 2004). Evolution at meso-level entails the transformation of behaviours and rules in functionally similar populations – meta-populations if seen from a micro perspective, sub-populations if seen from a macro standpoint. The meso-dimension construct is useful to analyze empirically functional agglomerations such as sectors, industrial districts, regional clusters et cetera.

In the study of industrial sectors the meso-dimension is often operationalized by means of classificatory exercises that take into account both characteristics of the component entities, viz. the micro-behaviours, as well as broader environmental attributes such as the institutional set-up (Peneder, 2007). The first of such studies was Pavitt's (1984) renowned categorization of technological trajectories that became the basis for a sectoral taxonomy organized in four meta-categories: supplier-dominated, scale-intensive, specialized suppliers, and science-based industries. This classification has been and continues to be a point of reference for scholars, policy makers as well as for statistical offices designing large-scale data collection programs (Archibugi, 2001). On a conceptual level the logic underpinning the taxonomy has inspired a great deal of research on sectoral characteristics such as technological opportunities, knowledge cumulativeness, knowledge bases, appropriability conditions, R&D intensity and skills (see e.g. Los and Verspagen, 2004; Breschi et al., 2000; Van Dijk, 2000; Malerba and Montobbio, 2003; Reichstein and Salter, 2006; Krafft et al, 2011). At the same time greater availability of sector-specific data (such as, for example, the European Community Innovation Survey) has expanded the intellectual scope and the policy remit of classification exercises. This is especially true for studies of innovation in services (e.g. Evangelista et al., 1997; Miozzo and Soete, 2001; Leiponen and Drejer, 2007; Castellacci, 2007) where greater understanding of the dynamics of technological paradigms has stimulated both the toning down of the arguably blunt separation between manufacturing and services and, at the same time, a stronger appreciation of the growing diversity that exists across service sectors (Castellacci, 2008; Peneder, 2010; Consoli and Elche, 2010; 2013).

Following on the above, the paper proposes a taxonomic exercise based on a hitherto overlooked dimension of analysis, namely the knowledge base underpinning occupational structures of industrial sectors. Drawing on the view that industrial sectors are populations of activities defined by the development and use of knowledge for strategic objectives (Richardson, 1972) we set out to capture the dynamic configurations of meso-level knowledge by analyzing their employment structures and the associated skill bases. Before that, however, it will be necessary to digress briefly on the choice of skills and employment as unit of analysis.

2.2 – Skills and employment: blueprints of knowledge application

The notion that the organization of labour impacts on technical change, and thus on growth and competitiveness, is a common, if understated, thread across various areas of scholarly research. The management literature focuses on strategic aspects related to the coordination of different kinds of knowledge and attitudes across employers (Cohen and Levinthal, 1989; Kogut and Zander, 1992). Scholars in business economics ascribe differences in firm performance to differential abilities within the workforce in creating and using knowledge (Geroski et al., 1993; Henderson and Cockburn, 1996; Johnson et al, 1996). More recent empirical work puts emphasis on the mutual influence between employees' skills and forms of innovation (see e.g. Leiponen, 2000; Freel, 2005; Lavoie and Therrien, 2005). Last but not least, a growing literature in economics explores the impact of Information and Communication Technologies on the content, the structure and the dynamics of employment with special emphasis on the sources of wage inequality (Galor and Moav, 2000; Autor et al, 2003; Goldin and Katz, 2008).

On the whole, we argue, these strands of research underestimate both conceptually and empirically the sheer diversity of forms of useful knowledge and, correspondingly, of the organizational processes that are necessary for their governance (Antonelli, 2006). The proposition advanced here is that skills are the building blocks of labour, and that employment is an instituted process for the coordination of knowledge. This particular nuance is arguably novel but, at the same time, conceptually fitting with the basic foundations of innovation studies, for at least two reasons.

The first concerns ontological aspects. Human labour is a transformative process based on the use of knowledge in converting energy and materials of a kind into energy and materials of a different kind (Marx, 1961).[1] Neither the energy and materials nor the knowledge that is needed to produce them are static but, rather, dynamic forces unfolding in a continuum of localized problem-solving efforts. As innovation scholars repeatedly point out, the relative stability of technological paradigms is punctuated by sudden phases of turbulence during which accumulated technical knowledge opens up the possibility of divergent breakthroughs (David, 1975; Nelson and Winter, 1977; Dosi, 1982). In turn these windows of opportunities cause alterations in the patterns of output and of resource use, so that the scope of capital investments expands and new activities emerge out of old ones in a perpetual reconfiguration of the functional relations across them (Rosenberg, 1976).[2] Especially in contexts like high-income countries, the new division of labour entails the proliferation of 'knowledge-producing' occupations to accommodate the demand for flexible specialization (Machlup, 1962: 396). Therefore further down the tracks indicated by Marx, and several iterations of industry evolution later, capitalistic development has seen the ontological role of knowledge shifting from tacit input embedded within the workforce to being an output of production.

Allied to the above is the second important aspect, the embedding of employment within legal, social and economic frameworks. History has shown repeatedly that the institutional set-up underpinning labour market arrangements acts as a powerful selection mechanism for the viability of particular technological regimes and patterns of comparative advantage (Hall and Soskice, 2001; Amable, 2003; Whitley, 2007). The sociology of labour organization adds to that by emphasising that the evolution of occupational contents and employment structures are neither instantaneous nor automatic but, rather, emergent processes (Sabel, 1982). This is true of both the mass-production regime, based on the combination of special-purpose machinery plus abundant low-skilled workforce plus centralized production (Marx, 1961), as well as the modern "service economy" commonly portrayed as the realm of high-skilled workers plus customized output plus decentralized production (Gershuny and Miles, 1983). In either context the division of labor is a socially mediated and historically-conditioned reality punctuated by struggles that reshape means (technology) and ends (production regime) (Sabel and Zeitlin, 1985). Far from happening in vacuum these processes are filtered through

[1] See Marx (1961: 123 - Volume 1 (Chapter 7): "In the labour-process (…) man's activity, with the help of the instruments of labour, effects an alteration, designed from the commencement, in the material worked upon. The process disappears in the product, the latter is a use-value, Nature's material adapted by a change of form to the wants of man. Labour has incorporated itself with its subject: the former is materialized, the latter transformed".

[2] The machine goods or the chemical processing industries are fitting examples of this (Rosenberg, 1976; Landau and Rosenberg, 1992).

institutional structures that absorb emergent feedback and, in turn, channel future behaviours and expectations to a "standardized pitch" (Douglas, 1987: 91).

One of the conceptual purposes of this paper is to highlight that while the focal points of the preceding paragraphs, knowledge and institutions, are certainly familiar to innovation scholars, there have been few attempts to integrate systematically the role of employment in the main theoretical apparatus.[3] Our proposed definition of employment as an instituted process for the coordination of knowledge should therefore appear like a novel, and hopefully appealing, recipe made with familiar ingredients.

In the framework proposed here, sectors are viewed as bundles of tasks whose execution entails the generation and/or application of specific knowledge (Nelson and Winter, 1982). Skills are individual abilities or proficiency in carrying out activities, and occupations are industry-specific pathways for matching skills with institutionally agreed tasks.[4] Therefore job specifications are blueprints – imperfect as they may be – of the repertoire of skills that the labour force is expected to possess and use in order to carry out successfully particular work tasks (Autor et al, 2003; Levy and Murnane, 2004). In aggregate, the composition of the workforce reflects the knowledge mix that is relevant in a particular industrial sector at a specific moment. By the same token, as industry needs change over time occupations evolve and so do the agreed tasks and the relevant skill mix.[5] This implies that the complementarities across different forms of knowledge matter a great deal for the ability of an individual worker to meet successfully their job requirements depends on the composition of the overall employment structure and on mechanisms of intra-occupations collaboration (Rosenberg, 1976). In turn, the emergence of novel configurations in the skill mix reflects changing styles

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[3] This is not to say that the issue has been completely neglected: Freeman et al (1982), Vivarelli (1995), Edquist et al (2001), and Petit and Soete (2001) are important contributions on the appreciation of the mutual influence of technology, especially Information Technology, and labour. Our claim is, rather, that there have been no attempts to build on that empirical evidence to the effect of integrating the dynamics of employment in a broad theoretical framework such as those of Nelson and Winter (1982) or Metcalfe et al (2006).

[4] Thus, some skills are generic and can be applied to a broad range of tasks while others are specific to particular tasks; some skills are used to generate cognitive responses, others involve physical activities; finally, some skills pertain to the individual's sphere while others facilitate interpersonal interaction.

[5] A fitting reference is the cake metaphor, popular among evolutionary economists (Nelson et al, 1967: 99): "Generally, a technique or technology is not describable by a unique routine; usually there are options in the program. These options permit some choice of inputs and input proportions (a recipe may work with either whole or powdered eggs) and some flexibility with respect to operations (the eggs may be added before or after the sugar). The operations may be performed in different ways; for example, different degrees of mechanization may be employed (the mix may be beaten with a spoon, a hand beater or an electric beater). Some variation in output specification may be possible (such as the shape of the cake or the kind of frosting)".

of framing and addressing job tasks by redistributing responsibilities across professional groups (Sabel, 1982).

Building on this conceptual background, the next section presents an empirical analysis of 290 industrial sectors in the United States over the period 2002-2011 with a view to uncover structural and dynamic aspects of industry evolution. Coherent with the above, the way in which skills combine with each other within occupational structures is a uniquely distinctive character of an industry, akin to a DNA code. This holds the promise of uncovering important specificities. On the other hand the specific repertoire of skills that is relevant at any time is likely to change as a response to evolving industry needs: this open-ended growth of knowledge is likely to engender differential dynamic behaviour across sectors.

3. Data and Analysis

This section presents the dataset and the empirical analysis. Stated succinctly, our objectives are: (i) analysing the skill base of industrial sectors to elucidate commonalities and differences; and (ii) observing how sector-specific skill repertoires evolve over time. The broader goal is the construction of a sectoral taxonomy based on their skill repertoires.

3.1 – Data description

Our empirical analysis is based on the Occupational Information Network (O*NET) electronic database of the U.S. Department of Labour (DOL). Data are collected using a classification system that organizes job titles into 1,102 occupations and collects information on their characteristics. For the purpose of our study we focus on information concerning the physical and cognitive abilities that are required from workers. This information is occupation-specific and is provided by trained occupational analysts, job incumbents and occupational experts who are asked to assign a score to 35 types of skills (see Appendix A) on the basis of their importance for performing the occupation. The current taxonomy encompasses information on two broad categories, basic and cross-functional skills. For what concerns the former, skills are further separated into "content" (e.g. reading, writing and listening) and "process" skills aimed at cognitive information processing activities.[6] The O*NET classification uses the Standard Occupational Classification (SOC) system and is therefore aligned with other sources of occupational information such as the US Bureau of Labor Statistics (BLS). Our database was built by merging employment statistics on 290 US

[6] For further information about O*NET see National Research Council (2010).

industrial sectors (NAICS coding) with the corresponding occupational information on skills contained in O*NET. Our observations for the period 2002-2011 are occupations within each sector, and for each occupation we consider the total employment (source: BLS), a vector of skill scores and the average number of years in excess of High-School (Standard Vocational Preparation) (source: both from O*NET).

For the purposes of the present paper we aggregate occupation-specific information on skills by industry using relative scores, that is, weighted measures of skill intensity (see Oldenski, 2012). Accordingly we normalize the raw skill values and compute the new skill scores as:

$$SkillScore_{s,j} = \sum_{occ} EmpShare_{occ,j} * SkillRaw_{s,occ}$$

where $EmpShare_{occ,j}$ is the relative importance in terms of employment of occupation occ in industry j and $SkillRaw_{s,occ}$ is the normalized raw skill score of skill s in occupation occ. Averaging over occupations in each industry yields an input intensity measure of each skill s in each industry j ($SkillInt_{s,j}$). After this transformation we are left with 290 industry-specific intensity measures for each of the 35 skill types for each of the ten years under analysis.

3.2 – Constructing the taxonomy: skills and sectors

The original data contains 35 skill variables. Recall that we are not interested in their absolute values but, rather, in the way skills combine within industry-specific occupational structures. Moreover, the raw scores of skill intensity are highly correlated with each other due to high complementarity across skill endowments at industry level. To meet the former goal and to overcome the latter limitation, we reduce the set of skill indicators to a smaller number of non-overlapping dimensions by means of a factor model (see e.g Castellacci and Archibugi, 2008). Table 1 presents a compact view of the skill constructs extracted from the 35 indicators of skill intensity for the period 2002-2011. Note that different methods of factor extraction – principal components, iterated principal factors and maximum likelihood – yield consistent results. Altogether the factors explain a large percentage of the variance.[7]

TABLE ONE ABOUT HERE

[7] The two factors are robust to alternative estimations for individual years and for various blocks of multiple years. Results are in line with those presented above and are available from the authors upon request.

Previous literature assists the interpretation of these two constructs on the basis of functional specificities (Autor et al, 2003; Wolff, 2006). The first factor includes items that involve the use of cognitive abilities in non-routine circumstances, like interpersonal interaction or abstract thinking. This is labelled Interactive & Abstract Skills. The second group, Technical & Analytical Skills, contains a broad range of cognitive and manual abilities employed for routine tasks such as managing or recombining existing information, or when operating specialized technical equipment. The cognitive and manual abilities within this last construct are normally employed to carry out highly routinized tasks prone to automation (see Autor et al, 2003). We note that our constructs fit squarely with the way in which Herbert Simon (1969) described problem-solving as a combinatorial process of different types of knowledge. In particular, the first skill factor matches the profile of 'semantically-rich' domains (Simon, 1969: 87), that is, task structures characterized by strong specificity and requiring high levels of cognitive responsiveness to construct ad-hoc mental frameworks and performance criteria. These differ from 'non semantically-rich domains' that instead require cognitive routine or non-cognitive abilities to carry out standardized tasks. In the latter domains the repertoire of problem-solving options is known ex-ante with a finer degree of precision, and replication of existing routines through non-cognitive skills suffices.

Following on the above sectors are grouped together on the basis of the skill distributions embedded in their occupational structures. In particular we apply clustering techniques to factors scores by means of regression methods (Thomson, 1951) and use them as inputs in the clustering algorithm.[8] This exercise yields three clusters (see Appendix B for a full summary). The first, Complex Production Activities, includes the majority of Hi- and Medium- Tech Manufacturing, and some knowledge intensive services.[9] The core of this cluster, calculated as the 90th percentile by mean skill intensity, includes industries like Satellite Telecommunications (NAICS: 517400); Software Publishers (511200); Computer Systems Design Services (541500); Manufacturing of Computer and Peripheral Equipment (334100); Data Processing and Related Services (518200); Architectural, Engineering, and Related Services (541300); Communications Equipment Manufacturing (334200). In the

[8] We use different hierarchical clustering methods (average linkage, centroid linkage and Ward's linkage) based on the Calinski-Harabasz pseudo F-statistic and the Duda-Hart index stopping rules for selecting the optimal number of clusters. Finally we check the robustness of the results with a Partition-clustering method.

[9] The labels Hi-, Medium- and Low-Tech for Manufacturing, and High- and Low-Knowledge-Intensity Services have been assigned on the basis of the NACE-based Eurostat classification, and subsequently converted to the NAICS system. See http://epp.eurostat.ec.europa.eu/statistics_explained/index.php/High-tech_statistics. For a critical view of this classification see Godin (2004).

second cluster, labelled Basic Production Activities, are the bulk of Lo-Tech Manufacturing industries and Service activities with low knowledge intensity, mostly commercial activities complementary to the former. At its core are Iron and Steel Mills Manufacturing; Commercial Refrigeration Equipment Manufacturing; Tobacco Manufacturing; Utility System Construction; Coal Mining; Vending Machine Operators; Automotive Repair and Maintenance. The last cluster, People Services, contains service activities characterized by direct interaction with customers such as Legal Services; Securities and Commodity Exchanges; Schools and Instruction Services; Insurance and Employee Benefit Funds; Central Bank; Internet Publishing and Broadcasting; Investment Pools and Funds.

From this classification one can readily appreciate the ubiquity of service activities as well as their functional specificities depending on whether they exhibit complementarity with manufacturing, as in the case of the first two clusters, or they rather stand in a category of their own like in the People Services construct. It is worth emphasising that this result resonates with recent analyses of sectoral specificities (see Castellacci, 2008 and Peneder, 2007). Moreover, and perhaps unsurprisingly, the industry composition observed in our empirical exercise differs from Pavitt's (1984) taxonomy. In the concluding section we will elaborate more on this and argue that the discrepancy is only superficial.

Next, we check for statistical correspondences between the two constructs, Skill-Factors and Sector-Clusters by regressing the likelihood of belonging to a particular cluster against the skill constructs.[10] The results (Table 2) indicate that the probability of belonging to the Complex Production Activities cluster is positively and significantly associated with both Interactive & Abstract Skills and Technical & Analytical Skills. This implies that the occupations of the industries within this cluster exhibit a broad knowledge base, and that their task structures require the full spectrum of cognitive and non-cognitive abilities. In contrast to the former the Basic Production Activities cluster is negatively associated with Interactive & Abstract Skills, meaning that the values of that particular group of skills are significantly below average compared to the other clusters. Finally we find, perhaps unsurprisingly, that the People Services cluster have a significant and positive association with Interactive & Abstract Skills and a negative one with Technical & Analytical Skills.

[10] The Breusch–Pagan test, significant at 1% level, indicates that the residuals of the three clusters are not independent and justifies the use of multivariate regression. It is worth stressing that in this method, different from multiple regression, dependent variables are jointly regressed on the same independent variables. The joint estimators of multivariate regression are built on the between-equation co-variances, and allow testing for relevant factors across equations. This way we can learn about their relative importance in each cluster.

TABLE TWO ABOUT HERE

Summing up, our analysis so far has proceeded in two directions. First, we synthesised the distributions of relative skill intensity across sectors by means of Factor Analysis to deal with a more parsimonious information set. The original 35 skill types were reduced statistically to two constructs that capture salient characteristics of the knowledge content of occupations: cognitive skills that are normally employed for non-routine tasks, and manual skills that are involved in carrying out routine activities. Following on this we fed back the results of the factor analysis in the 290 industrial sectors bearing in mind (see Section 3.1) that each industry's unique employment structure determines a particular configuration of skill. This last exercise yields three clusters that capture distinctive patterns of knowledge organization across industrial sectors.

3.3 – Dynamics: changing knowledge structures

The analysis so far has been concerned with uncovering structural aspects of the cognitive content of industries. In this subsection we explore the dynamic behaviour of the skill-factors and industry clusters that were generated in the previous subsection.

A first cogent question concerns the uniformity or diversity of skill-factor intensity across sectors. The kernel density distributions in Figure 1 offer two clear hints.[11] First, the right-skewed shapes suggest high concentration, or uneven distribution across sectors, more so for of Interactive & Abstract Skills (Factor 1) compared to Technical & Handling Skills (Factor 2). As for the longitudinal behaviour, the kernel curves for years 2002, 2006 and 2011 indicate significantly different patterns of change. The upward-left shift between 2002 and 2006 of the distribution of Factor 1 indicates that the majority of industries gather around low and medium-high levels of skill-factor intensity. In the second part of the decade the trend is reversed and skill concentration in 2011 is close to the levels of 2002, but still highly skewed. The case of Factor 2 is quite different in that the initial kernel density curve is bi-modal, and then it progressively becomes bell-shaped, though not normally distributed.[12] The observed patterns resonate with the common view that the distribution of soft skills, such as those in Factor 1, is uneven across sectors considering that they are heavily context-dependent and

[11] Here we select the industries whose skill intensity lies below the 90h percentile to control for outliers at the far extremes of the distributions.

[12] The coefficients of the Kolgorov-Smirnov test confirm the non-normal distributions: for Factor 1, 2002: 0.19***; 2006: 0.16***; 2011: 0.16***. For Factor 2: 2002: 0.17***; 2006: 0.09**; 2011: 0.1***

interactive, and thus harder to standardize (see Bartel and Lichtenberg, 1987; Autor et al, 2003; Vona and Consoli, 2011).

FIGURE ONE ABOUT HERE

The broad message of the above exercise is that there is a high variation in the distribution of skill intensity across industries. Following on this set of clues we focus on the longitudinal patterns of skill distributions within the cluster constructs with the visual aid of boxplots diagrams. From Figure 2 one can readily observe that the skill-factor intensity of Complex Production Activities follows a sinusoidal pattern with overall high dispersion (wide interquartile range) and high concentration (low position of the median within the box). This is broadly similar in shape, but not in magnitude, to the dynamics of skill intensity within the People Services cluster, with clearly increasing dispersion after 2005. The turbulence observed in the first two clusters differs from the substantially stable pattern of mean skill intensity in Basic Production Activities. In sum, we observe markedly different behaviour over time due to strong within-skill unevenness in two of the three clusters.

FIGURE TWO ABOUT HERE

The evidence so far suggests that not only industries have unique structural features (as per Section 3.2 above), but also that they exhibit distinctive patterns of transformation. These systematic differences afford the opportunity to enrich the notion of taxonomy that has been entertained so far. Assigning an industry to a particular group on the basis of shared, albeit differentially distributed, characteristics is a static exercise that yields a catalogue of meta-constructs like Pavitt's (1984) four categories, or the clusters in our analysis. Our proposal, however, is that once time is accounted for the taxonomy is not about types of industries but, rather, about types of transformative processes. In the last part of the analysis we seek to qualify and classify various typologies of transformations in the skill base of industries. We do so in two steps.

Let us begin by computing the Normalized Growth Rates (NGR) of the skill-factor intensities and looking at their distributions (Figure 3).[13] Comparing, again, 2002, 2006 and 2011 growth rates exhibit non-normal distributions for the first and the last year[14] thus suggesting strong correlation in the drivers of growth compared to what one would observe in normally

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[13] Given $S_{i,t}$ Skill-Factor intensity of factor i at time t, and $s_{i,t} = ln(S_{i,t}) - \frac{1}{T}\sum_t \ln(S_{i,t})$, the normalized growth rate of skill-factor intensity is computed as: $g_{i,t} = s_{i,t} - s_{i,t-1}$

[14] Again, the Kolgorov-Smirnov test is used to test for normal distributions and the coefficients for the three years under analysis are: 2002:0.1***; 2006: 0.06; 2011: 0.09**.

distributed (viz. independent) events (Bottazzi and Secchi, 2003; Dosi et al, 2008). The upshot is that cross-industry differences are persistent, if not increasing, over time.

FIGURE THREE ABOUT HERE

The second step consists in computing an industry-specific index of structural change. This is a quite common construct in the literature that analyzes economic development: under the three-sector-hypothesis, the analysis of structural change consists in accounting for the relative shares of primary, secondary and tertiary activities over time. Transposed to the aims of the present paper the units of interest are changes in the skill composition of each sector between two points in time measured by means of a structural change index (SCI) based on the Norm of Absolute Values (Michaely, 1962; Stoikov, 1966; Schiavo-Campo, 1978):

$$SCI_{t+1} = \frac{1}{4}\sum_{i}\sum_{t}|S_{i,t+1} - S_{i,t}|$$

where $S_{i,t}$ is the Skill-Factor intensity of factor i at time t. This construct provides a standardized measure of whether sectors maintain the same balance between skills over time: the lower the index the more stable the relative skill intensities in a sector and, vice-versa, the higher the value the stronger the re-composition.

By bringing together the last two constructs we can classify typologies of change depending on whether (i) skill intensity grows or declines; and (ii) the relative importance of skill-factors changes over time. The resulting spectrum of possibilities encompasses four outcomes. Two of them are readily intuitive, namely industries experiencing increase or decrease in skill intensity and maintaining the same structural composition of skills. These are indicated respectively as Up-Skilling or De-Skilling. In the remaining scenarios industries experience a significant alteration in the dominant skill set, in which case they are said to be either Re-Skilling Positively or Negatively, depending on the sign of the normalized growth rate. Thereby the Up-Skilling or De-Skilling sets contain two further subgroups of industries in which the evolution of the knowledge base is not only quantitative but also qualitative. Our rule of thumb of whether an industry is Re-Skilling is that the maximum average skill-factor does not change from the first to the second half of the decade. Where this does not happen, and therefore the ‘dominant’ skill-factor is invariant, the industry will have simply Up-Skilled or De-Skilled.

Figure 4 shows diagrammatically how industries in our dataset distribute according to the growth rates (horizontal axis) and degree of structural change (vertical axis) within the relevant cluster. According to the above, the NGR is an indicator of the direction of within-industry skill change while the SCI index captures the radicalness of this change. Accordingly, industries with above-average (below-average) SCI are in the upper (lower) part of the diagrams, while industries with positive (negative) NGR are located on the right-hand (left-hand). Put another way, industries in the top-right of the scatterplots are expected to have experienced high increase of skill-factor intensity and substantial changes in the ratio between Factor 1 and Factor 2; conversely, industries placed in the bottom-left would have undergone decline of skill intensity with a relatively stable skill configuration.

Narrowing the focus on individual clusters, Figures 4.a and 4.b and the tables below indicate overall skill decline for 81% of industries within Complex Production Activities (Cluster 1) and 60% within Basic Production Activities (Cluster 2). Conversely skill-factor intensity grows in 58% of sectors within People Services (Figure 4.c). As is to be expected, the drivers of these patterns differ across clusters. Within Complex Production Activities the decline in skill intensity is stronger among manufacturing industries, both Hi- and Medium-Tech, relative to services. The picture is more complicated in the Basic Production Activities cluster wherein the decline of skill-factor intensity is almost equal in both services and manufacturing, but where Low-Knowledge Intensive Services account for a greater proportion (26%) of up-skilling. Within Cluster 3, People Services, the majority (59%) of sectors enjoys growing skill intensity. At a finer disaggregation we observe that the skill configuration changes qualitatively in 24 out of 290 (8.2%) industries in our dataset; that where it takes place Re-Skilling is mostly negative (4.8%) rather than positive (3.4%); that Re-Skilling is slightly more frequent in Cluster 1 (12.5% compared to 9.6% of industries within Cluster 2) and among Low-Tech Manufacturing (18.9% across all clusters).[15]

FIGURE FOUR ABOUT HERE

Taken together the graphical analysis and the articulation of change processes illustrate the broad assortment of transformation processes, that is, of different velocities and direction in the reconfiguration of skill bases across clusters and industries. We believe that this way of looking at cross-industry variety offers an interesting framework to appreciate an ample spectrum of evolutionary transformations.

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[15] The small percentage of industries with different skill configuration over the ten-year period resonates, we think, with the argument that shifts in the knowledge base – which our analysis portray synthetically as Re-Skilling – entails a series of complementary transformations in the physical capital as well as in the organizational routines. Adjustment costs, especially in work organization, are likely to slow down the process (see Brynjolfsson and Hitt, 1996; Bresnahan and Greenstein, 1997; David, 2000).

4 Concluding remarks and the way ahead

This paper has presented a novel taxonomy of industrial sectors based on original data on the skill content of occupations, used here as proxy for the knowledge configurations embedded in the workforce. Let us sum up the main contributions of the present work.

The conceptual premise that employment is an instituted mechanism for the coordination of knowledge brings together loose threads in the area of innovation studies and, arguably, indicates a promising avenue for future research. Job specifications, it has been proposed, are blueprints of the repertoire of skills that the labour force is expected to possess and use in order to carry out particular work tasks. Accordingly, the distribution of skills in the employment structure is a close indicator of the particular knowledge configuration in an industry. Moreover as industry needs evolve over time the occupational structures and the relevant skills are, so to speak, engaged in an open-ended chase along the trajectory of knowledge growth which, as argued elsewhere, calls upon institutional responses to fill emergent skill gaps (Rosenberg, 1998; Vona and Consoli, 2011).

The second contribution of the paper is a novel taxonomy of industrial sectors based on specific skill configurations. The empirical analysis yields two skill factors and three industry clusters. The former capture parsimoniously the co-existence of different types of knowledge distinguished functionally depending on whether skills are employed for non-routine cognitive tasks or for manual activities. In turn, the distributions of these characteristics across the employment structures yield three main industry clusters. In the resulting taxonomy we observe that service activities are present everywhere, and appear complementary to manufacturing production (Clusters 1 and 2) or stand alone in the construct with the stronger interactive nature (Cluster 3). This result resonates with recent research suggesting that the traditional dualism with manufacturing is perhaps obsolete (Castellacci, 2008; Peneder, 2007) and casting a shadow on the persistent view of services as a homogeneous block of activities (Consoli and Elche, 2010; 2013).

The third substantive contribution is the kind of taxonomy that is proposed in the paper. A superficial comparison between our clusters and Pavitt's (1984) taxonomy may suggest discrepancies. We argue otherwise. True, the arrangement of sectors today is not what it was then (it's been 30 years!) but this only reaffirms the dynamic validity of that construct. If we consider the 'logic' of arranging sectors by functional similarities, the two sets of results are arguably not ontologically dissimilar. For the enduring legacy of Pavitt's classic taxonomy is the portrayal of sectors through snapshots of knowledge organization. Underpinning this heuristic model is the axiom that knowledge structures have transient nature: repeat the same exercise thirty years on and different configurations will be observed due to further evolution of the knowledge configurations.

It is worth reiterating that the paper calls attention to an overlooked nuance, namely that labour is the application of knowledge to a specific set of tasks, and that labour markets are instituted mechanisms for the coordination of such knowledge. In this view evolving skill structures are both the cause and the effect of shifting industrial regimes based on the generation, adaptation and diffusion of useful knowledge. At the same time, the match between work demands and useful knowledge is negotiated by means of the institutional processes that are a staple of the literature on innovation and economic development. But if the key dimensions involved, knowledge and institutions, are the bread and butter of the analysis of technological change, why has there been relatively little effort in integrating labour in the conceptual apparatus of innovation studies? On a related note, it seems appropriate to remind that the analysis of skill structures opens important windows on policy issues concerning skill mismatches, knowledge gaps and the role of education policy in responding to emergent industry needs. The growing availability of micro-longitudinal data such as those used here bodes well for future endeavors in this area of study.

To conclude, a cautionary remark is in order. It cannot be stressed enough that the analysis of this paper is but a preliminary step towards a promising direction. The most enticing prospect, and our next goal, is using specific information on sectors, such as economic (i.e. productivity, value added) or technological (i.e. patenting) performance, to explore statistical regularities with respect to changing skill configurations. Attractive as this future steps are, any empirical exercise in that direction required a prior effort of systematization of concepts and methods that, we hope, this paper contributes to outline.

Main text: 6556 words

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		Principal Component		Iterated Principal Factors		Maximum Likelihood	
		Factor1	Factor2	Factor1	Factor2	Factor1	Factor2
Factor 1 Interactive & Abstract	Active Learning	0.9427	0.322	0.9428	0.3241	0.9244	0.3742
	Active Listening	0.9736	0.1897	0.974	0.1909	0.9722	0.2203
	Complex Problem Solving	0.9101	0.4001	0.9095	0.4028	0.8808	0.4654
	Coordination	0.927	0.3382	0.9262	0.3404	0.9179	0.3584
	Critical Thinking	0.9464	0.3105	0.9466	0.3124	0.9302	0.3614
	Instructing	0.9216	0.156	0.9155	0.1611	0.9339	0.1509
	Judgment & Decision Making	0.9264	0.3553	0.926	0.3577	0.9046	0.4101
	Learning Strategies	0.943	0.1881	0.9398	0.1913	0.9466	0.2002
	Mathematics	0.7929	0.5464	0.7901	0.548	0.7452	0.627
	Manag of Financial Resources	0.8822	0.3144	0.877	0.3176	0.8456	0.3902
	Manag of Material Resources	0.8277	0.5265	0.8258	0.5293	0.7964	0.5637
	Manag of Personnel	0.9216	0.3269	0.92	0.3294	0.9031	0.363
	Monitoring	0.9523	0.2731	0.9522	0.2749	0.9457	0.2986
	Negotiation	0.9578	0.2	0.9564	0.2024	0.9428	0.25
	Operations Analysis	0.7981	0.5255	0.7949	0.5269	0.7376	0.6316
	Persuasion	0.9753	0.1703	0.9754	0.1718	0.9608	0.2258
	Programming	0.6437	0.4904	0.6371	0.4819	0.5586	0.6517
	Reading Comprehension	0.9503	0.2899	0.9504	0.2918	0.9401	0.3314
	Science	0.6526	0.5262	0.6475	0.5174	0.6338	0.5471
	Social Perceptiveness	0.9633	0.0154	0.9603	0.0192	0.9786	0.0187
	Speaking	0.9825	0.1438	0.9833	0.1446	0.9826	0.1749
	Service Orientation	0.9608	0.0245	0.9574	0.0286	0.9723	0.0328
	Systems Analysis	0.8132	0.5307	0.8108	0.533	0.7631	0.6153
	Systems Evaluation	0.8417	0.5021	0.8398	0.5049	0.797	0.5785
	Time Management	0.9566	0.2656	0.9567	0.2673	0.9491	0.2959
	Writing	0.9716	0.2132	0.9722	0.2145	0.9627	0.2602
Factor 2 Technical & Analytical	Equipment Maintenance	-0.0035	0.941	0.0006	0.9277	0.0078	0.8072
	Equipment Selection	0.5784	0.7847	0.5761	0.7866	0.5526	0.7789
	Installation	0.2513	0.9222	0.251	0.9176	0.2118	0.9106
	Operation and Control	0.2197	0.8961	0.2233	0.8808	0.2259	0.7946
	Operation Monitoring	0.1511	0.9346	0.1529	0.9253	0.1457	0.8504
	Quality Control Analysis	0.5373	0.8184	0.5348	0.8213	0.4934	0.8476
	Repairing	-0.0656	0.9425	-0.0618	0.9302	-0.0675	0.8328
	Technology Design	0.6143	0.7112	0.6121	0.7081	0.5541	0.7895
	Troubleshooting	0.4013	0.9022	0.398	0.9075	0.3626	0.9023
	% of variance explained	0.5824	0.2488	0.5446	0.3058	0.5768	0.256
	Cumulative % of var expl	0.5824	0.8312	0.5446	0.8504	0.5768	0.8328

Rotation method: Varimax with Kaiser normalization.

Table 1: Factor Analysis

	Complex Production (CL1)	Basic Production (CL2)	People Services (CL3)
Interactive & Abstract Skills	0.15***	-0.35***	0.20***
	(0.02)	(0.02)	(0.01)
Technical & Analytical Skills	0.21***	0.02	-0.23***
	(0.02)	(0.02)	(0.01)
Constant	0.17***	0.64***	0.19***
	(0.02)	(0.02)	(0.01)
N. of observations	290	290	290
R^2	0.49	0.53	0.61
Breusch-Pagan test	$\chi^2(3)=248.401$***		
Tests of equality of coefficients			
[Cluster 1] Factor 1 vs [Cluster 3] Factor 1	F(1,287) = 5.74**		
[Cluster 1] Factor 1 vs [Cluster 1] Factor 2	F(1,287) = 9.39***		

* p<0.10, ** p<0.05, *** p<0.01

Table 2: Multivariate Regression

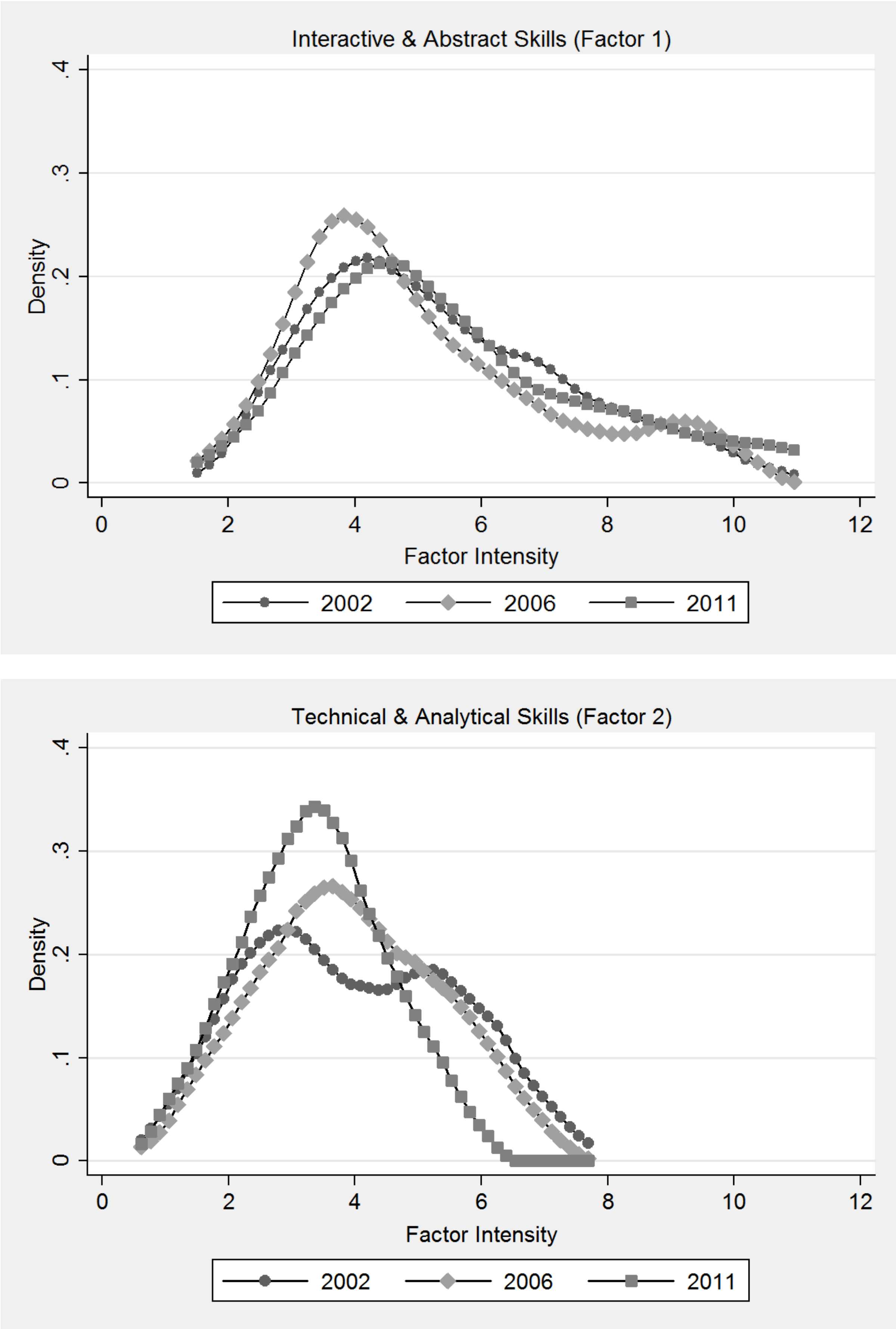
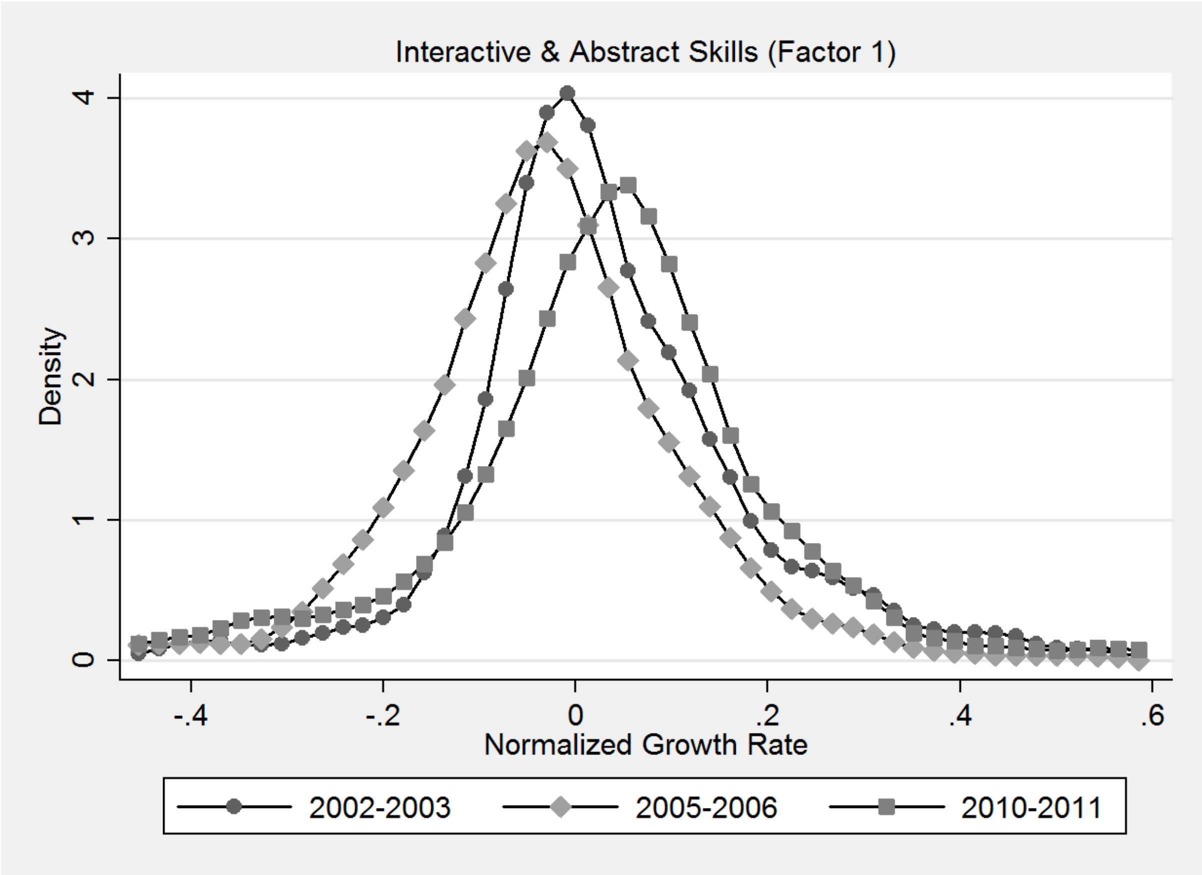


Figure 1: Kernel density distributions of Skill-Factors intensity across industries

Figure 2: Boxplots of Factor-skill intensity per Cluster



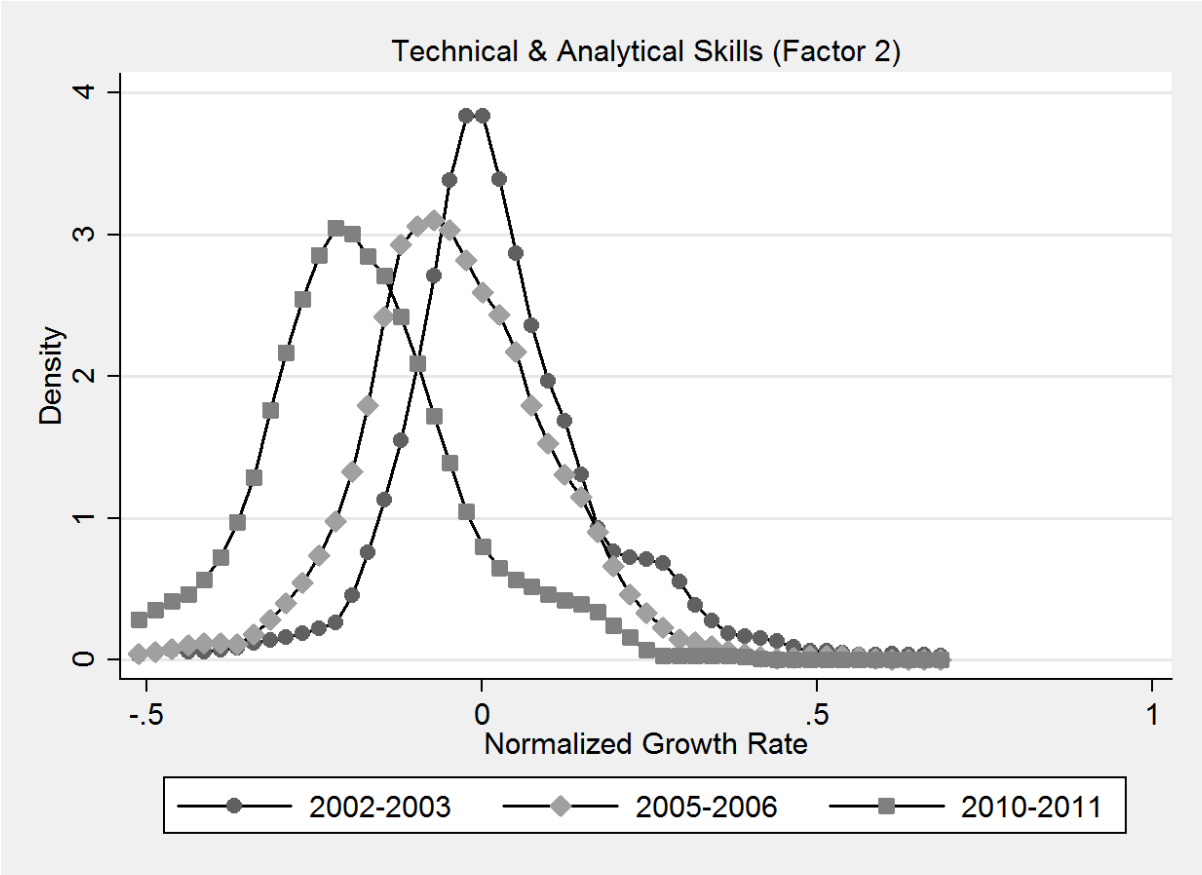


Figure 3: Kernel density distributions of Normalized Growth Rates of skill intensity

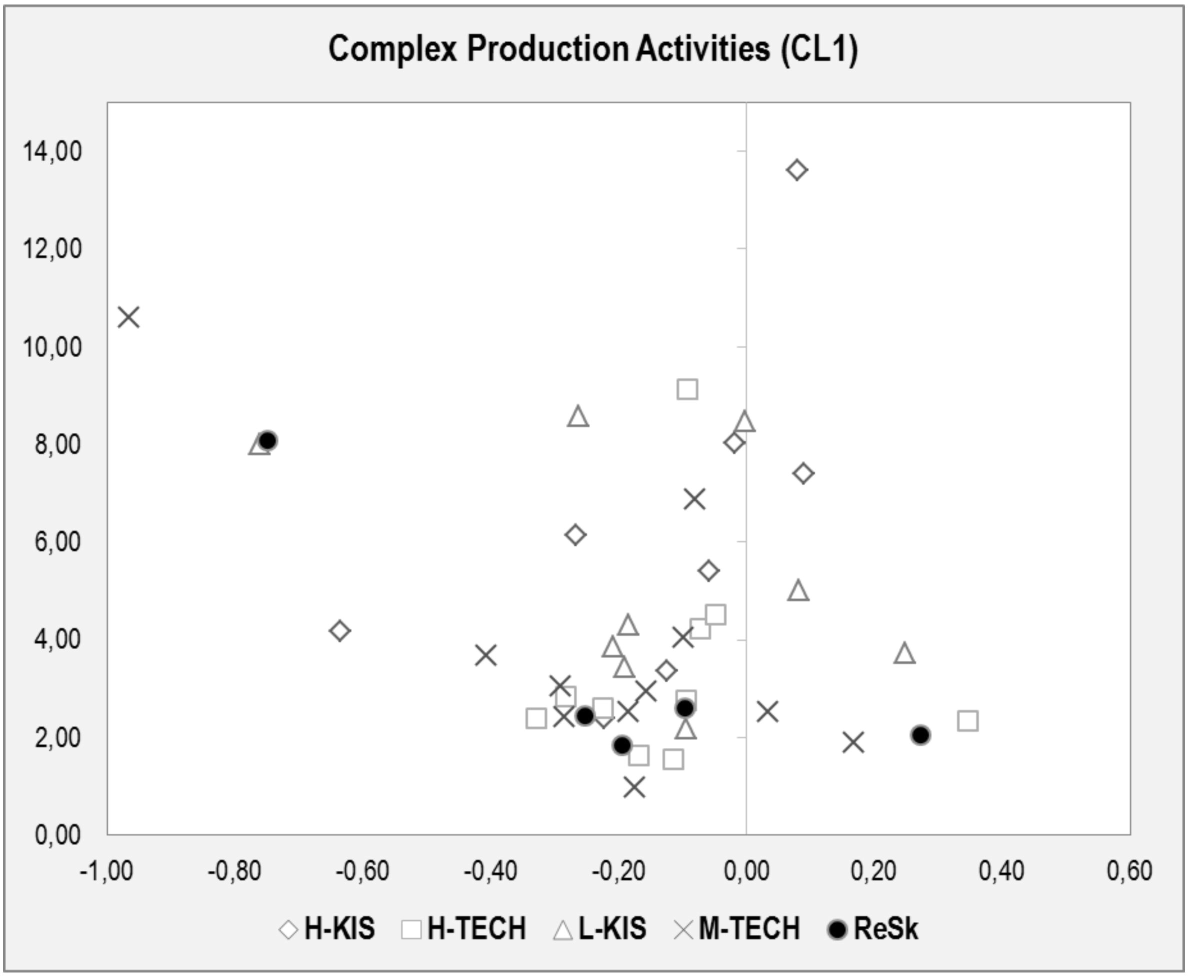


Figure 4.a: Scatterplot of Normalized Growth Rates by Structural Change Index (Cluster 1)

	H-KIS	H-TECH	L-KIS	M-TECH
De-Skilling	14.58%	18.75%	14.58%	18.75%
Re-Skilling (–)	2.08%		2.08%	4.17%
Up-Skilling	4.17%	2.08%	4.17%	4.17%
Re-Skilling (+)				2.08%
TOT	**10**	**10**	**10**	**14**

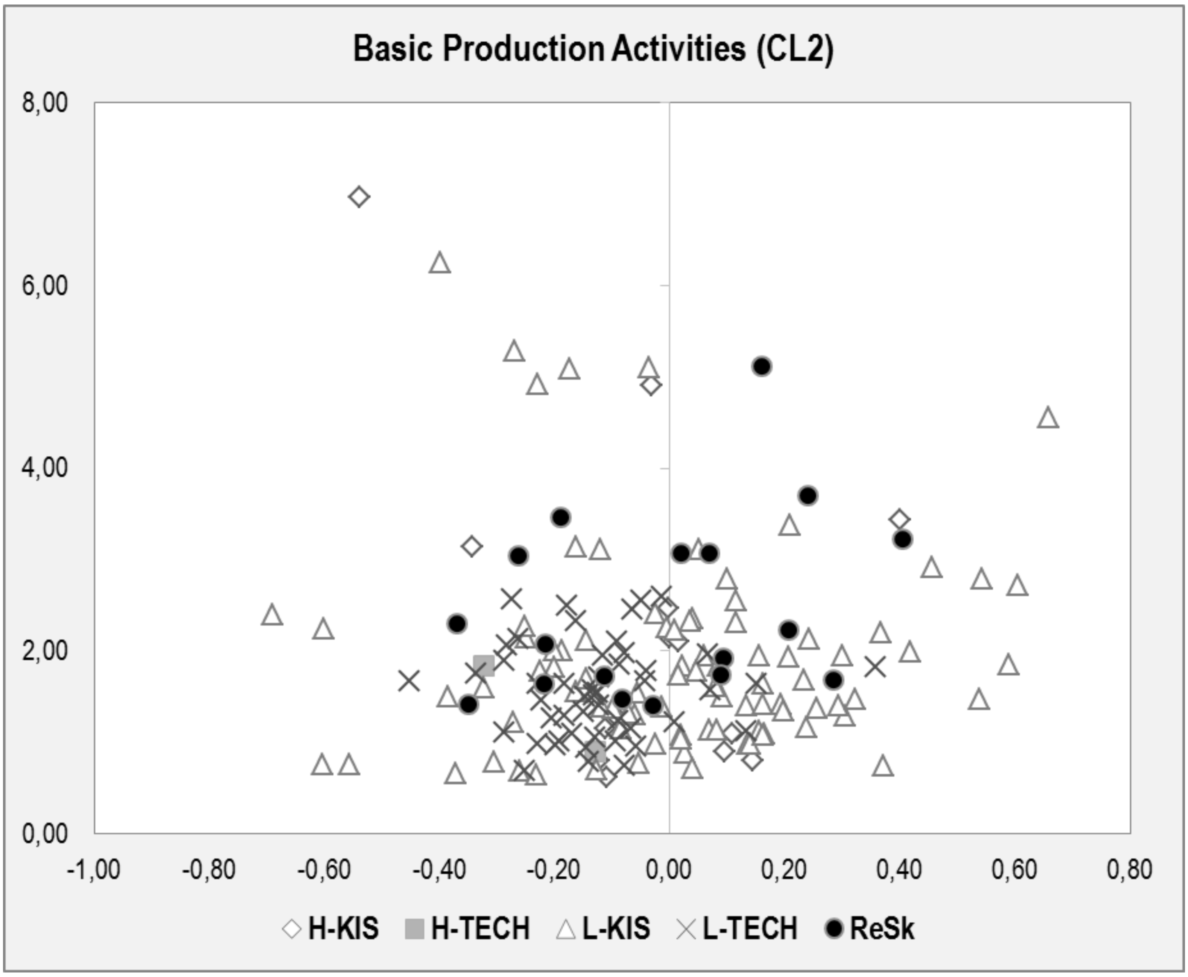


Figure 4.b: Scatterplot of Normalized Growth Rates by Structural Change Index (Cluster 2)

	H-KIS	H-TECH	L-KIS	L-TECH
De-Skilling	4.81%	1.07%	20.86%	22.99%
Re-Skilling (–)			0.53%	3.21%
Up-Skilling	2.67%		26.74%	3.21%
Re-Skilling (+)			2.14%	2.67%
TOT	**14**	**2**	**94**	**60**

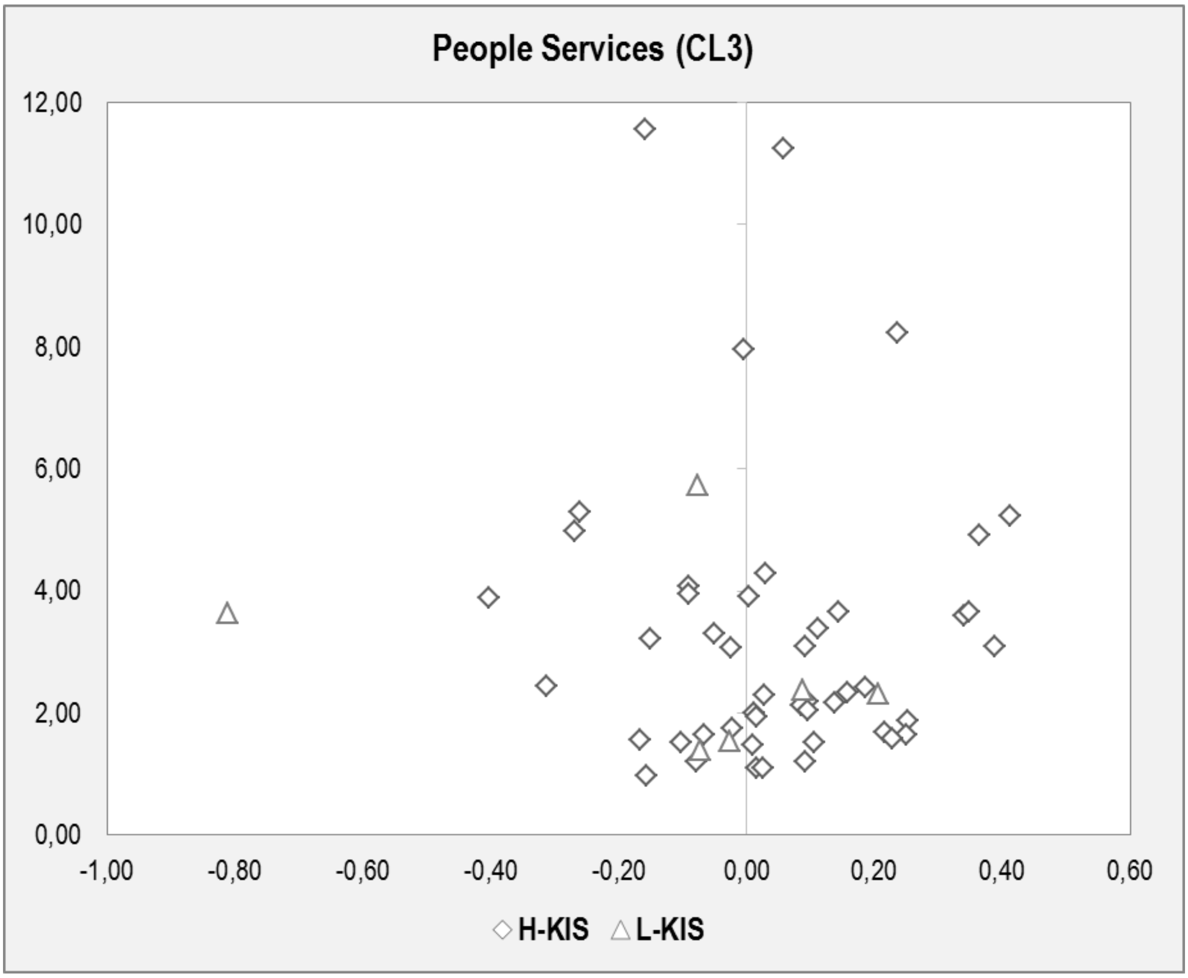


Figure 4.c: Scatterplot of Normalized Growth Rates by Structural Change Index (Cluster 3)

	H-KIS	H-TECH	L-KIS	L-TECH
De-Skilling	34.55%		7.27%	
Re-Skilling (–)				
Up-Skilling	54.55%		3.64%	
Re-Skilling (+)				
TOT	**49**		**6**	

Appendix A

O*NET, the Occupational Information Network, is a database of worker attributes and job characteristics maintained by the U.S. Department of Labor (DOL) and the National Center for O*NET Development, through its contractor Research Triangle Institute. It is the replacement for the Dictionary of Occupational Titles (DOT) and the primary source of occupational information for the US labour market. Data Collection is carried out in two steps: (1) identification of a random sample of businesses expected to employ workers in the targeted occupations, and (2) selection of a random sample of workers in those occupations within those businesses. New data are collected by means of a survey circulated among job incumbents (National Research Council, 2010). Occupations in O*NET are defined according to the criteria of the Standard Occupational Classification (SOC) system. Data Collection provides descriptive ratings based on the questionnaire covering various aspects of the occupation: Worker Characteristics, Worker Requirements, Experience Requirements, Occupation Requirements, Occupational Characteristics, and Occupation-Specific Information. In addition to the questionnaires completed by workers and occupation experts, additional ratings are provided by occupation analysts. Responses from all three sources – workers, occupation experts, and occupation analysts – are used to provide complete information for each occupation. The standardized skill set on which the questionnaire is built contains the categories reported in the table below.

I. Basic Skills	**IV. Social Skills**
Active Learning	Coordination
Active Listening	Instructing
Critical Thinking	Negotiation
Learning Strategies	Persuasion
Mathematics	Service Orientation
Monitoring	Social Perceptiveness
Reading Comprehension	**V. Systems Skills**
Science	Judgment and Decision Making
Speaking	Systems Analysis
Writing	Systems Evaluation
II. Complex Problem Solving Skills	**VI. Technical Skills**
Complex Problem Solving	Equipment Maintenance
III. Resource Management Skills	Equipment Selection
Management of Financial Resources	Installation
Management of Material Resources	Operation and Control
Management of Personnel Resources	Operation Monitoring
Time Management	Operations Analysis
	Programming
	Quality Control Analysis
	Repairing
	Troubleshooting
	Technology Design

Appendix B

	NAICS	F1	F2	Type
Cluster 1: Complex Production Activities				
517400	Satellite Telecommunications	20.38	17.38	H-KIS
511200	Software Publishers	18.94	12.30	H-KIS
541500	Computer Systems Design and Related Services	15.17	9.90	H-KIS
334100	Computer and Peripheral Equipment Manufacturing	14.57	10.25	H-TECH
518200	Data Processing, Hosting, and Related Services	13.12	8.19	L-KIS
486100	Pipeline Transportation of Crude Oil	12.14	11.26	L-KIS
621200	Offices of Dentists	12.00	8.02	H-KIS
487900	Scenic and Sightseeing Transportation, Other	11.65	12.00	H-KIS
541300	Architectural, Engineering, and Related Services	11.45	8.37	H-KIS
334200	Communications Equipment Manufacturing	10.85	8.33	H-TECH
517900	Other Telecommunications	10.73	7.82	H-KIS
486900	Other Pipeline Transportation	10.28	11.78	L-KIS
334500	Electromedical, and Control Instruments Manufacturing	9.75	7.41	H-TECH
211100	Oil and Gas Extraction	9.56	6.55	Other
334300	Audio and Video Equipment Manufacturing	9.37	7.89	H-TECH
325400	Pharmaceutical and Medicine Manufacturing	8.66	5.98	H-TECH
334600	Magnetic and Optical Media Manufacturing	8.55	6.89	L-TECH
486200	Pipeline Transportation of Natural Gas	8.53	7.47	L-KIS
336400	Aerospace Product and Parts Manufacturing	8.45	7.13	H-TECH
517100	Wired Telecommunications Carriers	8.24	6.79	H-KIS
334400	Semiconductor and Electronic Comp Manufacturing	8.15	6.96	H-TECH
333300	Commercial Industry Machinery Manufacturing	7.89	6.68	H-TECH
515200	Cable and Other Subscription Programming	7.80	6.25	H-KIS
333200	Industrial Machinery Manufacturing	7.74	6.84	H-TECH
811200	Electronic and Equipment Repair and Maintenance	6.84	8.16	L-KIS
221100	Electric Power Generation, Transmission, Distribution	6.65	6.47	Other
221200	Natural Gas Distribution	6.60	5.94	Other
481200	Nonscheduled Air Transportation	6.52	5.59	H-KIS
325100	Basic Chemical Manufacturing	6.47	6.01	H-TECH
485200	Interurban and Rural Bus Transportation	6.46	6.77	L-KIS
483200	Inland Water Transportation	6.12	6.59	L-KIS
336100	Motor Vehicle Manufacturing	6.10	9.16	L-TECH
336500	Railroad Rolling Stock Manufacturing	6.09	8.07	L-TECH
325300	Agricultural Chemical Manufacturing	6.05	5.63	L-TECH
336900	Other Transportation Equipment Manufacturing	6.03	6.20	L-TECH
325200	Artificial Synthetic Fibers Manufacturing	6.02	5.93	L-TECH
324100	Petroleum and Coal Products Manufacturing	5.97	5.68	L-TECH
335300	Electrical Equipment Manufacturing	5.94	6.01	L-TECH
333600	Power Transmission Equipment Manufacturing	5.88	6.21	L-TECH
332500	Hardware Manufacturing	5.88	6.11	L-TECH
488200	Support Activities for Rail Transportation	5.80	8.25	L-KIS
212200	Metal Ore Mining	5.69	7.16	Other
811300	Industrial Machinery Repair and Maintenance	5.61	7.40	L-KIS
333500	Metalworking Machinery Manufacturing	5.52	5.97	L-TECH
332400	Boiler, Tank, and Shipping Container Manufacturing	5.32	5.87	L-TECH
327400	Lime and Gypsum Product Manufacturing	5.03	6.22	L-TECH
336600	Ship and Boat Building	5.02	5.76	L-TECH
811400	Personal and Household Goods Repair and Maintenance	4.27	5.93	L-KIS

Cluster 2: Basic Production Activities				
331100	Iron and Steel Mills and Ferroalloy Manufacturing	4.14	5.62	L-TECH
332100	Forging and Stamping	4.94	5.55	L-TECH
333400	Commercial Refrigeration Equipment Manufacturing	4.92	5.53	L-TECH
312200	Tobacco Manufacturing	5.42	5.53	L-TECH
237100	Utility System Construction	4.41	5.46	Other
212100	Coal Mining	3.75	5.42	Other
454200	Vending Machine Operators	5.27	5.41	L-KIS
811100	Automotive Repair and Maintenance	3.66	5.41	L-KIS
332600	Spring and Wire Product Manufacturing	5.14	5.39	L-TECH
331300	Alumina and Aluminum Production and Processing	4.16	5.36	L-TECH
332200	Cutlery and Handtool Manufacturing	5.16	5.32	L-TECH
331400	Metal Production and Processing	4.78	5.30	L-TECH
237900	Other Heavy and Civil Engineering Construction	5.24	5.28	Other
333900	Other General Purpose Machinery Manufacturing	5.54	5.25	H-TECH
483100	Water Transportation	6.72	5.24	L-KIS
333100	Agriculture, Construction Machinery Manufacturing	5.00	5.24	L-TECH
325900	Other Chemical Product and Preparation Manufacturing	5.71	5.23	L-TECH
322100	Pulp, Paper, and Paperboard Mills	4.02	5.22	L-TECH
335100	Electric Lighting Equipment Manufacturing	5.31	5.21	L-TECH
313100	Fiber, Yarn, and Thread Mills	3.42	5.20	L-TECH
423400	Professional and Commercial Equipment Wholesalers	7.53	5.19	L-KIS
488300	Support Activities for Water Transportation	4.23	5.18	L-KIS
331200	Steel Product Manufacturing from Purchased Steel	4.57	5.16	L-TECH
335900	Other Electrical Equipment Manufacturing	5.10	5.15	L-TECH
562900	Remediation and Other Waste Management Services	5.65	5.14	L-KIS
335200	Household Appliance Manufacturing	4.49	5.05	L-TECH
332900	Other Fabricated Metal Product Manufacturing	4.88	5.02	L-TECH
325500	Paint, Coating, and Adhesive Manufacturing	6.18	5.01	L-TECH
221300	Water, Sewage and Other Systems	4.97	4.99	Other
336300	Motor Vehicle Parts Manufacturing	4.12	4.97	L-TECH
485500	Charter Bus Industry	4.83	4.96	L-KIS
331500	Foundries	3.79	4.94	L-TECH
332300	Architectural and Structural Metals Manufacturing	4.63	4.93	L-TECH
337200	Office Furniture (including Fixtures) Manufacturing	4.72	4.89	L-TECH
238200	Building Equipment Contractors	3.97	4.86	Other
332700	Turned Product; Screw, Nut, and Bolt Manufacturing	4.18	4.85	L-TECH
336200	Motor Vehicle Body and Trailer Manufacturing	4.30	4.81	L-TECH
311200	Grain and Oilseed Milling	4.19	4.81	L-TECH
213100	Support Activities for Mining	4.35	4.80	Other
237300	Highway, Street, and Bridge Construction	4.40	4.76	Other
488100	Support Activities for Air Transportation	4.13	4.74	L-KIS
316100	Leather and Hide Tanning and Finishing	4.45	4.64	L-TECH
326200	Rubber Product Manufacturing	3.66	4.63	L-TECH
325600	Cleaning Compound Manufacturing	5.11	4.55	L-TECH
212300	Nonmetallic Mineral Mining and Quarrying	3.64	4.52	Other
423600	Electrical and Electronic Goods Merchant Wholesalers	7.05	4.51	L-KIS
327100	Clay Product and Refractory Manufacturing	4.18	4.50	L-TECH
485100	Urban Transit Systems	4.52	4.47	L-KIS
532400	Commercial and Industrial Machinery Rental	5.26	4.46	L-KIS
327900	Other Nonmetallic Mineral Product Manufacturing	4.18	4.44	L-TECH
238100	Foundation, and Building Exterior Contractors	3.92	4.42	Other
327200	Glass and Glass Product Manufacturing	3.69	4.40	L-TECH
337900	Other Furniture Related Product Manufacturing	4.26	4.40	L-TECH

236200	Nonresidential Building Construction	5.54	4.39	Other
441300	Automotive Parts, Accessories, and Tire Stores	4.51	4.36	L-KIS
326100	Plastics Product Manufacturing	3.68	4.34	L-TECH
339100	Medical Equipment and Supplies Manufacturing	4.73	4.30	H-TECH
332800	Coating, Engraving, Heat Treating	3.83	4.24	L-TECH
441200	Other Motor Vehicle Dealers	4.93	4.24	L-KIS
512100	Motion Picture and Video Industries	7.26	4.19	H-KIS
487200	Scenic and Sightseeing Transportation, Water	4.76	4.19	L-KIS
446100	Health and Personal Care Stores	7.07	4.18	L-KIS
316900	Other Leather and Allied Product Manufacturing	4.67	4.16	L-TECH
313300	Textile and Fabric Finishing and Fabric Coating Mills	4.01	4.16	L-TECH
423800	Machinery, Equipment Merchant Wholesalers	5.10	4.15	L-KIS
562200	Waste Treatment and Disposal	4.96	4.15	L-KIS
322200	Converted Paper Product Manufacturing	3.64	4.12	L-TECH
492100	Couriers	4.71	4.09	L-KIS
313200	Fabric Mills	3.54	4.09	L-TECH
532300	General Rental Centers	5.27	4.09	L-KIS
315100	Apparel Knitting Mills	3.38	4.05	L-TECH
315900	Apparel Accessories and Other Apparel Manufacturing	4.30	4.04	L-TECH
339900	Other Miscellaneous Manufacturing	4.19	4.01	L-TECH
113300	Logging	3.59	3.99	Other
314900	Other Textile Product Mills	3.79	3.98	L-TECH
238900	Other Specialty Trade Contractors	3.57	3.98	Other
482100	Rail Transportation	3.38	3.97	L-KIS
511100	Newspaper, Periodical, Book, and Directory Publishers	6.68	3.97	H-KIS
321200	Engineered Wood Product Manufacturing	3.22	3.93	L-TECH
488900	Other Support Activities for Transportation	4.64	3.90	L-KIS
443100	Electronics and Appliance Stores	5.52	3.88	L-KIS
337100	Household and Institutional Furniture Manufacturing	3.15	3.87	L-TECH
485400	School and Employee Bus Transportation	3.72	3.87	L-KIS
321100	Sawmills and Wood Preservation	3.02	3.86	L-TECH
238300	Building Finishing Contractors	3.50	3.85	Other
423500	Metal and Mineral Merchant Wholesalers	5.37	3.84	L-KIS
237200	Land Subdivision	7.29	3.83	Other
487100	Scenic and Sightseeing Transportation, Land	4.74	3.80	H-KIS
327300	Cement and Concrete Product Manufacturing	3.47	3.78	L-TECH
492200	Local Messengers and Local Delivery	6.77	3.75	L-KIS
323100	Printing and Related Support Activities	3.92	3.71	L-TECH
541900	Other Professional, Scientific, and Technical Services	6.08	3.62	H-KIS
236100	Residential Building Construction	4.50	3.62	Other
424600	Chemical and Allied Products Merchant Wholesalers	5.61	3.58	L-KIS
321900	Other Wood Product Manufacturing	3.00	3.58	L-TECH
424700	Petroleum and Petroleum Merchant Wholesalers	4.98	3.57	L-KIS
316200	Footwear Manufacturing	3.40	3.55	L-TECH
999100	Federal Executive Branch and Postal Service	6.77	3.55	H-KIS
314100	Textile Furnishings Mills	3.02	3.54	L-TECH
561200	Facilities Support Services	4.94	3.53	L-KIS
481100	Scheduled Air Transportation	4.13	3.52	H-KIS
532100	Automotive Equipment Rental and Leasing	4.70	3.50	L-KIS
454300	Direct Selling Establishments	4.06	3.44	L-KIS
115200	Support Activities for Animal Production	4.48	3.44	Other
488400	Support Activities for Road Transportation	3.74	3.44	L-KIS
311100	Animal Food Manufacturing	3.74	3.41	L-TECH
441100	Automobile Dealers	4.91	3.39	L-KIS

423700	Plumbing and Heating Equipment Wholesalers	5.51	3.39	L-KIS
311400	Fruit and Vegetable Manufacturing	2.80	3.37	L-TECH
315200	Cut and Sew Apparel Manufacturing	3.38	3.34	L-TECH
115100	Support Activities for Crop Production	2.89	3.32	Other
311300	Sugar and Confectionery Product Manufacturing	2.96	3.31	L-TECH
424100	Paper and Paper Product Merchant Wholesalers	5.72	3.29	L-KIS
488500	Freight Transportation Arrangement	6.32	3.28	L-KIS
562100	Waste Collection	3.57	3.26	L-KIS
423200	Furniture and Home Furnishing Merchant Wholesalers	5.54	3.19	L-KIS
531300	Activities Related to Real Estate	5.31	3.17	L-KIS
485300	Taxi and Limousine Service	3.88	3.17	L-KIS
311500	Dairy Product Manufacturing	2.84	3.17	L-TECH
311700	Seafood Product Preparation and Packaging	2.96	3.16	L-TECH
812300	Drycleaning and Laundry Services	3.37	3.13	L-KIS
423100	Motor Vehicle and Supplies Merchant Wholesalers	4.14	3.10	L-KIS
311900	Other Food Manufacturing	3.27	3.06	L-TECH
485900	Other Transit and Ground Passenger Transportation	3.92	3.01	L-KIS
444200	Lawn and Garden Equipment and Supplies Stores	4.09	3.01	L-KIS
424200	Drugs and Druggists' Sundries Merchant Wholesalers	5.82	2.98	L-KIS
424300	Notions Merchant Wholesalers	5.88	2.97	L-KIS
312100	Beverage Manufacturing	3.30	2.96	L-TECH
423300	Construction Materials Merchant Wholesalers	4.19	2.91	L-KIS
712100	Museums, Historical Sites, and Similar Institutions	5.70	2.89	H-KIS
623100	Nursing Care Facilities	5.39	2.88	H-KIS
424500	Farm Product Raw Material Merchant Wholesalers	4.14	2.88	L-KIS
531100	Lessors of Real Estate	3.91	2.88	L-KIS
454100	Electronic Shopping and Mail-Order Houses	5.42	2.86	L-KIS
311600	Animal Slaughtering and Processing	1.93	2.81	L-TECH
711300	Promoters of Performing Arts, Sports Events	5.22	2.80	H-KIS
561900	Other Support Services	4.14	2.73	L-KIS
424800	Alcoholic Beverage Merchant Wholesalers	5.30	2.72	L-KIS
999300	Local Government (OES designation)	5.09	2.72	H-KIS
484200	Specialized Freight Trucking	2.82	2.70	L-KIS
423900	Miscellaneous Durable Goods Merchant Wholesalers	3.97	2.68	L-KIS
425100	Wholesale Electronic Markets and Agents and Brokers	4.67	2.65	L-KIS
484100	General Freight Trucking	2.66	2.62	L-KIS
311800	Bakeries and Tortilla Manufacturing	2.39	2.58	L-TECH
721200	Recreational Vehicle Parks and Recreational Camps	4.08	2.56	L-KIS
561700	Services to Buildings and Dwellings	2.46	2.45	L-KIS
493100	Warehousing and Storage	2.74	2.41	L-KIS
721300	Rooming and Boarding Houses	3.61	2.40	L-KIS
561600	Investigation and Security Services	3.60	2.37	H-KIS
561300	Employment Services	3.07	2.37	H-KIS
711200	Spectator Sports	3.81	2.29	H-KIS
561400	Business Support Services	4.58	2.27	L-KIS
531200	Offices of Real Estate Agents and Brokers	4.61	2.24	L-KIS
453100	Florists	4.35	2.23	L-KIS
424900	Nondurable Goods Merchant Wholesalers	3.62	2.23	L-KIS
453200	Office Supplies, Stationery, and Gift Stores	4.26	2.16	L-KIS
448200	Shoe Stores	4.91	2.07	L-KIS
444100	Building Material and Supplies Dealers	3.95	2.05	L-KIS
561500	Travel Arrangement and Reservation Services	4.73	2.03	L-KIS
623300	Community Care Facilities for the Elderly	3.98	2.01	H-KIS
713100	Amusement Parks and Arcades	3.43	2.01	L-KIS

424400	Grocery and Related Product Wholesalers	3.05	2.00	L-KIS
442200	Home Furnishings Stores	3.67	2.00	L-KIS
453900	Other Miscellaneous Store Retailers	3.60	1.98	L-KIS
442100	Furniture Stores	3.80	1.92	L-KIS
447100	Gasoline Stations	3.52	1.92	L-KIS
448300	Jewelry, Luggage, and Leather Goods Stores	3.78	1.89	L-KIS
812100	Personal Care Services	3.90	1.82	L-KIS
445200	Specialty Food Stores	3.14	1.79	L-KIS
812900	Other Personal Services	2.80	1.75	L-KIS
532200	Consumer Goods Rental	3.53	1.75	L-KIS
451100	Sporting Goods, Hobby, and Musical Instrument Stores	3.49	1.70	L-KIS
445300	Beer, Wine, and Liquor Stores	3.92	1.66	L-KIS
713200	Gambling Industries	2.91	1.65	L-KIS
813400	Civic and Social Organizations	4.05	1.63	L-KIS
721100	Traveler Accommodation	2.19	1.57	L-KIS
451200	Book, Periodical, and Music Stores	3.88	1.57	L-KIS
713900	Other Amusement and Recreation Industries	2.60	1.57	L-KIS
452900	Other General Merchandise Stores	2.90	1.56	L-KIS
452100	Department Stores	3.09	1.47	L-KIS
453300	Used Merchandise Stores	2.87	1.39	L-KIS
448100	Clothing Stores	3.20	1.36	L-KIS
445100	Grocery Stores	2.34	1.24	L-KIS
722400	Drinking Places (Alcoholic Beverages)	2.07	1.19	L-KIS
722300	Special Food Services	2.11	1.16	L-KIS
722100	Full-Service Restaurants	1.74	1.01	L-KIS
722200	Limited-Service Eating Places	1.74	1.00	L-KIS
Cluster 3: People Services				
523200	Securities and Commodity Exchanges	30.29	11.83	H-KIS
611400	Business Schools and Management Training	17.48	6.06	H-KIS
611200	Junior Colleges	16.27	5.38	H-KIS
525900	Other Investment Pools and Funds	15.52	5.79	H-KIS
611500	Technical and Trade Schools	15.02	5.18	H-KIS
711400	Agents and Managers for Artists, Athletes, Entertainers	15.01	4.78	H-KIS
611600	Other Schools and Instruction	14.75	4.83	H-KIS
525100	Insurance and Employee Benefit Funds	14.14	5.20	H-KIS
512200	Sound Recording Industries	14.10	7.64	H-KIS
521100	Monetary Authorities - Central Bank	14.09	6.95	H-KIS
519100	Internet Publishing and Broadcasting	13.50	7.37	H-KIS
611700	Educational Support Services	13.31	4.39	H-KIS
611300	Colleges, Universities, and Professional Schools	13.19	4.97	H-KIS
533100	Lessors of Nonfinancial Intangible Assets	12.85	5.27	L-KIS
621400	Outpatient Care Centers	11.21	4.66	H-KIS
541700	Scientific Research and Development Services	11.19	6.49	H-KIS
621900	Other Ambulatory Health Care Services	10.81	6.30	H-KIS
624200	Community Food and Housing Services	10.44	2.63	H-KIS
624400	Child Day Care Services	10.37	3.07	H-KIS
523100	Securities and Commodity Brokerage	10.36	3.93	H-KIS
541400	Specialized Design Services	10.35	6.17	H-KIS
622200	Psychiatric and Substance Abuse Hospitals	10.25	4.31	H-KIS
517200	Wireless Telecommunications Carriers	10.22	6.22	H-KIS
623900	Other Residential Care Facilities	9.81	2.62	H-KIS
813100	Religious Organizations	9.72	2.95	H-KIS
515100	Radio and Television Broadcasting	9.71	5.90	H-KIS

622300	Specialty Hospitals	9.64	5.32	H-KIS
611100	Elementary and Secondary Schools	9.62	3.68	H-KIS
813200	Grantmaking and Giving Services	9.48	3.17	L-KIS
523900	Other Financial Investment Activities	9.46	3.70	H-KIS
522300	Activities Related to Credit Intermediation	9.31	3.51	H-KIS
541100	Legal Services	9.23	2.30	H-KIS
622100	General Medical and Surgical Hospitals	9.21	5.29	H-KIS
621500	Medical and Diagnostic Laboratories	9.17	5.60	H-KIS
813300	Social Advocacy Organizations	9.14	2.79	L-KIS
522200	Nondepository Credit Intermediation	8.88	3.46	H-KIS
621300	Offices of Other Health Practitioners	8.62	4.43	H-KIS
624100	Individual and Family Services	8.38	2.31	H-KIS
621100	Offices of Physicians	8.31	4.74	H-KIS
623200	Mental Health and Substance Abuse Facilities	8.25	2.44	H-KIS
541600	Consulting Services	8.18	4.03	H-KIS
711500	Independent Artists, Writers, and Performers	8.15	4.76	H-KIS
624300	Vocational Rehabilitation Services	8.15	2.47	H-KIS
541200	Accounting, Tax Preparation, Bookkeeping Services	7.93	3.11	H-KIS
812200	Death Care Services	7.83	3.46	L-KIS
711100	Performing Arts Companies	7.83	4.16	H-KIS
999200	State Government (OES designation)	7.58	3.32	H-KIS
551100	Management of Companies and Enterprises	7.48	3.66	H-KIS
621600	Home Health Care Services	7.48	3.64	H-KIS
541800	Advertising and Related Services	7.33	3.96	H-KIS
524100	Insurance Carriers	7.30	3.13	H-KIS
522100	Depository Credit Intermediation	7.20	2.81	H-KIS
813900	Business, Professional, Labor, Political Organizations	7.15	2.92	L-KIS
561100	Office Administrative Services	7.08	3.35	L-KIS
524200	Agencies, Brokerages, and Other Insurance Activities	6.29	2.45	H-KIS