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Industry Dynamics and Labour Mobility

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Contents

Introduction

The present Thesis brings together two distinct fields of economic research – industrial dynamics and labour mobility.

As is often the case with academic work, the central topic of the Thesis came to my mind as a result of intellectual uneasiness. The year before I started my PhD in Economics at Bocconi University (in September 2002), I was asked to conduct a study on the innovation dynamics (and its impact on performance) among Portuguese Information Technology (IT) consultancy firms, in the context of a Governmental program dedicated to the promotion of innovation in Portugal (Proinov). As many students of the tertiary sector are well aware of, consultancy activities are the extreme expression of the peculiarity of services as economic activities: their product is essentially immaterial, product and process are hard to distinguish, it is difficult to separate production from consumption (clients and providers interact intensively, in what can be seen as a process of co-production), the relevant knowledge is hard to protect through intellectual property laws (reputation is often the main appropriability mechanism). In spite of all the work that has been done in the field of services' innovation, such features still represent a challenge to many of those theories and research methodologies that constitute the bulk of the Economics of Innovation and Technical Change (to a large extent, those theories and methods were the result of decades of research done on the evolution of manufacturing industries, where such consultancy-related features were frequently absent). This was, on itself, a good enough reason to motivate my interest in this type of industries.

What was not so clear for me in the beginning of my research on IT consultancy firms was how the specificity of those activities translated into the determinants of firms' competitive performance and, through this, into the dynamic patterns of structural change in industries. Students of industrial dynamics have often incorporated the insights and results from innovation studies in order to provide explanations for the entry and exit of firms, changes in market shares, the evolution of market concentration through time, and other features of industry turbulence. Among other things, this was a direct result of the evidence showing that the relation between technical change and market structure – a seminal debate in the Economics of Innovation – is far from an unidirectional one, being often at the core of the changes in both the pace and patterns of technical change and in industry structures. The theoretical efforts to bridge those two domains have based their analyses on such ingredients as: the relation between the uncertainty surrounding a new technology and the initial diversity in product designs; the size of the firms and the incentives to invest in process innovation; the conditions for appropriating the results of innovation efforts and their implication in the intensity of industry competition; among others.

While those relations are in fact crucial in the dynamics of many industries (what justifies the influence exerted by innovation-based analysis on the studies of industry evolution), they refer to innovation categories that are characteristic of manufactures, but are often hardly applicable to extreme cases of immaterial activities such as consultancy services. Innovation and knowledge will most probably have a role to play in the evolution of immaterial services industries as well, but this will usually not take the same form as in industries characterised by material production. In particular, as suggested above, in this type of activities product and process innovation tend to be intermeshed in the current activity of the service providers, and to a large extent embedded in the practice of the specialised workers who are employed by those firms.

In fact, studying the IT consultancy industry in Portugal made me realise for the first time how central labour markets can be to the performance of firms and to industry turbulence. This is an industry which has experienced a strong demand in the product market(s) for an extended period of time, and the growth of which has been essentially hampered by the scarcity of qualified labour. In such contexts, competition among firms is felt at least as strongly in the labour market as in the product market; the capacity to recruit and retain skilled workers is often a crucial determinant of incumbent firms' performance; and the mobility of workers represents risks and opportunities for both incumbents (including the recent entrants) and potential entrants. In sum, It is hard to think of the evolution of this type of industries without taking into account what happens in the corresponding labour markets.

This, however, was clearly at odds with what I found when I started to study the main models and empirical work in the field of Industrial Dynamics (which I chose as my main field during the first part of the PhD program at Bocconi). In fact, the most influential models of industry dynamics focus on the role of technical change, financial constrains, and/or information incompleteness concerning firms' productivity – but they typically abstract from the importance of the labour market and the inter-firm mobility of workers. As such, I had the impression that, when applied to many services industries (including some of the most dynamic industries of our times), those models risked missing the main features of the processes they intended to explain.

My next step was to look at the economic literature on labour mobility, in order to assess to what extent the link from labour mobility to the performance of firms and industries had been established here. To my surprise, and notwithstanding some developments that have taken place since the early 1990s, I concluded that the two fields of economic research – industrial dynamics and labour mobility – have essentially developed in parallel in the last half century, leaving open many questions concerning the interdependence between changes in industry structures and the flows of workers among firms.

Such interdependence delimits the scope of this Thesis. My contribution in the present context is done in three steps. First, I review some major contributions to the literatures on labour mobility and on industrial dynamics in order to convince the reader about the need to, and the opportunity of, an integrated approach to the dynamics of industries and labour mobility. This is done in the first chapter, which concludes with a list of questions that may inform a research agenda dedicated to such integrated approach. The second chapter consists in a computer simulation model, the main aim of which is to illustrate how the dynamics of industries and of worker flows can be coupled in a single framework, and how this contributes to our understanding of some well-known statistical regularities in both fields of research. Finally, the third chapter adds to the existing evidence about the relation between industry dynamics and labour mobility on the basis of an econometric analysis of the impact of worker flows on the surviving chances of firms.

A final note to the reader is required. Although they are all somehow related to each other, the three chapters that constitute the core of this Thesis were written as three separate, self-contained papers. This implies that the central focus of each of these papers are not necessarily articulated; and it explains why there is some (even if, hopefully, limited) repetition of some ideas in the three texts.

The Java/Repast[1] computer code that was used in the simulation model of Chapter 2 is included as a general annex to the Thesis.

[1] Repast is a software framework for creating agent based simulations using the Java language, which was initially developed at the University of Chicago. It provides a library of classes for creating, running, displaying and collecting data from an agent based simulation. Further information is available at http://repast.sourceforge.net/.

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Between September 2002 and August 2005 I was allowed to concentrate exclusively on my Doctoral studies, without any other professional duties whatsoever. This was only possible because I have benefited from a three-years teaching leave at the Economics Department of the Higher Institute for Business Studies and Social Sciences (ISCTE – Lisbon), where I have been teaching since 1999. During this period, while I was still getting my wage and having time to follow courses, study for exams and do my own research at Bocconi, other colleagues have seen their workload increase in order to cover my absence. This situation was only partly reverted since September 2005 (when I resumed my duties at ISCTE), giving me the opportunity to have some extra time to work on the final revision of the Thesis. This makes me indebted to the Department as a whole (and especially to Sandro Mendonça). I am also grateful for the personal encouragement and institutional support I received during the last three years from colleagues with high responsibilities at my home Department, namely Helena Lopes, Isabel Salavisa and José Castro Caldas.

Even though I cannot really complain about my salary as a teaching assistant in Portugal (mostly after I realised the financial pressure under which many Italian colleagues live), it would have been impossible for me to live in Milan and to pay for my fees without the partial grant (ref. SFRH/BD/8765/2002) I received from the Portuguese Science and Technology Foundation.

Still on an institutional level, the Portuguese Ministry of Employment and Social Solidarity has allowed me to access the data used in the third chapter of this Thesis. The support provided by this institution – and in particular by Mr. José Malveiro – is gratefully acknowledged.

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The past three years were years of intensive (and not always pleasant) work, during which I have benefited from the encouragement and support of many friends and family. Incurring in the risk of forgetting someone who does not deserve to be left aside, I would like to express my gratitude to Carlos, Catarina, Carlota, Eduardo Condorcet, João Rodrigues, Luis Carlos, Luis Rego, Manuel Beja, Manuel Godinho, Mónica, Odete, Rosa and Zé Mamede, for the moments in which their (physical or virtual) presence was more important than they probably imagine.

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Chapter 1

Towards an integrated approach to industry dynamics and labour mobility

1. INTRODUCTION

Industrial dynamics and studies of labour mobility are two fields of economic research that have developed fast in the past two decades. In both cases such development was very much related with the increased availability of micro data, of computational resources, and of statistic and econometric tools suitable to their treatment. These, in turn, have favoured the identification of a number of empirical regularities (which are often taken as 'stylised facts' in both domains). On the basis of such evidence, existing theoretical models were tested and new models were developed aiming at a better explanation of the regularities found in the data.

A further common feature of those two fields of research is the fact that both deal with what can be seen as epiphenomena of the dynamic nature of the contemporary capitalist societies. We now know that the turbulence in industry structures – as a result of entry and exit of firms, changes in market shares, changes in property control, etc. – is striking. For example, using a harmonised firm-level dataset of 24 industrial and developing countries, Bartelsman et al. (2004) found that, even when micro firms (i.e., firms with less then 20 people) are excluded, the annual sum of entries and exits is between 3% and 8% of the total number of firms in most industrial countries; with micro firms included, the figure increases to 20-25%. When we look at the figures on labour market dynamics, the picture is no less impressive: according to the OECD (1999), the annual turnover of the workforce in industrial economies (understood as the sum of hires and separations) varies between 10% and 15% (whilst total employment typically does not change more than 1-2%).

There are plenty of reasons to believe that changes in industry structures and worker mobility are not entirely independent phenomena. At the most obvious level, the growth of existing firms and the creation of the new ones is necessarily related to an inflow of workers to those firms, just as the contraction and the closure of firms have the opposite effects on the supply-side of the labour markets (Davis et al., 1996). Moreover, industry turbulence affects the labour markets not only in such direct way, but also indirectly through the vacancy chains that are opened and closed by firms' growth/founding and contraction/failure (as pointed out, e.g., by Haveman, 1995). Reverting the direction of the causality, it has been noted for a long time (e.g., Staw, 1980) that worker turnover has both positive and negative consequences for organisations, and in this sense they may constitute an important determinant of industry dynamics. More recently, research on the importance of previous experience for entering firms (e.g., Helfat and Lieberman, 2002) draws attention to the role of workers' turnover in bringing competences to, and therefore increasing the survival prospects of, newly founded firms.

In this paper I will argue that, notwithstanding all the possible links between industry evolution and labour market dynamics, there remains a lack of systematic discussion about the details of such interdependencies and its implications. In fact, most theoretical models of industrial dynamics (for surveys see, e.g., Dosi et al., 1997; Sutton, 1997; Caves, 1998) tend to focus on the technological or financial determinants of changes in the structure of industries, abstracting from the influence of labour market determinants. In the same vein, the reference models of worker mobility (for a survey see, e.g., Farber, 1999) typically underestimate the mutual influence between industry dynamics and labour market forces. With a few notable exceptions, most of the empirical work that has been done in both fields of research has followed along the same lines.

In many contexts, ignoring the mutual influence between the evolution of industry structures and the patterns of worker mobility does not do much harm to the progress of knowledge. While it is difficult to imagine situations in which the two dynamic processes are entirely independent, it is clear that the movement of workers between firms tends to be a minor issue in the evolution of several industries (specially those that essentially rely on low-skilled, homogeneous labour, and/or in which firms operate as monopsonists, or quasi-monopsonists, within the relevant labour markets); similarly, the movement of workers in the labour market is only partly determined by the evolution of the firms that employ them – cultural, institutional, and/or idiosyncratic factors usually exert their influence and may often be more relevant than industry turbulence in determining the patterns of worker mobility. In such contexts, abstracting from the influence of worker turnover on industry evolution, or vice-versa, simply reflects the need to concentrate on the essentials and leave aside the details, which is common to any scientific endeavour.

However, we also know that such mutual influence can be crucial in many other contexts. In fact, historical accounts of industries which are highly dependent on a specialised labour force often show that the patterns of firms' evolution and of labour force mobility are intrinsically related. For example, in relation to both hi-tech (Baron, 2004) and professional services industries (Mamede, 2002; Gallouj, 2002) it has been emphasise that the performance of firms is very much affected by their capacity to recruit skilled workers and to avoid poaching by competitors. Such 'recruitment-based competition' (to use the expression suggested by Sørensen, 2004), together with the highly turbulent character of some of those industries (especially those in the early phases of their life-cycle), also imply that the movement of workers will be strongly influenced by the dynamics of the relevant population of employing organisations. When this is the case, theoretical and empirical inquires of industry evolution which abstract from the role of labour market dynamics – or vice-versa – risk missing the main elements of the dynamic picture they propose to explain.

It is thus worthwhile to look at where we stand in our knowledge of the interdependencies between the evolution industry structures and the patterns of worker mobility between firms, to signal the gaps in the relevant literature, and to point towards possible developments that may help us elucidate the dynamic processes involved. These constitute the central aims of this paper.

The remaining sections are organised as follows. Sections 2 and 3 are dedicated to the separate analysis of two opposite influences: first I discuss the extent to which the existing literature has considered the role of firms and industries in explaining the turnover of workers, and then I turn to the analysis of the literature related to the impact of workers turnover on the evolution of industries. Section 4 discusses different possible strategies to put industry and labour market dynamics together in an integrated theoretical framework. Section 5 summarises the main arguments and concludes the paper.

2. THE ROLE OF FIRMS AND INDUSTRIES IN EXPLAINING THE INTER-FIRM MOBILITY OF WORKERS

This section deals with the impact of industry dynamics on worker mobility. First it will look at a number empirical regularities which have been identified in relation to the inter-firm movements of workers, and at examples of influential theories which provide alternative explanations for the regularities found in the data. While the typical explanations for the usual patterns of worker mobility focus on factors related to the supply-side of the labour market or to job-match quality issues, there is now a considerable amount of evidence emphasising the relevance of demand-side turbulence in determining worker mobility. Still, the empirical studies that can be found in the literature capture only part of the possible links between industry dynamics and worker mobility – as should become clear by the end of the section – leaving open a number of questions associated with the dynamic relation under discussion.

2.1. Empirical regularities and typical theoretical explanations of inter-firm worker mobility

Drawing on an extensive review of empirical studies concerned with the analysis of the stability and mobility of employment relations, Farber (1999) emphasises three central facts describing inter-firm worker mobility in modern labour markets: (i) long-term employment relationships are common (i.e., a significant proportion of workers are involved in durable employment relations), (ii) most new jobs end early, and (iii) the probability of a job ending declines with time (the relation is not necessarily monotonic – some studies find that the probability of a job change may first increase with tenure, before starting to decrease).

To provide an instance of such regularities, drawing on data from unemployment insurance systems in the U.S., Andersen and Meyer (1994) have found that: most turnover (55%) is due to a minority of individuals (22%) who frequently change jobs; about 40% of employment relations last no more than one year; and the impact of tenure on the dissolution of job matches is negative (after controlling for other relevant factors, such as wage levels).

Different types of models have been put forward which can account for such statistical regularities. However, the most influential of such models have one thing in common: they typically abstract from the effects of industry turbulence on labour mobility (putting the burden of the explanation on factors belonging to the supply-side of the labour market, or on the quality of the match between employer and worker). The following examples illustrate this point.

The first case consists in models of worker mobility which are based on individual heterogeneity. The idea underlying these approaches is that individuals have different propensities towards work and mobility (which may be captured, at least partially, in the empirical work by such variables as age, gender, ethnicity, education background, etc.). Faber (1999) presents a simple model of this type to show how individual heterogeneity can lead to the three regularities mentioned above: suppose there are two types of workers, which only differentiate by their turnover probability; in order to have a high percentage of long tenures, we just have to assume that less turnover-prone individuals are highly represented in the population; since highly mobile workers have a lower probability of experiencing long tenures, most of the workers involved in durable employment relationships will be of the low-turnover type and, consequently, the probability of separations decreases with tenure; finally, since the less mobile workers are typically involved in long tenures, most new job vacancies will be filled by high-turnover individuals and, therefore, many new job matches will end early.

A second example of an influential model explaining those patterns of job turnover is the one put forward by Jovanovic (1979). The building block of this model is the idea that the productivity of each particular job match is not known in advance – it is gradually revealed, since output constitutes a noisy signal of match quality. As the expectations of both firms and workers are updated on the basis of each period's output, both sides can decide whether to continue or to stop the employment relationship. Jovanovic's model is particularly successful in replicating the statistical regularities listed above, since it allows for a non-monotonic relation between tenure and probability of turnover: initially, even if the observable output signals a bad-quality match, workers tend to remain in the firm since they know the signal is noisy; as time goes by, the assessment of match quality becomes more precise, leading either to a separation (because the match quality is too low) or to a permanent match (because its quality is high); thus, in an early phase more and more workers will decide to move, but on the other hand an increasing number of workers is involved in enduring employment relationships.

These are two instances of models that successfully replicate a few central statistical regularities of worker mobility, and they both illustrate the tendency (often noted among students of the labour markets) to abstract from demand-side disturbances as determinants of employee turnover. Such tendency has been gradually reverted in recent years, as more and more studies have shown the extent to which labour market dynamics are influenced by the turbulence experienced on the employers' side. Quoting Davis and Haltiwanger (1999, p.2715), «*It is now apparent, as perhaps it was not a decade ago, that a satisfactory account of worker mobility dynamics in market economies requires a major role for demand-side disturbances as well as for supply-side and match-quality effects.*» A major role for industry turbulence in labour market analyses is provided by the literature on job creation and destruction, which will be dealt with in the next section.

2.2. Industry dynamics and the gross creation and destruction of jobs

The literature on job creation and destruction provides the first instance of a direct link between research on industrial dynamics and work on labour market flows. In fact, this literature – which focuses on traditional topics in labour economics – as both benefited from and contributed to the theory and evidence produced in the realm of industrial dynamics.

During the 1980s, the evidence on the pervasiveness of entry and exit of firms in the markets accumulated continuously. Dunne, Roberts and Samuelson (1988), for example, have used data from the US Census Bureau, which included information collected by 5 Census of Manufacturing from 1963 to 1982, to study the patterns of entry and exit in US manufacturing industries. They have shown that, even excluding the smallest firms, 38.6% of the firms included in each census were not included in the previous one (which typically took place 5 years before). The authors have also shown that, although numerous, entrants tend to be much smaller than incumbent firms, being responsible for only 15.8% of the industry output. Similar results were obtained with respect to firm exits (with the market share of the exiting firms being slightly higher). These results corroborated the evidence already produced by the empirical literature on the so-called 'Gibrat's Law' (e.g., Evans, 1987; Hall, 1987)[1], which has also shown that firm growth is negatively related with firm size and age, with younger firms facing a higher probability of failure but also better growth perspectives for those that survive.

The literature on job creation and job destruction has established a link between such patterns of turbulence in industry structures and the gross flows of jobs in the labour markets. The following definitions (or minor variations of it) are central to the establishment of such link in the context of this literature (see, e.g., Davis and Haltiwanger, 1992): *gross job creation at time t* corresponds to the employment gains summed over all business units that expand or start up between t-1 and t; *gross job destruction at time t* corresponds to the employment losses summed over all business units that contract or shut down between t-1 and t; *gross job reallocation at time t* is the sum of all business unit's employment gains and losses that occurred between t-1 and t (it equals the sum of gross job creation and job destruction). The corresponding rates are obtained by dividing those variables by the total employment at t (or, as is often the case, by the arithmetic mean of total employment in periods t and t-1).

This stream of literature has produced an immense amount of evidence on some crucial aspects of the labour market dynamics. Davis and Haltiwanger (1999) review the main results that were obtained in studies conducted in several different countries during the 1990s; on the basis of such studies they show that: around 10% of jobs are created and other 10% are destroyed every year; in every country the rate of job reallocation is higher than 10% for most of the sectors at a two-digit desegregation level (using the international system of industrial classification); most of the job creation (destruction) is due to the expansion (contraction) of existing firms, rather than to firm entries (exits).

For example, using data from the US Annual Survey of Manufacture between 1972 and 1986, Davis and Haltiwanger (1992) have found that: the annual rates of job creation and job destruction at the plant level were 9.2% and 11.3%, respectively (Dunne et al.,

[1] For a review of the debate surrounding the 'Gibrat's Law' of proportionate effects see Sutton (1997).

1989, have reached similar results, using different data); entries were responsible for 20% of job creation and exits by 25% of job destruction (thus confirming the notion that both entering and exiting firms are typically smaller than the average incumbent); not only is job destruction mostly driven by the contraction of existing firms, but about ¾ of job destruction takes place in plants that lose more than 20% of employment in one year.

More importantly in the present context, Davis and Haltiwanger (1992) show that the inter-sectoral reallocation of jobs plays a minor role in explaining total job reallocation (this is true even if sectors are defined not only in terms of industrial classification, but also according to plants' age, size, ownership type, or region); that is, they show that explaining total employment reallocation implies taking into account the causes underlying the simultaneous occurrence of job creation and job destruction within each sector.[2]

As one could expect, different industries do not show the same intensity of job reallocation. Some of the studies that have been done within this line of inquiry since the early 1990s have thus tried to identify the determinants the inter-industrial differences in the patterns of job creation and destruction. For example, using data on the Swedish economy between 1986 and 1997, Antelius and Lundberg (2003) have found that job reallocation is: lower in manufacturing industries than in services; higher in more innovative and fast growing industries, higher in industries with smaller firms and lower returns, lower in industries with more stables market shares, lower in the more export-oriented industries in which the presence of foreign capital is more pronounced. These results clearly suggest that the same kind of features that characterise the more turbulent industries – innovativeness, fast growth, competitive pressure, etc. – are also present in the explanation of higher degrees of job reallocation.

Such coincidence, however, is not at all surprising. In fact, the definitions of job creation, job destruction, and job reallocation which were presented above are indeed not indicators of worker flows, but rather indicators of net employment changes

[2] The authors show that, although all two-digit sectors have experienced a contraction in total employment during the period under analysis (1972-1986), in every such sector there were plants in which job creation took place (the same applies up to the four-digit desegregation).

summed over all business units belonging to some category. And it is only natural that higher levels of net employment changes (in absolute terms) occur in firms belonging to more turbulent industries.

The use of such definitions constitutes both the crucial strength and the crucial weakness of the 'job creation and job destruction' type of approach. It constitutes a strength because it has allowed the production of a considerable amount of new evidence on the heterogeneity of business units in terms of job dynamics (which had a significant impact in such diverse fields of labour economics, industrial organisation, and macroeconomics), drawing on data sources that were readily available. While most evidence on labour market mobility had been previously produced using information on individuals, Davis, Haltiwanger and others took advantage of databases dedicated to the demand-side of the labour market (actually using the same type of information used by researchers of industry dynamics) to explore this field from a different perspective. On the other hand, by looking only at the net employment changes in business units, research on job creation and destruction is unable to capture a significant part of the labour market flows; for example, it ignores all the changes in the composition of the workforce that do not lead to variations in total employment within firms. The type of work to be discussed in the following section has tried to overcome this limitation by looking simultaneously at both sides of the labour market in the analysis of worker mobility.

2.3. Worker turnover in excess of job reallocation

The last two sections dealt with two contrasting approaches to the analysis of labour market dynamics: on one hand, we have those contributions focusing on worker flows, which typically emphasise the role of labour market supply-side or match-quality factors, and which rely on data on individual workers, in order to explain the observable patterns; on the other hand, the 'job creation and job destruction' approach focuses on strictly demand-side determinants of labour market flows. Both types of approaches present obvious shortcomings: the first one tends to underplay the role of industry turbulence, and its impact on the demand for labour, in explaining the patterns of workers' moves; the second approach is unable to account for movements of workers that exceed the net changes in total employment within each productive unit.

Both cases represent real obstacles to the understanding of the mutual influence between industry dynamics and worker mobility. On the one hand, it is not indifferent to a firm whether the amount of changes in the composition of its workforce has exceeded or not the number of hires/separations needed to accommodate the expansion/contraction of the firm: even if the total number of employees has remained the same, if half of the people left since last period and half of the personnel is new to the firm in the current period this may have a significant impact in the firm's performance. On the other hand, hires or separations that are not related to changes in the dimension of the firm probably are motivated by factors other than purely demand-led job reallocations, and it may be worthwhile to consider those differences.

To a large extent, the shortcomings of the approaches which were discussed before reflect the absence of adequate data to carry out an integrated analysis of labour market dynamics: while the availability of longitudinal data from different countries concerning either individual workers or business units has increased sharply since the early 1980s, databases matching the trajectory of both workers and firms in different time periods – the kind of data that allow the joint consideration of supply and demand in the analysis of worker mobility – are still scarce.

The use of matched employer-employee longitudinal databases[3] provides the basis for more precise estimations concerning the relative importance of demand- and supply-side determinants in explaining the mobility of workers between productive units. In one of the first studies providing direct evidence on this issue[4], drawing on data for eight States in the U.S., Andersen and Meyer (1994) estimate that 31% of the quarterly

[3] For an overview of the different studies that have used matched employer-employee data see Abowd and Kramarz (1999). Hamermesh (1999) discusses some research avenues (which overlap only partly with what is discussed in the present paper) that are opened with the increased availability of this type of data.

[4] As a matter of fact, Davis and Haltiwanger (1992) were able to estimate indirectly the approximate impact of demand-led disturbances on worker mobility by combining plant-level data with information from different sources on the mobility in the labour markets. They suggested that 35% to 56% of the transitions between employment states were due to employment opportunities related to job creation and destruction. Although it is only an approximate estimation, this interval is not incompatible with more precise estimations obtained on the basis of matched employer-employee data.

total worker turnover (i.e., the sum of all hires and separations) was explained by the creation and destruction of jobs (this proportion is lower for manufacturing industries and higher for services). Similar results were achieved by Hamermesh et al. (1996) in their study of the Dutch economy in the period 1988-1990 (job turnover rate was found to be 6.2%, about one third of the figure estimated for worker turnover, 22%). Albaek and Sorensen (1998), using data from Denmark for the period 1980-1991, found that, on average, job creation constituted 42% of hiring, and job destruction represented 41% of separations. Abowd et al. (1999) used a representative sample of French establishments from 1987 to 1990 to show that annual job creation is characterised as hiring three persons and separating two for each job created in a given year, and that annual job destruction is characterised as hiring one person and separating two for each job destroyed in a given year. Finally, using quarterly data for the State of Maryland in the U.S., Burgess et al. (2000) found that job flows account for nearly 30% of the worker flows in non-manufacturing industries, and about 37.6% in manufactures.

All these studies demonstrate that underneath the net changes in total employment at the firm level, there is a considerable amount of simultaneous hiring and separations going on. In fact, many of those studies have shown that the turnover of workers is only loosely connected to job creation and job destruction. For example, Hamermesh et al. (1996) show that: the flows of workers are large even in firms where net employment changes are small; most firing is done by firms that are also hiring; although hiring is higher for firms with expanding employment, hiring rates in firms with declining employment average 5.9%; and while matches dissolve more intensively among firms with declining employment, firms with expanding employment still fire 1.1% of their workers each year, and (voluntary) quite rates seems relatively unaffected by conditions within the firm.

The fact that the turnover of workers is only partly determined by the expansion and contraction of business units should not, however, be taken as an indication of little mutual influence between labour market flows and industry dynamics. While there are a number of different factors which may explain worker flows in excess of job reallocation – or 'churning', as Lane, Stevens and colleagues (see references below) call it – it is plausible that at least part of those factors are strictly related with the dynamics of firms and industries. The next section is dedicated to the discussion of this topic.

2.4. The dynamics of firms and industries as a determinant of churning[5]

The level of worker turnover may differ across industries or across firms for several reasons, for example: high hiring and training costs may reduce turnover, and such costs can vary across industries (or between different phases in the lifecycle of the same industry) due to differences in the production process and the nature of worker skill requirements; implicit contracts may develop between firms and workers, and such contracts may vary with firm size and product demand; there may also be economies of scale in screening devices, which may help increase the initial quality of job matches in bigger firms; moreover, firms may learn to develop more effective screening devices as they age, which means that turnover is expected to be lower for older firms (Lane et al., 1996). All these examples suggest that the type and amount of turnover expected to be found (and/or to be desirable) in different firms, in different industries, or in different phases of the lifecycle of firms and industries may vary is some consistent manner.

Unfortunately, the amount of evidence on this is still modest. Again, this is mainly due to the scarcity of data: not only matched employer-employee databases still do not abound, moreover the information included in the available datasets often does not allow a systematic discussion of the links between worker turnover and the dynamic features of firms and industries. The implication is that the available evidence related to such links was produced on the basis of very few data sources; therefore, the following results should be seen as preliminary ones.

(i) *Firm size is not on itself a determinant of worker turnover.* The discussion above seemed to suggest that bigger firms would experience lower turnover rates. Some empirical studies have in fact suggested this relationship: for example, DiPrete (1993) regressed the number of worker separations per organisation on the dimension of firms (and other variables related to the industry and the worker type) and found an inverse relationship between the two variables. However, other studies seem to contradict this

[5] Churning flows are typically computed at each period as the difference between total worker turnover (i.e., the sum of hires and separations occurring in that period) and the absolute value of net job changes. I.e., $CF=WF-|H-S|$, where CF are the churning flows, WF are the total worker flows ($WF=H+S$), H are the hires, and S stands for the separations in the period.

result: Burgess et al. (2001) found that churning is unrelated with size; in the same vein, Martin (2003) finds that the effect of firm's dimension on worker turnover is not significant. While the comparability of this studies is somewhat hampered by differences in the variables they purpose to explain (separations, churning, total worker turnover) and in the type of data being employed, there are reasons to believe that firms' sizes exert their influence on workers mobility by means of other organisational features – and therefore the statistical significance of their impact tends to wither as the relevant variables are included in the regressions. For example, in the study just mentioned, Martin (2003) finds that worker turnover is negatively related to wages, while not significantly related to firm size; on the other hand, wages have been shown to be systematically related with the size of firms (Oi and Idson, 1999); therefore, it may happen that a negative statistical relation between worker turnover and firm size will be rendered insignificant when wage is included as an explanatory variable in the regression. [6]

(ii) Churning is positively related to firm's growth. The study by Burgess et al. (2000) concludes that increases in firms' employment lead to higher churning rates, while reductions in employment have the opposite effect; in explaining this result, the authors suggest that the expansion of firms' workforce lead to an increase in bad matches, thus justifying the simultaneity of hires and separations at the firm level (again, the contraction of the workforce has the opposite effect). [7]

(iii) Churning rates decrease with firm age. Lane et al. (1996) found that churning is slightly decreasing in the age of the firm. In order to analyse churning rates over the lifecycle of firms, Burgess et al. (2000a) divided firms into 4 lifecycle categories[8]: (1) firms that survive 12 quarters or less, (2) continuing firms within 12 quarters, (3) non-infant firms within 12 quarters of death, and (4) the rest (i.e., continuing mature firms).

[6] Of course this will depend on the factors that underlie the size-wage positive relation. Oi and Idson (1999) discuss alternative theories that account for such robust result.

[7] A few studies have tried to analyse the relative incidence of hires and separations as firms adjust to their new dimensions, but the results seem contradictory: Burgess et al. (2001) found that growing firms mostly increase their hiring and do not act to reduce turnover; declining firms generally maintain hiring but increase separations; on the contrary, Abowd et al. (1999), found that employment adjustments are primarily made by adjusting entry, rather than exit rates; the later result is consistent with the findings of Anderson and Meyer (1994) and of Albæk and Sørensen (1998).

[8] The same firm could be classified into different categories, depending on its current condition in different periods.

The results showed that the worker flow rate (i.e., churning rate plus job reallocation rate) decreases monotonically from category 1 (65,4%) to 4 (30,4%); but they also showed that hires and separations are important in every category, making churning flows more common across categories than job reallocation. This implies, for instance, that in continuing mature firms, which typically experience smaller changes in net employment (see section 2.2), the weight of churning as a percentage of worker flows is particularly high. Still, the analysis of a specific cohort of firms confirmed the idea that churning rates tend to decrease with firm age.[9]

(iv) Churning rates are a persistent, distinctive feature of firms. In order to explain the heterogeneity among firms in the rates of labour market flows, Burgess et al. (2000) run separate regressions for job flows and for churning flows, including as independent variables time dummies, seasonal dummies, industry dummies, and employer dummies (fixed effects). While these regressors were able to explain only a very small part of the heterogeneity in job flows, about 50% of the variation in churning rates was explained with those variables, with employers' fixed effects assuming particular relevance. These results clearly suggest that it is possible to identify firms that have systematically high churning rates and other which have systematically low churning rates (while the same cannot be said about the changes in net employment). In the same vein, Lane et al. (1996) have found that churning rates are positively dependent on past churning, which also points to the presence of persistent differences between firms in relation to churning rates.

(v) The determinants of churning play different roles according to the characteristics of firms. Given that firms persistently differ in churning rates, it is reasonable to expect that some of the determinants of churning that have been discussed up to now will have different impacts according to the type of firm. By estimating a number of quantile regressions (at the 25th, median, and 75th percentiles) Burgess et al. (2001) find some evidence on this, for example: while churning is not significantly related with size for the pooled sample of firms, it shows to be decreasing in size for high churning firms and

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[9] There are two possible explanations for this: (i) the churning rate is reduced as firms ages due to better job matches, and (ii) high churning firms have lower survival probabilities, so those firms that survive have typically low churning rates. Two pieces of evidence that will be discussed below – the negative relation between churning rates and firm survival, and the persistent heterogeneity of churning rates between firms – seem to favour the second explanation.

increasing in size for low churning firms; quantile regressions also show that, while churning rates tend to decrease in tight labour markets, the aggregate labour market conditions have a significantly greater effect on high churning firms than on low churning firms; similarly, the negative relationship between churning and wages is much weaker in low churning firms.

(vi) The incidence of churning is particularly high in some industries. Several studies have also revealed the presence of some industry specificities in churning rates. For example, Burgess et al. (2001) included industry dummies as regressors in an empirical model of the determinants of churning; their results show that, while the impact of most industries does not quantitatively differ in a significant manner, for a few other industries – namely, finance, insurance and real estate, and professional services – the effect on churning rates is particularly high.

(vii) Industry turbulence seems to lead to higher churning (and not only to the reallocation of jobs). While the literature on job creation and job destruction clearly shows the impact of changes in industry structures in the reallocation of jobs (see section 2.2), the evidence on the impact of industry turbulence on worker flows in excess of changes in firms' net employment changes is still rather scarce and unsystematic. For example, Haveman and Cohen (1994) have shown that organisational founding, organisational dissolution, and mergers and acquisitions have all had a significant impact on the mobility of executive employees between firms, using data on the California savings and loans industry between 1969 and 1988. Using a sample extracted from the US Statistical report on Mergers and Acquisition between 1979 and 1981, Walsh (1988) also found that turnover rates in the acquired top management teams were significantly higher than usual. The results in Burgess et al.(2000) pointing to a mutual influence between changes in net employment and churning rates at the firm level further suggest that turbulence in firms' market shares typically lead to an increase of worker flows in excess of job flows.

2.5. Summing up

It should now be clear that industry dynamics has a relevant impact on the mobility of workers in the job market, both in direct and indirect ways. Research on 'job creation and job destruction' has shown that firms' entries, exits, expansions, and contractions, which occur simultaneously at several levels of the economic system, are directly responsible for the creation of about 10% of new jobs, and the destruction of other 10% of existing jobs, every year. On the other hand, research on churning flows has shown that movements of workers between firms which are caused by such processes of job creation and destruction usually represent no more than 1/3 of total worker mobility, what could be taken as an indication of the relatively small role played by industry dynamics on worker mobility. However, we have also seen that worker flows in excess of job flows can also be related, at least partially, to the dynamics of industry structures: first, because the creation and destruction of jobs affect the mobility of workers not only directly, but also indirectly through vacancy chains; second, since several determinants of worker turnover – such as the costs of hiring and training, the efficiency of screening devices, wages levels, among others – are often systematically related with the size and age of firms, with different phases of their lifecycle, and with the type of industry (and the competition for human capital between firms in each context).

In other words, there are reasons to believe that the observable patterns of worker mobility emerge from the consistent behaviour of both workers and firms, who systematically take into account the dynamic features of industries. Moreover, it has been shown that varying degrees of worker turnover seem to be a persistent characteristic of firms. That is, *the influence of persistently heterogeneous employers acting in the context of changing industry structures* emerges from this discussion as central features in the understanding of the patterns of worker turnover.

Notwithstanding, we have seen that the most influential models of worker mobility tend to ignore such features in their explanatory frameworks.[10] Furthermore, in was shown

[10] It is worth noting that, following the empirical work that revealed the significance of 'job creation and job destruction', many models have considered the interactions between the demand side of the labour market and gross labour market flows (e.g., see the survey by Pissarides and Mortensen, 1999). Those models, however, typically aim at explaining certain aggregate regularities, such as the positive relation between wage and labour productivity, or the aggregate behaviour of unemployment and gross job flows

that the evidence on the impact of industry dynamics on worker mobility (in particular, on worker flows in excess of net employment changes) is still rather scarce. In sum, there seems to be plenty of room for both theoretical and empirical developments related to the understanding of such relation.

I will come back to this issue in the concluding section of the paper. For the moment I will turn to the other direction of the causality in the relation between industry dynamics and worker mobility.

3. THE IMPACT OF WORKER TURNOVER ON THE EVOLUTION OF FIRMS AND INDUSTRIES

The aim of the present section is to discuss to what extent this second nexus of causality has been considered in both the theoretical and the empirical literature on industry dynamics. As before, I start by presenting the main statistical regularities which have been found in this field, and discuss the role played by worker turnover in the most influential models that explain those regularities. This discussion will reveal the typical absence of labour mobility elements in theories of industry dynamics; this contrasts with the notion that worker turnover may exert a significant influence on the performance of firms, and on the patterns of change in industry structures. After discussing a number of theoretical arguments that suggest different ways in which such influence can be felt, I analyse the empirical evidence on that causal relation, drawing on studies related to different research streams. As before, the achievements and limitations of both theoretical and empirical analysis of industry dynamics concerning the integration of labour mobility factors will be emphasise at the end of the section.

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and not the central facts on the patterns of inter-firm worker mobility, which were emphasized by Faber (1999), and which were presented in the beginning of section 2 as the focus of the present discussion. On the other hand, one can find models that focus specifically on worker mobility, while at the same time considering the role of demand-side factors as the one by Jovanovic and Moffit (1990); this model nests match quality and sectoral shocks as determinants of labour mobility; however, as is usually the case with models of this kind, it only considers productivity shocks that are common to all firms in each sector; that is, although they take into account changes on the firms' side, such models still abstract from the role of industry turbulence in determining worker mobility – which is the topic of interest here.

3.1. Empirical regularities on the dynamics of industries and usual explanations

As in the case of labour mobility, the empirical evidence drawn from several studies on industry dynamics allows the identification of some statistical regularities (for surveys see Caves, 1998; Dosi et al., 1997; Geroski, 1995), including the following: the entry and exit of firms are two frequent, and very often correlated, phenomena; the distribution of the size of the firms is typically biased towards smaller scales; new firms are smaller than the average incumbent, have a small probability of survival, and those that survive grow faster than the average; the variability in firms' growth rates diminishes with size; several industries experience shake-outs in the number of firms, after reaching a peak in the number of incumbents.

Many formal models have integrated those (and other) regularities in their assumptions and/or replicated them in their outcomes, thereby providing alternative explanations for the observable patterns of industry dynamics. In spite of the diversity of the causal mechanisms put forward in those theoretical exercises, the most quoted models of industry dynamics tend to focus on technological, informational, or financial determinants of changes in the structure of industries, abstracting from the possible impact of labour market dynamics on those changes.

Two of the most influential contributions illustrate the point. In the evolutionary models of Nelson and Winter (1982), the selection of firms is determined by their innovativeness, which is a stochastic function of firms' investments in R&D; innovative behaviour of firms hence determines the structure of the industry and its evolution, which follows the above mentioned patterns for the relevant part of the space of parameters. Contrasting with these models, in which agents actively invest in learning, Jovanovic's (1982) model is able to replicate many of the statistical regularities of industry dynamics assuming instead that firms are born with certain level of efficiency; such level is not known with certainty by firms when they enter the market; over time, production outcomes gradually reveal the true efficiency levels, leading to decisions by firms to either expand or contract (and eventually exit the market). The same type of emphasis on information updating or on technological learning – and the absence of labour mobility among the causal mechanisms – can be found in other reference models of industry dynamics, including the ones by Hopenhayn (1992), Jovanovic and McDonald (1994), Ericson and Pakes (1995), Klepper (1996), and Winter et al. (2003).

Although such models were relatively successful in replicating a number of statistical regularities associated with industry dynamics, they shed little or no light on the ways through which changes in industry structures may be influenced by the mobility of individuals in the labour markets. And, still, there are both theoretical and empirical reasons to suspect that a relevant part of the picture is thus being left aside. The following two sections discuss such reasons.

3.2. Theoretical arguments on the impact of labour turnover on firms' performance

It has been noted for a long time that worker turnover has both positive and negative consequences for firms. In a paper that influenced many later developments in organisation studies, Staw (1980) discusses in detail the main costs and benefits of turnover to organisations. Some of such costs were already mentioned in section 2, and include: costs of selection, recruitment and training (which are specially high for complex jobs in the context of tight labour markets, in particular for firms which cannot rely on dedicated departments and/or internal mobility); operational disruption (particularly when turnover affects central functions in the context of highly interdependent structures); de-moralisation of organisational members (when turnover affects group cohesion). While organisational costs of worker mobility are often emphasised, turnover may also be beneficial to the performance of organisations in several ways, such as: new hires can be associated with more motivated, more competent, and more educated workers; the exit of workers (in the form of either fires or quits) is one of the possible solutions to entrenched organisational conflicts; worker turnover (both inwards and outwards) can lead to a diversification of the external links of organisations, with benefits in terms of access to different types of resources.

The discussion on the costs and benefits of turnover, together with the moderating role played by a number of different factors, suggest that the mobility of workers may reveal some consistent relations with the performance of firms. Furthermore, given that firms typically show different, persistent propensities for employee turnover (see section 2), one can expect to find some systematic impacts of turnover on the relative performance of firms – and, through this, on the evolution of industry structure.

Moreover, beyond its impact on individual firms, employee turnover can shape the patterns of competition between firms. For example, students of technological innovation and diffusion have often noted that the mobility of workers is an important mechanism of knowledge spillovers, thereby affecting firms' incentives for R&D investment (see Møen, 2005, for recent evidence on this issue). In a different vein, Sørensen (1999, 1999a) has suggested that the patterns of mobility of workers among firms affect their strategies by influencing the degree of overlap in firms' competences. To put it more generally, the mobility of human resources between organisations can be a source of increased strategic interdependency among competing firms.

The idea that turnover can have deleterious consequences which are somewhat anticipated by firms in their strategies has indeed provided the basis for the explanation of labour market related phenomena. For example, efficiency wage theories (see Akerloff and Yellen, 1986) incorporate the idea that employee turnover is reduced by increasing current and (expected) future wages and other benefits. In those cases in which reducing turnover rates is beneficial to the firm (e.g., increasing productivity by promoting investments in firm-specific capital, and/or reducing the costs of searching and recruitment), that idea explains why wages are often higher than expected, or why incentive regimes are particularly generous in rewarding tenure (as found, for example, by Møen, 2005, in the case of technical staff in R&D-intensive firms, where the wage-tenure profile is particularly steep).

The fact that firms respond to the risks posed by employee turnover resorting to internal incentive systems may suggest that, ultimately, this renders the mobility of workers irrelevant (since firms would optimally respond to the possibility of turnover). However the fact that firms display persistent differences in their propensity for labour mobility may be an indication that the later is not always the result of optimal turnover strategies – and, therefore, labour mobility may indeed autonomously contribute to the dynamics of industry structures. In the following section I present some more direct evidence in support of this idea.

3.3. Evidence on the impact of turnover on industry dynamics

While the empirical work on the dynamics of industries tends to mirror the situation found in the theoretical front in what concerns the absence of labour mobility factors in the analyses (see section 3.1), it is possible to find a few studies that have produced some evidence on this topic. Such studies can be divided in three types: the first type includes econometric analyses of the impact of turnover on the performance of firms (in terms of growth, productivity, profitability, etc.); the second type of studies consists on statistical analyses of firm survival which include variables of workers mobility among the regressors; the third type corresponds to case-studies of specific industries.

One instance of the first type is the work by Kramarz and Roux (1999). Using a matched employer-employee database for France in the period 1976-1995, the authors estimate the effects of employee turnover on firm performance on the basis of firms' tenure structure. They find that a low turnover rate is associated with higher productivity, but a high turnover rate slightly favours profitability (suggesting the simultaneous presence of cost and benefits of labour mobility for firms). The simultaneity of harmful and beneficial turnover as also been identified by Garino and Martin (2005), using cross-sectional data for the UK; they found that the impact of worker mobility on firms would depend not only on the costs of recruitment and training, but also on the way wages are fixed in each context – turnover tends to have positive consequences for firms when wages are fixed exogenously (the authors explain this on the basis of the idea that when firms are free to fix the wages, they minimise labour costs, leading turnover rates to increase over the optimal level).

Still in relation to the first type of empirical studies mentioned above, in analysing the relation between churning flows (that is, worker turnover in excess of absolute net job changes) and job flows, Burgess et al. (2000) have found that increases in churning flows typically lead to reductions in the size of firms (specially for firms in the smaller size classes). Using revenues, instead of total employment, as a proxy of firms' size, Baron et al. (2001) also found that turnover (here understood as the proportion of individuals leaving the firm) has a negative impact on growth.

Among the second type of studies – those dealing with the relation between worker mobility and firm survival – Lane et al. (1996) have used a hazard rate model in order to test the prediction that high turnover firms will have lower survival rates. Together with other variables, the authors included as regressors the lagged churning rate of the firm (with various lags) to capture the effects of persistent churning. Their results strongly support the view that firms with high churning rates are less likely to survive than firms with lower churning rates, with the coefficients on churning rates lagged as much as three quarters showing to be consistently negative and significant. Burgess et al. (2000) have also analysed the relation between past churning and the probability of survival, modelling the probability of survival at time t as a function of the average churning up to t; the impact of past average churning on firms' survival was found to be lower than current churning, but it was still significant. This result suggests that turnover is not simply the anticipation by workers of the future misfortunes of firms, and reinforces the argument that high churning may not be optimising for firms.

Evidence on less obvious impacts of labour mobility on the hazard rates of firms is provided by studies focusing on the relation between the probability of survival and the previous experience of firms' founders. For example, Eriksson and Kuhn (2004) analyse whether spin-offs[11] take advantage of intangible assets such as industry-specific knowledge, personal networks, or trust among its founders, in terms of their survival prospects (in comparison to other start-ups); they found that spin-offs were in fact associated with lower death risks than other types of entry. Pointing towards similar results, the expanding literature on entry by spin-offs (see Klepper and Sleeper, 2005, and Helfat and Lieberman, 2002, for two influential papers related to the topic) is accumulating evidence on the relevance of the movement of workers out of incumbent firms and into new ventures in determining the evolution of industry structures.

Finally, the centrality of labour market dynamics was shown to be a distinctive feature of a number of competitive contexts on the basis of industry specific case-studies. For example, the performance of firms was found to be very much affected by firms' capacity to recruit skilled workers and to avoid poaching by competitors in industries such as professional services (Mamede, 2002; Gallouj, 2002) and hi-tech industries

[11] Spin-offs are understood in this context as new firms originating from within an existing company.

(Baron, 2004). In such cases, the patterns of worker turnover and firms' persistently heterogeneous competences in managing human resources are clearly influential features in determining the patterns of industry evolution.

3.4. Summing up

The picture that emerges from this discussion on the impact of turnover on industry dynamics is not exactly similar to the one resulting from the discussion on the reverse impact (see section 2). In fact, while in both cases the most influential theoretical models have typically ignored the mutual influence between the two types of dynamics – labour mobility and changes in industry structures – on the empirical front the differences are more pronounced. In section 2 we have seen that, although many gaps remain to be filled (specially those concerning the role of industry dynamics in explaining worker flows in excess of job flows), a significant amount of evidence on the impact of firms' entry, exit, expansion and contractions on the mobility of workers is now available, making it unequivocal the existence of a link between the two domains. On the contrary, the evidence produced by empirical studies dealing with the impact of worker turnover on industry dynamics (which, as we saw, is essentially restricted to the analysis of the impact of turnover on firms' performance and survival prospects, or to case-studies of specific industries) is only enough to suggest that the development of theoretical accounts pointing towards that direction may not be absurd.

There may be good reasons, though, for such asymmetry in the available empirical evidence concerning the mutual influence between industry dynamics and labour mobility. In fact, while the net changes in the total employment of firms always leads to the movement of workers in the labour market regardless of the specific context under analysis[12], the movement of workers between firms is typically irrelevant to the evolution of several industries (for example, those that essentially rely on low-skilled, homogeneous labour, and/or in which firms operate as monopsonists, or quasi-monopsonists, within the relevant labour markets). This suggests that while the empirical work on the impact of industry turbulence on the mobility of workers can

[12] At least to the extent that firms' expansion/contraction imply the creation/destruction of jobs.

usually ignore the existence of inter-industry differences (as is often the case[13]), the identification of the reverse effect (i.e., the impact of worker turnover on industry dynamics) may require the consideration of industry specificities.

I will come back to this issue and its implications for future research in the concluding section of the paper. Now I will turn to the discussion of the simultaneous analysis of the mutual influences between industry dynamics and labour mobility.

4. THE COUPLED DYNAMICS OF INDUSTRY STRUCTURES AND WORKER MOBILITY: POSSIBLE ALTERNATIVE STRATEGIES FOR THEORETICAL DEVELOPMENTS

Examples of industries where competition is based on recruitment (to borrow the expression used by Sørensen, 2004) were given above; those examples suggest that the evolution of industry structures in such contexts can be highly influenced by the patterns of worker turnover and by the heterogeneous competences of firms in this matter. On the other hand, the highly turbulent character of some of those industries (especially those in the early phases of their life-cycles), implies that the movement of workers between firms is strongly influenced by the dynamics of the relevant population of employing organisations. That is, one can expect to observe causality running in both ways[14], suggesting the opportunity for – and the usefulness of – an integrated approach to the dynamics of industry structures and labour mobility.

Nevertheless, as could be expected from the discussions in section 2 and 3 above, examples of theoretical analyses taking into account the joint dynamics of industry

[13] In most of the studies which were discussed in section 2, the only way inter-industry specificities enter the empirical models is through the inclusion of industry dummy variables as determinants of worker turnover. While this may reveal some differences across industries in the scale of turnover rates, it does not allow to capture industry specificities concerning the determinants of turnover. The introduction of interaction effects between industry dummies and other variables, or running separate regressions for different industries – two strategies which would allow to captures more fundamental industry specificities – is often conditioned by the amount of data available (specially in those studies using matched employer-employee data).

[14] Burgess et al. (2000) is the only paper I am aware of providing statistical evidence on such type of two-way causality. Using VAR analysis, the authors show that the relation between job flows (i.e., absolute net changes in total employment) and churning flows (i.e., worker flows in excess of job flows) is bidirectional.

structures and labour mobility do not abound in the literature. Given this scenario, the aim of this section is to discuss possible strategies for the development of theoretical approaches to the coupled dynamics of industry structures and labour mobility.

The question of interest here is: what are the conceivable mechanisms through which industry turbulence (understood as the entry and exit of firms, changes in sizes and in market shares, changes in property control, evolution in industry concentration, etc.) and labour market mobility would mutually influence each other? Answering this question is equivalent to sketch the main features of alternative models dealing with the problem at hand.

One possible strategy for the development of such approach to this problem is suggested by bridging the literature on organisational ecology (or corporate demography – for an extensive review see Carrol and Hannan, 2000) and the research on internal organisational demography (e.g., Pfeffer, 1985). An example of such bridging can be found in Haveman (1995), who starts from the idea that the founding, dissolution and merging of organisations has systematic impacts on firms' internal demographic composition (namely, in terms of tenure distribution). She suggests, for example, that while short-tenured employees are more likely to exit firms in general (because they may not fit their jobs or firms well, or because they have developed little firm-specific capital), moving into new ventures is an especially attractive opportunity for long tenured employees because they possess the reputations, expertise and external contacts on which new ventures rely. Thus, in periods of high entry rates the proportion of long-tenured to short-tenured employees leaving established companies will increase (and since not all long-tenure individuals leave their firms, the tenure dispersion in organisations will increase). In the same vein, the author discusses the type of changes in internal organisational demography that result from the increase in exit rates or in organisational mergers.

Although Haveman's paper does not discuss the feedback effects from changes in organisational tenure distributions to the evolution of firms and industries, this has been a central concern for research done in the field of internal organisational demography. According to Pfeffer (1985), two central suggestions have been put forward (and investigated) by organisational demographers: (i) the idea that tenure (and other demographic characteristics) strongly influence the managerial competences of individuals; and (ii) that the distribution of the competences among management teams has a significant impact on the performance of firms (the impact in terms of relative performance may depend on the distribution of competences in the management teams of the direct competitors, as suggested by Sørensen, 1999).[15]

In sum, on the one hand, as Haveman (1995) suggests, different dimensions of industry turbulence (entry, exit, merger, etc.) lead to selective changes in the internal demography of firms (namely, in terms of tenure distributions); on the other hand, as organisational demographers emphasise, such changes imply a reconfiguration of the set of competences in firms, which may be expected to affect the performance of firms (and, when the population of firms in an industry is jointly considered, to affect the structure of the industry as well). Thus, the coupled dynamics would be here obtained on the basis of the causal sequence «specific elements of industry turbulence – selective worker turnover – changes in internal demography of firms – differential impacts on the performance of firms – further industry turbulence – ...».

Another possible way to establish the bidirectional link between industry dynamics and worker mobility is through the consideration of social networks as part of the structure of both the industry and the labour market. The fact that social networks can, and often do, influence the dynamics of labour markets has long been emphasised by economic sociologists (see Granovetter, 1995), and has been increasingly discussed by labour economists (e.g., Montgomery, 1991; Bentolila et al., 2004; Pellizzari, 2004). Studies within this tradition have revealed that employers and employees tend to know (or, at least, have information about) each other even before the beginning of their labour relation; and that social networks are extensively used by both firms and workers to find jobs and fill vacancies.[16]

[15] The idea that the individual characteristics of top managers can have strong implications for the strategy and performance of firms has also been central to the research tradition in management studies frequently referred to as research on the 'upper echelons' (for a seminal paper, see Hambrick and Mason, 1984).

[16] Granovetter (1995) tends to emphasize the benefits of social networks for individual (not necessarily social) outcomes in the labour market; namely, he suggests that: information given by personal acquaintances about the nature of a job is often considered more reliable; friends may facilitate individual integration and learning in organizations; having personal acquaintances among colleagues can facilitate the access to promotion and other discretionary benefits (especially, if those acquaintances are well positioned in the organizational power structure, and if contracts are more difficult to be drawn

Granovetter's approach has a clear dynamic flavour: worker mobility is not only (partly) determined by the social structure, but it helps in turn to change the social structure itself – since new personal links are being established as workers move between firms. And while his framework does not take into account the dynamics of firms and industries, it is not difficult to think of ways in which social networks, industry structures and worker mobility can actually co-evolve. One possibility would be to focus on the informational consequences of mobility (the crucial element in Granovetter's analysis) and suggest that a firm has an incentive to hire individuals who are known to its employees (since this would facilitate the access to detailed information about the competences and personality of prospective employees); and since social links are expected to be more easily established between individuals with similar demographic characteristics (age or tenure cohorts, educational or socio-economic background, etc.), one can expect that the impact of social networks on the mobility patterns will also affect firms' performance and, therefore, help to shape the evolution of industries; to the extent that social links are possibly formed when individuals work for the same firm, the evolution of industries feeds-back on the network structure and on the patterns of future mobility. Another possibility would be to apply this logic of «structure shapes mobility, mobility shapes structure» (where 'structure' refers both to social networks and populations of firms), not in terms of the informational role of networks in determining job matches, but in terms of workers' preferences in their choices of employers (e.g., all else being equal, individuals will prefer to work for those organisations in which they have acquaintances).

The two types of causal sequences presented above are only instances of alternative processes that may underlie the co-evolution of industry structures and labour mobility. Whether these specific processes will show to be relevant in jointly explaining the patterns of industry dynamics and of worker mobility observed in specific industrial contexts, is left to investigation. In any case, those examples may help to stimulate the further development of integrated models dealing with the problem at hand.

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exhaustively and to be enforced). On the other hand, it has been shown that in some contexts jobs found through acquaintances may be associated with lower wages – see, e.g., Bentolila et al. (2004); Pellizzari (2004).

5. CONCLUSIONS AND OPPORTUNITIES FOR FUTURE RESEARCH

The idea pervading this paper is that the mobility of workers in the labour markets and the patterns of industry evolution can, and often do, influence each other, and that both empirical and theoretical research in those two domains should take into account such interdependencies. Having that idea in mind, I have reviewed different streams of literature in order to identify the main empirical and theoretical results and the remaining gaps, and discussed examples of how an integrated approach to the dynamics of industries and worker mobility could be develop. It is now time to summarise the main results and to point towards the future avenues of research that are suggested by this discussion.

Concerning the empirical work, it was shown that studies focusing on the impact of entry, exit, expansion, and contraction of firms over the creation and destruction of jobs abound in the literature, and point towards the importance of that direct effect of industry dynamics on labour mobility. But we have also seen that job creation and destruction is typically only a small part of total worker flows, and that the studies which try to relate the dynamics of industries to worker flows in excess of job flows (or 'churning') are still very scarce. On the basis of the few studies available I have suggested a number of regularities which seem to emerge, which include the following: churning rates are positively related to firm's growth, decrease with firm age, and do not seem to have a systematic relation to firm size (as long as other variables such as firms' age and wages are considered); even within restrictively defined industries, firms are typically heterogeneous in terms of churning rates, and are persistently so; the incidence of churning is particularly high in some industries; and industry turbulence seems to lead to higher churning (and not only to the reallocation of jobs). However, contrarily to many of the statistical regularities which have been recurrently found in the realms of both industry dynamics and labour mobility (which can be, and have been, taken as 'stylised facts') the results listed above are derived from a rather small number of studies, and therefore should be considered with care. The same applies to the results available in the literature concerning the reverse direction of causality (that is, the impact of labour mobility on the dynamics of industries); we have seen that the evidence available in this case is basically restricted to the analysis of the impact of turnover on firms' performance and survival prospects, and is also based on a small number of studies. In sum, while it is possible to find in the literature some evidence suggesting the presence of the bidirectional link under discussion, there is the need for further empirical work analysing such two-way causality.

The possibilities for such empirical developments are growing as more and more matched employer-employee database are becoming available. While this type of data has been increasingly used within labour economics, its potential for the advance of knowledge in the field of industrial dynamics is still rather unexploited.[17] And even in labour economics such data could be used to analyse more systematically the influence of industry turbulence on the patterns of worker mobility. The following are examples of research questions which could be further investigated on an empirical level:

- What are the indirect impacts (i.e., beyond direct job creation and destruction) of entry, exit, expansion, and contraction of firms on worker mobility, namely in terms of vacancy chains?
- How are worker turnover and its determinants (such as the costs of hiring and training, the efficiency of screening devices, wages levels, among others) related with the size and age of firms, and what impact does it have on the post-entry performance of firms?
- Do workers cluster within specific firms according to their propensity to turnover? If yes, what are the dynamic features of such firms?
- Do highly mobile labour markets lead to lower survival chances for some types of firms?
- Are entry rates determined by the patterns of worker mobility?

[17] One example of a fruitful use of matched employer-employee data in the field of industrial dynamics – which is not exactly related to the problem dealt with in this paper – was recently given by Benedetto et al. (2004). Empirical work in industrial dynamics has often used administrative data to follow the firms' trajectories trough time; one problem with such data, which has been recurrently identified (but not satisfactory solved), is the fact that entry and exit can be mistakenly measured, since simple changes of ownership or legal form of organizations may modify the administrative identifiers with no other change in economic activity. In that paper the authors describe how those new datasets can provide information about the flows of clusters of workers across business units in order to identify longitudinal linkage relationships in business data.

- Do rates of worker turnover systematically vary between different phases of industries' life-cycles?

- To what extent the impact of worker turnover on the performance of firms depends on the different phases of their lifecycle, and on the type of industry?

- To what extent differences in the way firms adjust their sizes (which are highly influenced by national laws and regulations) have an impact on the dynamic patterns of both industries and labour markets?

Such questions remain largely unanswered, and interesting results could arise by investigating them empirically.

If that is true for the empirical side, the need – and opportunity – for further work concerning the mutual influence between industry turbulence and worker mobility is even more pronounced on the theoretical front. Calls for the development of models of labour mobility that incorporate the influence of industry dynamics have been explicitly put forward before (for example, Haveman and Cohen, 1994; Lane et al., 1996), but still, as we have seen, most models providing explanations for the statistical regularities on labour market flows tend to focus on essentially supply-side or match-quality determinants. This contrasts with the results discussed in this paper, which suggest that the observable patterns of worker mobility emerge from the consistent behaviour of both workers and firms (both of them persistently revealing heterogeneous characteristics), who systematically take into account the dynamic features of industries. In the same vein, models of industry dynamics typically focus on technological and/or financial determinants, ignoring the possible role of worker mobility in their explanatory frameworks.

In this paper I have discussed possible strategies that would allow filling such gaps in those literatures, and provided a couple of examples of causal sequences that could constitute the basis for integrated models of industry structures and labour mobility. Just as in the case of separate models of worker turnover and of industry dynamics, those integrated models of industry structures and labour mobility should take into account, either in their assumptions or has desire properties of their outcomes, the statistical regularities that have been found to prevail in these domains (and which were mentioned in the preceding paragraphs).

One should not expect, however, that such integrated models will be of universal applicability. As was emphasised before in this paper, the movement of workers between firms is mostly irrelevant to the evolution of several industries, particularly those that rely on a low-skilled, homogeneous workforce. Similarly, the role of industry dynamics in determining the patterns of labour mobility is, of course, not expected to be high if the industry's turbulence is minimal.

However, taking into consideration the mutual influences between changes in industry structures and the mobility of workers may be crucial to the understanding of the dynamic patterns observable in many contexts. In particular, an integrated approach to industry dynamics and labour mobility may be particularly adequate to the analysis of industries in the early phases of their lifecycles (when structural turbulence tends to be highest) and in which competition is strongly based on the recruitment of highly-skilled workers. These criteria would often include some of the most dynamic industries in the contemporary societies – such as higher education, biotechnology, consultancy, law firms, among others – to which the prevailing models of industry dynamics and labour mobility are not particularly well suited.

6. References

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Chapter 2

Labour mobility, industry dynamics and social networks: a co-evolutionary model

1. INTRODUCTION

There are reasons to believe that changes in industry structures and worker mobility are not entirely independent phenomena. At the most obvious level, the growth of existing firms and the creation of the new ones is necessarily related to an inflow of workers to those firms, just as the contraction and the closure of firms have the opposite effects on the supply-side of the labour markets (Davis et al., 1996). Moreover, industry turbulence affects the labour markets not only in such direct way, but also indirectly through the vacancy chains that are opened/closed by firms' growth/founding and contraction/failure (as pointed out, e.g., by Haveman, 1995). Reverting the direction of the causality, it has been noted for a long time (e.g., Staw, 1980) that worker turnover has both positive and negative consequences for organisations, and in this sense it may constitute an important determinant of industry dynamics. More recently, research on the importance of previous experience for entering firms (e.g., Helfat and Lieberman, 2002) draws attention to the possible role of workers' turnover in bringing competences to, and therefore increasing the survival prospects of, newly founded firms. Finally, historical accounts of industries which are highly dependent on skilled labour (and specially those industries in the early phases of their lifecycles) have shown that the patterns of firms' evolution and of labour force mobility are intrinsically related.[1]

Notwithstanding all the possible interdependencies between industry evolution and labour market dynamics, a lack of systematic discussion about the details of such co-evolution and its implications prevails in the literature. In fact, most theoretical models of industrial dynamics (for surveys see, e.g., Dosi et al., 1997; Sutton, 1997) tend to focus on the technological, informational, or financial determinants of changes in the structure of industries, abstracting from the influence of labour market determinants. In the same vein, the reference models of worker mobility (for a survey see, e.g., Farber, 1999) typically underestimate the mutual influence between industry dynamics and labour market forces. And while it is clear that the movement of workers between firms tends to be a minor issue in the evolution of several industries – specially those that

[1] See, for example, Baron (2004) on Silicon Valley's hi-tech firms, or Mamede (2002) on IT consultancy in Portugal. One could include here other industries such as higher education, biotechnology, management consultancy, law firms, among others; for a discussion of the specificities of this type of industries see, for example, Gallouj (2002).

essentially rely on low-skilled, homogeneous labour – in many other interesting contexts models of industry evolution which abstract from the role of labour market dynamics – or vice-versa – risk missing the main elements of the dynamic picture they propose to explain.

This paper intends to contribute to fill such gap in the existing literature, by presenting a model that analyses the interdependencies between labour market dynamics and the evolution of industries' structure, in situations where individuals' job decisions are influenced by interpersonal links among workers. Being inspired by the case of those industries in which competition is based on recruitment (to borrow the expression used by Sørensen, 2004; see footnote 1), the model takes into account some other features typically found in these contexts.

The basic features of the model are the following. There are only two types of agents: firms and specialists. Firms want to recruit as many specialists as possible, and want to attract the best specialists in the market. In this intent they face two crucial constraints: first, the total number of specialists available in the market is limited by a certain amount, so firms compete among them in recruitment; and second, firms are not able to assess the real skills of specialists (they form expectations about individuals' real skills on the basis of their previous professional trajectories). On the other side of the market, each specialist is willing to work for firms with good technical performances, but they also value working for firms in which a high number of their acquaintances are employed. Specialists face as well a basic constraint: firms have a limited number of job positions to fill at each period, and therefore only the specialists with the highest levels of expected skills will be recruited by the most desirable employers.

The fact that firms cannot know with certainty the real skills of specialists is a central feature of the model. In the absence of such uncertainty, the outcome of the industry's evolution would be very straightforward: the most successful firms would employ the most skilled specialists and would unequivocally grow (and eventually eliminate all the rivals). Introducing information incompleteness in the functioning of the labour markets has a number of interesting implications, which the present model allows to analyse.

More specifically, this model is able to replicate a number of well-known statistical regularities of both industry evolution and labour mobility, on the basis of causal mechanisms which clearly differ from the ones that are found in most models available in those two streams of literature (and being arguably more suitable than those models to the analysis of some industries). For illustrative purposes, the underlying mechanisms of the model to be presented below will be compared with the main features of Klepper's (1996) model of industry life-cycle and the ones in Jovanovic's (1979) model of job turnover.

The next section of the paper discusses the relation of the present contribution with the existing literature. Section 3 presents the model, and section 4 discusses the main results of the simulation. Section 5 summarises the main conclusions and implications.

2. RELATED LITERATURE

The model that will be presented in section 3 can be related to five streams of literature: studies of labour mobility, theories of industry dynamics, contemporary evolutionary approaches to economics (which partly overlap with the previous stream), research on the role of social networks in the labour markets, and case-studies of specific industries. In what follows I discuss the similarities and differences between the present model and each of those streams of research.

2.1. Labour mobility

Drawing on an extensive review of empirical studies that analyse of the stability and mobility of employment relations, Farber (1999) emphasises three central facts describing inter-firm worker mobility in modern labour markets: (i) long-term employment relationships are common (i.e., a significant proportion of workers are involved in durable employment relations), (ii) most new jobs end early, and (iii) the probability of a job ending declines with time (the relation is not necessarily monotonic

– some studies find that the probability of a job change may first increase with tenure, before starting to decrease).

Different types of models have been put forward which can account for such statistical regularities. A particular influential example of such models is the one put forward by Jovanovic (1979). The building block of this model is the idea that the productivity of each particular job match is not known in advance – it is gradually revealed, with output being a noisy signal of match quality. As the expectations of both firms and workers are updated on the basis of each period's output, both sides can decide whether to continue or to stop the employment relationship; furthermore, it is assumed that there is a fixed cost in starting a new relationship. Jovanovic's model is particularly successful in replicating the statistical regularities listed above: initially, even if the observable output signals a bad-quality match, workers tend to remain in the firm since they know the signal is noisy and moving to a new firm involves costs; as time goes by, the assessment of match quality becomes more precise, leading either to a separation (because the match quality is too low) or to a permanent match (because its quality is high); thus, in an early phase more and more workers will decide to move, but on the other hand an increasing number of workers is entering enduring employment relationships – and this allows to explain the non-monotonic feature of the tenure-separation relation.

In spite of its success in replicating a number of statistical regularities of worker mobility, Jovanovic's model illustrate the tendency, often noted among students of the labour markets (see, e.g., Davis and Haltiwanger, 1999), to abstract from the effect of demand-side disturbances on employee turnover. On the contrary, in the model proposed in the present paper, the entry, exit, growth and contraction of firms is an essential (though not exclusive) ingredient in determining the inter-firm mobility of workers.

2.2. Industry dynamics

As in the case of labour mobility, the empirical evidence drawn from several studies on industry dynamics allows the identification of some statistical regularities (for surveys see Caves, 1998; Dosi et al., 1997; Geroski, 1995), including the following: the entry and exit of firms are two frequent, and very often correlated, phenomena; the distribution of the size of the firms is typically biased towards smaller scales; new firms are smaller than the average incumbent, have lower chances of survival, and those that survive grow faster than the average; several industries first verify an increase in the number of incumbents until they reach a peak, and then experience a shake-out in the number of firms, after which changes in market shares become less frequent, entry and exits are strongly reduced, and the industry structure stabilises.

Many formal models have integrated this type of regularities in their assumptions and/or replicated them in their outcomes, thereby providing alternative explanations for the observable patterns of industry dynamics. Klepper (1996) provides an example of a model that has been particularly successful in explaining several regularities found in the data – particularly in those industries that have experienced a shake-out in the number of incumbents. Shake-outs had been previously explained by Abernathy and Utterback (1978) on the following basis: after an initial period of uncertainty in which several firms offer their product innovations, a dominant design emerges in the market, reducing the uncertainty about the future technological trajectories; this creates an incentive for firms to invest in cost-reducing innovations, and the firms who are less efficient in the production of the dominant design are driven out of the market. Klepper (1996) has reversed the direction of causality, suggesting that the emergence of a dominant design is a result of the shake-out, rather than being at its origin; and the causes for the shake-out are to be found elsewhere: they are related to the fact that cost-reducing investments are more rewarding for firms operating at larger scales; firms that grow first tend to have lower costs and drive others out of the market. After the shake-out, as prices decrease further and margins are compressed, the incentives to grow above the average will vanish, and the industry stabilises.

Again, in spite of the success of Klepper's model in replicating a number of statistical regularities associated with industry dynamics, it sheds little or no light on the ways through which changes in industry structures may be influenced by the mobility of individuals in the labour markets[2] – a topic which is central to the model that will be presented below.

2.3. The evolutionary approach[3]

According to Nelson (1995), the evolutionary mode of explanation is characterised by its focus on a variable, or set of variables, which experience changes through time, and its main theoretical concern consists in understanding the dynamic process underlying the observed changes. Evolutionary theories suggest that the variable (or set of variables) under analysis is subjected to partially random disturbances that generate diversity in the system, and that there are mechanisms that systematically filter (i.e., select) the diversity thus generated (as Nelson notes, the predicted power of these theories strongly relies on the specification of the selective forces).

Given this general framework, the usual premises in evolutionary models are the following (Dosi and Nelson, 1994): (i) there is a continuous introduction of novelty in economic systems (which is partly exogenous to the system, and partly generated within the system); (ii) the actual and potential novelties are subjected to the pressures exerted by market (and possibly other) forces, which determine the adequacy and viability of those novelties; (iii) agents have an imperfect understanding of the present and future contexts of their actions (which is associated with the permanent introduction of novelty in the system, but also with the agents' limited cognitive capacities), (iv) agents are heterogeneous, to the extent that they diverge in their understanding of the context and on their expectations about the future. Systems characterised by such features often display path-dependency and other properties which overrule the use of analytical approaches to modelling. On the contrary, computer simulation models – which are

[2] This characteristic is shared by most models of industry dynamics, including the ones put forward by Nelson and Winter (1982), Jovanovic (1982), Hopenhayn (1992), Jovanovic and McDonald (1994), Ericson and Pakes (1995), Klepper (2002), and Winter et al. (2003).

[3] In the present context, the 'evolutionary approach' is understood as the type of modelling strategy that followed Nelson and Winter's (1982) models of industry dynamics and of economic growth.

particularly well-suited to the analysis of the patterns of structural change – are typically used as the basic instrument of theoretical development. [4]

Notwithstanding the fact that the prevailing evolutionary models of industry dynamics are basically silent about the role of labour mobility, the model to be presented below has all the features listed in the previous paragraph – and in this sense can be considered as being part of the evolutionary family.

2.4. The role of social networks in the labour markets

The fact that social networks can, and often do, influence the dynamics of labour markets has long been emphasised by economic sociologists (see Granovetter, 1995), and has been increasingly discussed by labour economists (e.g., Montgomery, 1991; Bentolila et al., 2004; Pellizzari, 2004). Studies within this tradition have revealed that employers and employees tend to know (or, at least, have information about) each other even before the beginning of their labour relation; and that social networks are extensively used by both firms and workers to find jobs and fill vacancies.[5]

Granovetter's sociological approach has a clear dynamic flavour, which is of interest here: worker mobility is not only (partly) determined by the social structure, but it helps in turn to change the social structure itself – since new personal links are being established as workers move between firms. And while his framework does not take into account the dynamics of firms and industries, it can easily be extended in order to consider the co-evolution of social networks, worker mobility and industry structures.

[4] In computer simulation models the conclusions obtained are in the form of time series of specific numerical values, contrasting with analytical models where the conclusions sought are usually in the form of relations among the variables and parameters (for an early, and stimulating, discussion on this contrast see Cohen and Cyert, 1961).

[5] Granovetter (1995) tends to emphasise the benefits of social networks for individual (not necessarily social) outcomes in the labour market; namely, he suggests that: information given by personal acquaintances about the nature of a job is often considered more reliable; acquaintances may facilitate individual integration and learning in organisations; having personal acquaintances among colleagues can facilitate the access to promotion and other discretionary benefits (especially, if those acquaintances are well positioned in the organisational power structure, and if contracts are more difficult to be drawn exhaustively and enforced). On the other hand, it has been shown that in some contexts jobs found through acquaintances may be associated with lower wages – see, e.g., Bentolila et al., 2004; Pellizzari, 2004.

The model presented in this paper applies the same «structure shapes mobility, mobility shapes structure» kind of logic, to a context in which 'structure' refers both to social networks and to a population of firms. However, the role played by networks in determining job matches is not related here to the availability of information about job opportunities (the main focus of Granovetter's analysis), but rather to the way they affect workers' preferences in their job decisions.[6]

2.5. Industry specific case-studies

The basic motivation for the development of the model to be presented below is the fact that the mutual influence between the dynamics of industries and the inter-firm mobility of workers is often shown to be crucial in many industries, notwithstanding the scarcity of models considering such bidirectional causation. Theoretical and empirical inquires of industry evolution which abstract from the role of labour market dynamics (or vice-versa) in those contexts may be leaving aside some of the most relevant elements of the dynamic picture they want to explain.

The strategy followed in the development of the present model was based on the attempt to capture, in a stylised form, some basic mechanisms and factors which affect the evolution of a specific type of industries (as they emerge from the empirical studies of such industries).[7] In the present case, the model is inspired by my previous work on the evolution of the IT consultancy industry in Portugal (Mamede, 2002). In that paper I have suggested that the growth of firms was very much affected by their capacity to recruit new specialists and to avoid poaching by competitors. I have also suggested that the general level of employee's skills strongly influences the quality of the services provided, and therefore firms' reputation and their prospects for future growth.

[6] The idea that individuals prefer to work in organisations that already employ their acquaintances can be rationalised, for example, in terms of reduced costs of integration, easier access to promotions and other discretionary benefits, or emotional comfort.

[7] In this sense, this model is close to the so-called 'history-friendly models of industry evolution' (Malerba et al., 1999). However, my intention here is not to confront the outcomes of the simulations with the historical trajectory of any specific industry, as is often claimed to be the case with models belonging to the 'history-friendly' type. Instead, simulations are here used as 'computer-aided thought experiments' (in line with the approach suggested by Simon, 1996) that allow to rigorously analyse the implications of theoretical claims concerning causal mechanisms that are active in the 'real world', but they do not intend to capture the 'core ingredients' that determine the historical evolution of any specific industry.

Problems of incomplete information are pervasive in those industries. Consultancy is a highly idiosyncratic process in which the employees of both the services providing firms and of the client organisations interact extensively, and the outcomes of which strongly depend on the quality of the interactions between the personnel of both organisations. Given the relevance of idiosyncratic elements for performance, the relevant individual skills are not easily assessed on the basis of diplomas or other certificates. Moreover, consulting projects are most of the times a work done by teams of specialists, and it is often the case that firms are not able to differentiate between the individual contributions of each of the members involved. These features have two important implications: first, employers have to rely on less than perfect proxies of individual skills – such as individuals' past job trajectories; second, individuals are typically not paid on the basis of their individual productivity – performance prizes that compensate all the members of the teams without discriminating on the basis of individual efforts are a common feature in the industry (giving an incentive for individuals to move to the best performing firms, where collective prizes are expected to be higher). Similar features are usually drawn from other studies on professional services industries (see Gallouj, 2002).

As will be clear in the following section, the assumptions of the model (though not necessarily its outcomes – see footnote 6) try to reflect some essential features of such industries.

3. THE MODEL

In this model there are only two types of agents: firms and specialists (M is the set of firms, and N is the set of specialists). Firms provide consultancy services to the market, while specialists are employed by those firms. The consultancy services are assumed to be in high demand, so the size of the industry is constrained only by the number of specialists available. At each period (i.e., at each simulation step) specialists decide to which firm they want to work in that period, and firms decide which specialists they want to recruit. In their intent firms face two crucial constraints: first, the total number of specialists available in the market is limited by a certain amount, so firms compete among them in recruitment; and second, firms are not able to assess the real skills of specialists (they form expectations about individuals' real skills on the basis of their previous professional trajectory). On the other side of the labour market, specialists are willing to work for firms with the best performance (since it is assumed that specialists' financial rewards are partly dependent on their employers' performance levels), and their choice may also depend on their location in the social network of specialists (it is assumed that specialists attach a positive value to working with personal acquaintances); but specialists face as well a basic constraint: firms have a limited number of job positions to fill at each period, and therefore only the specialists with the highest levels of expected skills will be recruited by the most desirable employers.

These basic features constitute the basis of the coupled dynamics which is central to the model: firms' entry, exit, growth and contraction depend on the mobility of specialists in the labour market; the job decisions determining worker mobility are influenced by both the performance of firms and the establishment of social links among workers; the evolution of the social network is shaped by both the mobility of workers and the evolution of firms.

In what follows I present the assumptions concerning the decisions of firms and individuals, the role of social networks, the functioning of the labour market, and the dynamics of the industry.

3.1. Firms' size, performance, and expectations

Size. Let B^t: $N \times M^t \rightarrow \{0,1\}$ be a function defining the nature of the work relationship between each $i \in N$ and each $q \in M^t$, such that:

$$\begin{cases} b_{iq}^t = 1 & \text{if} \quad \text{i works for q at time t} \\ b_{iq}^t = 0 & \text{if} \quad \text{i does not work for q at time t} \end{cases}$$

The set of specialists working for firm q at time t is given by $S^t(q) = \{i \in N : b_{iq}^t = 1\}$ and the size of firm q at time t is given by $d_N^t(q) = |S^t(q)|$. The set of firms for which specialist i is working at time t is given by $E^t(i) = \{q \in M^t : b^t_{iq} = 1\}$, and the following condition is imposed: $d^t_M(i) = |E^t(i)| \leq 1$ (i.e., each specialist is employed at most by one firm at each period).

Performance. The performance of a firm in each period is determined by the skills of the specialists working for the firm during that period. Specialists' real skills are assumed to be identically and independently distributed, according to a normal probability distribution function (with the mean μ and the standard deviation σ being parameters of the model), at the beginning of the simulation, and to stay fixed thereafter. Let *s(i)* represent the level of real skills of specialist i. Then, the performance of firm q at period t, PF^t_q, is given by the average real skills of the firm's employees, that is:

$$(1) \qquad PF^t_q = \frac{\sum_{i \in S^t(q)} s(i)}{d^t_N(q)}$$

where, as before, $d^t_N(q)$ is the number of individuals working for firm j at time t.

Expectations on skills. Individuals' real skills cannot be directly observed by the market. In order to assess individuals' skills, the demand side of the labour market takes into account the performance of the firms for which the individual has worked in the past; when individuals enter the labour market for the first time, their expected skills are equal to μ (the mean value of the distribution of real skills). Accordingly, the skills individual i is expected to hold at time t, $\forall t > 1$, are given by the equation:

$$(2) \qquad ES^t_i = \begin{cases} \beta * ES^{t-1}_i + (1-\beta) * PF^{t-1}_{E^{t-1}(i)} & \text{if } \ |E^{t-1}(i)| = 1 \ \text{ and } t > 0 \\ ES^{t-1}_i & \text{if } \ |E^{t-1}(i)| = 0 \ \text{ and } t > 0 \\ \mu & \text{if } \quad t = 0 \end{cases}$$

where $\beta \in [0,1]$ is the autocorrelation factor of individuals' expected skills (it is the same for all individuals), and $PF^{t-1}_{E^{t-1}(i)}$ is the last period's performance of the firm employing individual i by that time. It is assumed that all the agents in the market (i.e, both firms and individuals) form their expectations about individual i's skills at time t according to equation (2).

3.2. The decisions of specialists and firms

The following assumptions concerning the determinants of individuals' and firms' behaviour are made.

(i) Firms' revenues and costs. The level of fees per specialists of firm q at time t, P_q^t, is directly proportional to the firm's performance in the previous period: $\partial P_q^t / \partial PF_q^{t-1} > 0, \forall q \in M, \forall t \in T$; the total revenues of firm q at time t are given by $TR_q^t = P_q^t\,(\mathrm{PF}_q^{t-1}) * Q_q^t\,[d_N^t(q)]$, where Q represents the scale of services provision. Labour costs are the only costs to the firm, and the firm's total revenues are entirely redistributed among the firm's employees.

(ii) Specialists' compensation. There are two elements in specialists' financial compensation: wages (w) and performance prizes (wz). Specialist i's wage at time t, w_i^t, is independent of the employing firm and is directly proportional to the specialist' expected skills at t (which is common to all firms in the market, as seen above): $\partial w_i^t / \partial ES_i^t > 0, \forall i \in N, \forall t \in T$. On the contrary, the performance prize of specialist i at time t, wz_i^t, varies between employers and is determined in the following way:

$$wz_i^t = \frac{\mathrm{TR}_q^t - \sum_{i \in S^t(q)} w(ES_i^t)}{Q[d_N^t(q)]}, \qquad \forall \mathrm{i} \in \mathrm{S}^t(\mathrm{q}), \forall q \in \mathrm{M}, \forall \mathrm{t} \in \mathrm{T}.$$

Put differently, the difference between a firm's total revenues and total wage costs is equally distributed among the firm's employees.[8]

[8] This reflects the notion that firms are only able to observe the performance of teams of specialists, not the individual contributions to performance. Therefore, every employee receives a share of the surplus, regardless of his actual contribution to the firm's performance.

These assumptions imply that individuals prefer to work for firms with a better performance, for two reasons: first, firms which perform better pay higher performance prizes; second, the wage component of specialists' financial compensation is proportional to their expected skills, and the latter depend on the performance of the firms they have worked for in the past.

On the other hand, it is not obvious from those assumption what should be the behaviour of firms (namely, since all the revenues are distributed among the workers and thus profits are null). To keep matters simple, it is assumed that the firms' goal is to survive for as many periods as possible, and that in order to fulfil that goal they follow two simple decision rules in every period: (a) they want to hire as many specialists as possible, and (b) they prefer to hire those specialists with the highest (expected) skills.[9]

However, there is a limit to firms' growth per period. The maximum total number of job contracts each firm can perform at each period, MC^t_q, is fixed according to the following equation:

$$(3) \qquad MC^t_q = \begin{cases} 0 & \text{if} \quad t < t^q \quad \text{or} \quad d_N^{t-1}(q) = 0 \\ \gamma + \delta * d_N^{t-1}(q) & \text{if} \quad t > t^q \quad \text{and} \quad d_N^{t-1}(q) > 0 \\ \lambda & \text{if} \quad t = t^q \end{cases}$$

where t^q is the time of entry of firm q, $d_N^{t-1}(q)$ is the number of employees of firm q in the previous period, $\gamma \in \Re^+$ is a fixed maximum growth parameter (it is positive to assure that the potential rate of growth is higher for smaller firms[10]), $\delta > 1$ is a growth rate parameter, and $\lambda \in N_0^+$ gives the maximum number of employees of a firm at the time it enters the market, t^q.

Finally, in assessing the value of working for each firm, individuals consider not only the performance of that firm, but also the number of links they have with other

[9] The adequacy of such rules in the present context is discussed below, and in particular in annex A.1.

[10] This is in accordance with most empirical findings concerning the so-called 'Gibrat's Law' of proportionate effects (for a survey, see Sutton, 1997).

specialists working for the same firm. The way interpersonal links (and their value for specialists) are formalised is described below.

3.3. The role of social networks

Let A^t: NxN $\rightarrow \{0,1\}$ be a function defining the nature of the relationship between any two individuals, such that, for any i,j $\in$ N:

$$\begin{cases} a_{ij}^t = 1 & \text{if} \quad \text{i and j are friends at time t} \\ a_{ij}^t = 0 & \text{if} \quad \text{i and j are not friends at time t} \end{cases}$$

The set of interpersonal links individual i has with individuals working for firm q at time t is then given by $L_q^t(i) = \{j \in S^t(q) : a_{ij}^t = 1\}$, and the total number of interpersonal links individual i has among *firm q*'s employees at time t is given by $d_{Nq}^t(i) = | L_q^t(i) |$.

Interpersonal links between individual specialists arise from the dynamics of the labour market.[11] Two individuals may become linked at time t only if they are working in the same firm at t. The probability of two not yet linked colleagues establishing an interpersonal link among them (conceptualised as a Bernoulli trial) is a decreasing function of the size of the employing firm.[12] I.e., for every i, j $\in$ N:

$$(4) \qquad p(a_{ij}^t = 1 \mid a_{ij}^{t-1} = 0) = \begin{cases} 0 & \text{if} \quad E^t(i) \neq E^t(j) \\ \dfrac{1}{d_N[E^t(i)]} & \text{if} \quad E^t(i) = E^t(j) \text{ and } E^t(i) \neq \{\ \} \end{cases}$$

where $d_N[E^t(i)]$ is the number of specialists employed by i's (and j's) employer at time t. Futhermore, it is assumed that $p(a_{ij}^t = 1 \mid a_{ij}^{t-1} = 1) = 1$ (that is, once they are formed, interpersonal links are never dissolved).

[11] It is assumed for simplicity that there are no interpersonal links before the start of the industry's evolution. The model can be easily extended in order to analyse different configurations of the initial network structure.

[12] The intuition here is that as the scale of the firm increases there will be less opportunities for any two fellow employees to established a link in each period.

As suggested above, when choosing between two identically performing firms, specialist i will choose to work for the firm that employs the highest number of her personal acquaintances. The value to individual i of working for firm q at time t (given that q was an incumbent at t-1 – otherwise, see below), $V_i^t(q)$, is then given by:

$$(5) \qquad V_i^t(q) = PF_q^{t-1} * [1 + LF(\alpha, d_{Nq}^t(i))]$$

where PF_q^{t-1} is the performance of firm j at time t-1, $LF()$ is a function specifying the impact of interpersonal links on individual's i valuation of firm q as an employer, $d_{Nq}^t(i)$ is the number of interpersonal links individual i has among *firm* q's employees at time t, $\alpha>0$ is a scale parameter (which defines the value specialists attach to each individual they know in each firm). That is, when assessing the value of working for a certain firm, each individual takes into account that firm's performance level and adds to this value some percentage points for each link he has among the firm's employees, according to the 'link function' $LF()$. This function can assume alternative forms. In the simplest possible case, $LF()$ assumes a linear functional form, $LF(\alpha, d_{Nq}^t(i)) = \alpha.d_{Nq}^t(i)$, implying that the marginal value of each link is constant (that is, the same value is attached to every new link, irrespectively of the number of links the individual already has among the firm's employees).

3.4. The matching mechanism

The job matching is done in the following way. Every period the labour market opens up. The list of specialists in the market is sorted in decreasing order of their expected skills and, for each individual, the list of firms is sorted in decreasing order of their value as employers. The first specialist in the list of individuals is allocated to the first job vacancy available, starting from the firm he values the most as an employer, and following the sorted list of firms; when the matching between the first individual and his preferred job vacancy has been achieved, the process is repeated for the other individuals in the list, following the ranking of expected skills, until all specialists have been allocated to some firm.[13]

3.5. Entry and exit of firms

At time t=0 (that is, before the beginning of the simulation) there are no firms. From t=1 onwards, at each simulation step $t \in T$, one individual (the 'entrepreneur') is randomly picked among all the specialists[14], and starts a new firm (firm q enters the industry at $t=t^q$, for every $q \in M$).

New firms are assessed on the basis on their entrepreneurs' skills (and not, as before, on the basis of the firm's past performance, of course). Let e(q) represent the entrepreneur of firm q; then, the value to individual i of working for firm q at time $t= t^q$ is given by

$$(5') \qquad V_i^{t^q}(q) = ES_{e(q)}^{t^q} * [1 + LF(\alpha, d_{Nq}^{t^q}(i))]$$

where $d_{Nq}^{t^q}(i) = \{0,1\}, \ \forall i \in N$ (that is, when a new firm is formed, each specialist has at most one link – the entrepreneur her self – with the firm's specialists).

Accordingly, the dynamics of this industry works as follows. In the first step of the simulation, one specialist is randomly chosen to start a new firm. At this point, the system has not produced any further information: there are no interpersonal links to influence job decisions; specialists have all the same expected skills (formally, $ES_i^t = ES_j^t, \forall i, j \in N, i \neq j$), including the new firm's entrepreneur; therefore, a given

[13] The most attentive reader will note a contradiction between this assumption of the labour market opening up in every period, and the assumption that specialists choose employers according to the interpersonal links they have in each firm. In fact the former assumption seems to suggest that specialists are changing firms at every period, so it does not seem to make much sense to consider who was working where in the previous period. In fact this is not the case: while that matching scheme greatly simplifies the computation of the dynamics, the labour market turbulence associated with it is only apparent – as soon as interpersonal links are formed, specialists will start to cluster within some firms, meaning that they will usually find their acquaintances in the firms to which they choose to work (some coordination failures are in any case expected to occur, especially in the more turbulent phases of the industry's evolution – as it happens in the real world, in fact).

[14] The probability of becoming next period's entrepreneur is uniformly distributed among individuals.

number of specialists (see parameter λ in equation 3) will be randomly allocated to the first firm entering the market. But from the very first period onwards, firms will display different performance levels (since specialists' real skills differ), a network of personal links will start to be formed, and consequently firms will start to differ in their capacity to recruit specialists. On the other side of the labour market, specialists will immediately start to differ in their expected skills according to the firms they have been working for. Each new firm entering the market will then inherit the characteristics of its entrepreneur, what includes the entrepreneurs' expected skills (which is initially taken as a proxy of the firms' competences) and her position in the network of interpersonal links; in other words, the post-entry performance of each new firm will partly depend on the pre-history of its entrepreneur (it will also depend on the firm's success in the noisy process of recruitment).

Throughout the simulation run some firms will grow and others will shrink. When incumbent firms loose all their employees (or when a new firm is not able to recruit any specialist besides its founder for a number of subsequent periods) they exit the industry; in the case of unsuccessful entries, the new firms' entrepreneurs will re-enter the labour market, and eventually be recruited by an incumbent firm.

I turn now to the analysis of the possible outcomes of such dynamics.

4. The results of the simulation

The main aim of the model that was presented before is to study the implications of the interdependency between industry dynamics and labour mobility, in a context where interpersonal links influence individuals' job decisions. Given that aim, the analysis of the simulation outcomes is focused on the variations in the value of parameter α (which determines the worth that specialists attach to links with other individuals when assessing firms as potential employers – see equations 5 and 5') – while other parameters are left unchanged.

Thus, in all the simulations to be discussed below both the number of specialists and the number of periods (which determines the number of firms entering the market) were fixed at 250. The mean of the distribution of individuals' real skills was normalised to 1 and the standard deviation was fixed at 0,25. The autocorrelation factor of individuals' expected skills (parameter β in equation 2) was fixed at 0,9. The initial maximum size of potential entrants was fixed at 3, and parameters γ and δ in equation 3 were fixed at 2 and 1.05, respectively. Each simulation for each set of values of these parameters was repeated 30 times in order to analyse the robustness of the results. In section 4.3 below, I discuss the criteria underlying the choice of these values and the consequences of changing them in terms of simulation outcomes.

The main indicators used in the analysis were the following[15]:

final number of incumbents:	the number of firms employing more than 1 individual at the final step of the simulation;
four-firm concentration ratio:	the combined market share of the four largest firms in the industry (ranging from 0 to 100) (C4);
Hirshman-Herfindahl index:	the sum of squares of the market shares of all the firms in the market (ranging from 0 to 10.000) (HHI);
industry turbulence rate:	the sum of firm exits and entries divided by the total number of incumbents;
proportion of job changes:	the number of individuals who have moved to a new firm divided by total employment;
network density:	the number of pair-wise links that were established among individuals over the total number of possible pair-wise links;

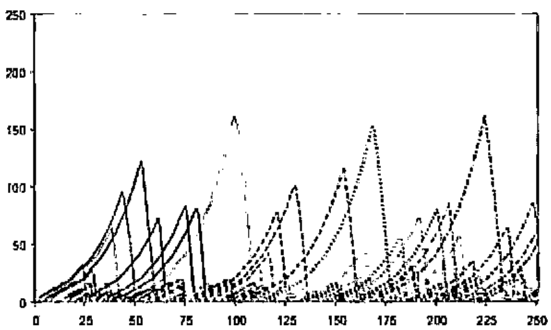
The remainder of this section presents the most relevant results of the simulation exercises.

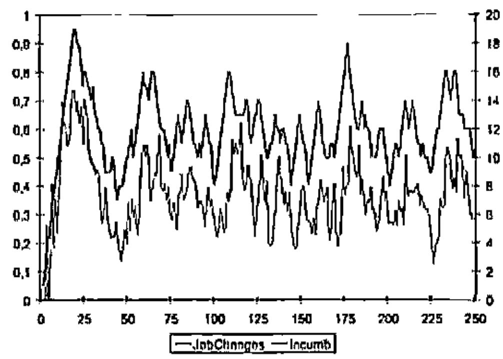
[15] With the exception of the first one in the list, all indicators are computed at every step of the simulation.

4.1. When interpersonal links are irrelevant (α=0)

When specialists do not attach any value to interpersonal links (or when these are simply absent), individuals' job decisions are determined only by the performance of the firms in the market. That is, individuals will prefer to work for firms with the best performance possible. But since firms' performance levels are determined by the average value of real skills of their employees, the performance levels of firms will vary as they grow and as workers move from firm to firm. This gives rise to such dynamic patterns as the ones illustrated in Figure 1 below.

Figure 1 - Industry and labour market dynamics when links among individuals have no value (α=0)





The graphs presented above illustrate the main patterns of industry evolution and labour market dynamics. On the left-side we have the evolution of firms' size, with the vertical axis measuring the number of employees. The right-side graph shows both the evolution in the number of incumbents and the proportion of individuals changing jobs at each period.

In Figure 1 we observe a situation of great instability, where each firm grows quickly after it enters the market, until it reaches a peak. After that point the number of employees rapidly decreases, and the firm eventually exits the market. It can also be noticed that the patterns of job mobility follow closely the evolution of incumbent firms: when the number of incumbents is small, the proportion of employees moving to a different firm in each period is lower; contrarily, it is in the periods during which a higher number of firms is able to survive after entry that we observe the highest levels of job changes.

Such pattern has already been identified and discussed in a previous paper (Mamede, 2005). As was pointed out then, the cause for such behaviour resides on a paradoxical process in which competitive success is itself the cause of firms' failure. As a result of both the random process of firm creation (which leads to firms entering the market with varying levels of performance, depending on their entrepreneurs' skills) and the noisy job matching mechanism, a certain firm is able to sustain high levels of performance for a number of periods. Its superior performance allows it to hire more employees than the competitors, and consequently it grows above the average. Ideally, this firm would be able to identify the best specialists to hire, and the most skilled individuals in the market would want to be employed by such firm (since it would certainly be the best performing firm in the industry). But as the firm grows, since the assessment of individuals' real skills is less then perfect, it will eventually start to hire specialists whose skills are below the firm's current average, and therefore its performance will start to decrease. The most direct competitors will soon surpass the firm's performance level and start to attract its employees, starting with the ones most valuable to the market (what accelerates the process of declining performance and consequent shrinking of the former leading firm). One of such competitors eventually becomes the biggest firm in the industry, and as it reaches its highest level of performance the same process happens again and again, until the end of the simulation.[16]

In the following sections I discuss how the outcomes of the model change when social networks are considered.

[16] In such scenario one may question the validity of the assumption that firms are willing to grow as much as possible; in this context the outcome of such decision is eventually deleterious to firms' performance, and one could question whether firms would not be able to prolong survival by imposing some threshold on the expected skills of prospective employees. In annex A.1 I make use of survival analysis in order to show that employing as much specialists as possible (irrespectively of their expected skills) is on average the best strategy to follow; this is even more so as soon as social networks start playing a role in specialists' job decisions, as will be shown. The reason for this result is to be found on the strong information incompleteness that characterises the model.

4.2. The value of interpersonal links

As explained in part 2 above, the worth of interpersonal links (henceforth referred to as 'link value') is here modelled in a straightforward fashion: given any two firms with identical performance levels, a specialist prefers to work to the firm within which she has the highest number of personal links. In the present section I concentrate on the case of the linear form of the 'link function', and discuss at the end the implications of using alternative specifications.

It should be clear what to expect in terms of individual decisions when we start considering the presence of valuable interpersonal links: as the industry evolves, individuals will establish links with some of the other employees working for the same firm; while the number of interpersonal links is low, these should not prevent the mobility of workers between firms; but such links will subsist even if individuals move to different firms, and they will influence individuals' future job trajectories; firms employing a higher number of someone's acquaintances will become more attractive to that individual as potential employers; thus, we can expect to observe groups of linked individuals ending up working for the same firms; furthermore, as interpersonal links are fostered inside firms, when individuals stay for longer periods in the same firm it becomes more probable that they establish links with all the others co-employees (namely, with those that did not influence the individual's initial decision to work there). In sum, introducing interpersonal links as a factor influencing individuals' job decisions is expected to bring about some stabilisation in the evolution of the industry's structure.[17]

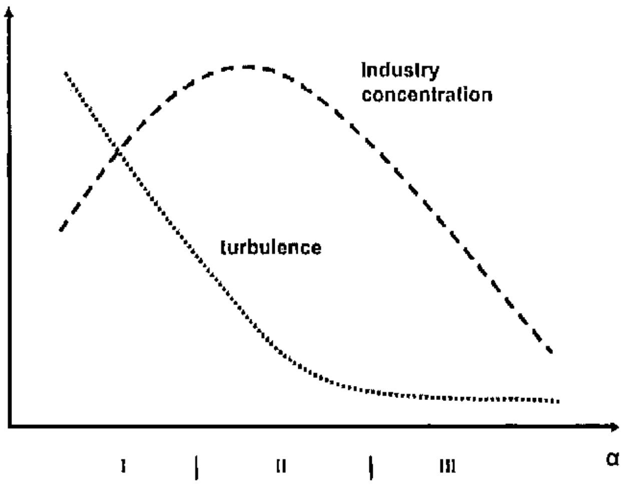
In fact, this will be shown to be the case. Irrespectively of the functional form used to account for the value of interpersonal links, as the level of 'link value' increases, the proportion of individuals changing jobs at each period decreases and the industry becomes less turbulent (i.e., the number of incumbent firms stabilises). The precise way

[17] There are alternative ways to introduce stability in the system under analysis. In Mamede (2005) I discuss the effects of introducing mobility costs in the context of a similar baseline model. Still another possibility would be to change the hypothesis on information (in)completeness in labour market decisions, possible through the informational effects of labour markets.

in which that happens, and its consequences in terms of industry evolution and labour market dynamics will become clear below.

Figure 2 illustrates how increases in the level of the 'link value' parameter, α, affect the patterns of the industry's structural evolution, namely in terms of industry concentration and of turbulence in both sides of the labour market.

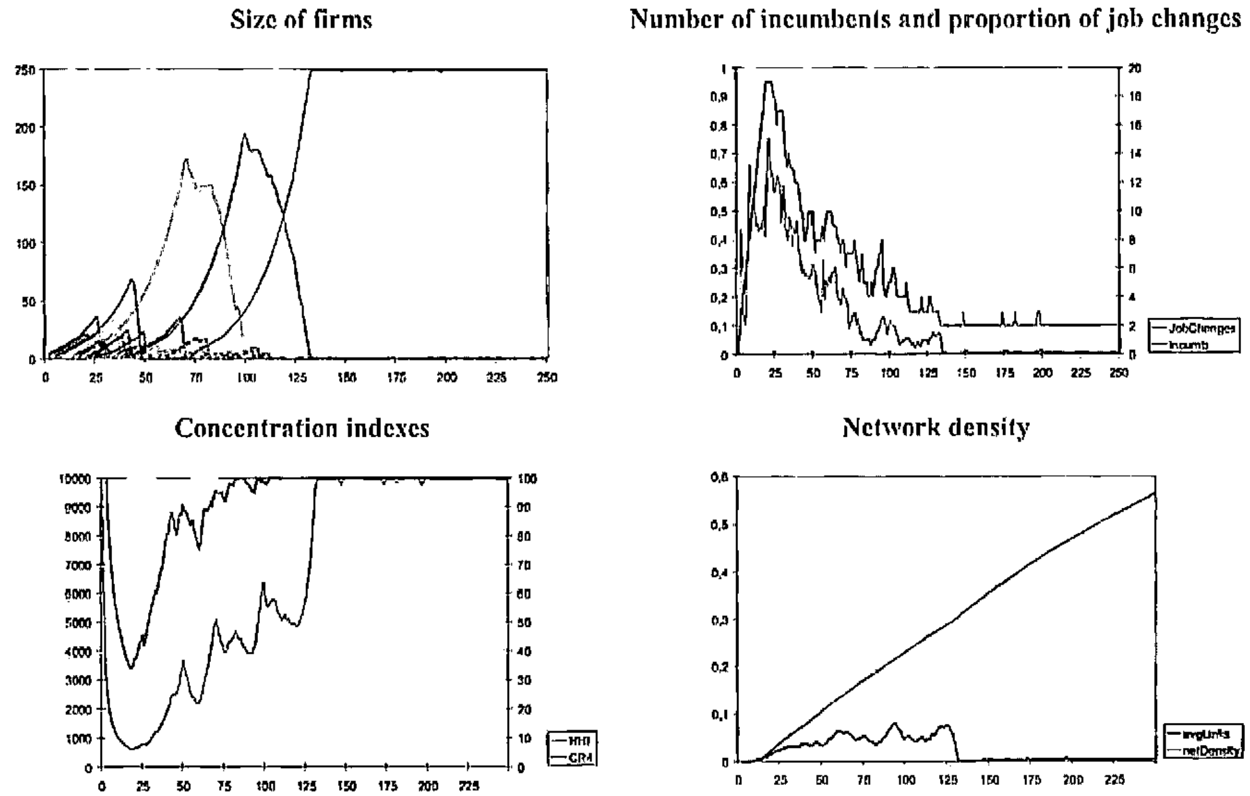
Figure 2 – The impact of changes in 'link value' (parameter α) on the patterns of industry evolution



The graph displays three distinct areas, which correspond to different types of outcomes that are obtained as the level of 'link value' increases. As one could expect, for low levels of 'link value' (area I) the model does not behave differently from the case of valueless interpersonal links (see section 4.1): in this case, the patterns of industry evolution and labour mobility are characterised by great instability, with workers frequently moving between firms and firms rapidly contracting after they have reached a peak in size.

However, as the 'link value' increases the model starts to reveal more stable dynamic patterns. For intermediate levels of the 'link value' parameter (area II in Figure 2), after an initial period of high industry turbulence and frequent job changes, the industry stabilises in a highly concentrated structure, typically a monopoly. Figure 3 below shows the main features of such situation (the 'link value' parameter is here fixed at 1%).

Figure 3 - Industry and labour market dynamics for intermediate levels of the 'link value' parameter



In addition to the graphs displaying the firms' size and the turnover of firms and individuals (which were introduced in Figure 1 above), Figure 3 presents two other graphs. On the lower-left quadrant we have the C4 and the HHI concentration indexes. The lower-right chart shows the evolution of the network density, together with the external links statistic (which only considers the links among individuals working for different firms, when calculating the network density).

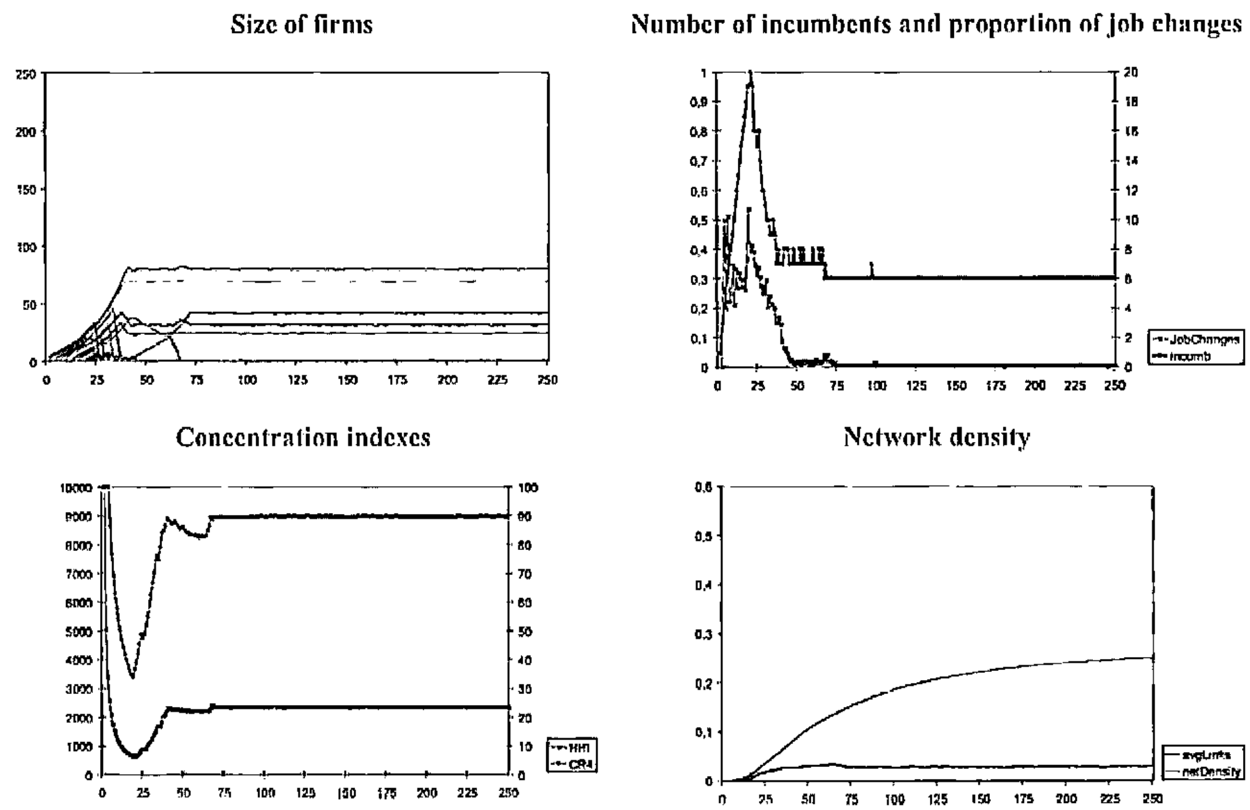
Just as in the case of irrelevant interpersonal links, during the first half of the simulation run we can observe a recurrent situation in which some successful firm grows above the others for some periods, and then it invariably starts shrinking until it looses all its employees. However, two main differences in comparison to the situation analysed in section 4.1 can be identified from the simple inspection of Figure 3: first, the successive leading firms are able to reach increasing scales and survive for longer periods; second, in this sequence of successive leaderships, at some point one firm is able to capture all the labour force, and from that moment onwards it becomes the indisputable monopolist.

Again, it is immediately clear how the introduction of interpersonal link effects brings about this aggregate outcome. At every step of the industry's evolution, new interpersonal links are being established among co-workers. As the number of links grows, they increasingly interfere in individuals' job decisions. During the initial stage of the process the number of links is not sufficiently high to avoid great job turnover; this allows the simultaneous presence of a relatively high number of incumbent firms, which operate in a rather unstable competitive environment (along the lines described before for the baseline simulation). But as the number of links grow, the 'link effect' will allow some firms to attract an increasingly high number of individuals to their ranks; the reverse of this is that it becomes ever more difficult for other firms to survive, leading to a 'shake-out' in the number of incumbents, soon after the industry has reached its highest number of operating firms. After some firm has become the dominant player in the industry (i.e., after it captures about 40% of the labour force), very demanding conditions are required for another firm to overcome the dominant one.

In order to understand how changes in industry dominance can take place, one needs to take into account the fact that firms are not born equal; in fact, when they enter the market their initial performance is dependent on the skills of their first employees, in particular the ones of the founding entrepreneur. Furthermore, entrepreneurs are differently positioned in the network of interpersonal links, which means that, from the very beginning, firms are differently able to attract individuals and retain them in their ranks. After the industry's shake-out takes place, only firms that enter the market with very high performance levels and with adequate links to other firms' employees are able to survive. Still, these are necessary, but not sufficient conditions for survival. In fact, it may happen that a firm which enters the market with the 'right' characteristics (in terms of expected performance and interpersonal links) is nevertheless unlucky during the noisy job matching processes (i.e., in a number of successive periods the firm hires individuals whose skills are lower than expected). In sum, for intermediate levels of the 'link value' parameter, as the selection conditions become tougher (due to the increasing density of interpersonal networks, especially within the dominant firms), firm survival demands not only superior characteristics but also chance. At a certain stage the density of the network of interpersonal links is too strong for any entering firm to be able to capture employees to its ranks, and the industry stabilises in a monopolistic structure.

Finally, for higher levels of the 'link value' parameter (area III in Figure 2), we obtain less concentrated and even more stable patterns of industry structure. In fact, after some threshold, further increases in the level of 'link value' imply an increase in the average number of incumbents and a corresponding decrease in the concentration ratios. Figure 4 below presents the typical outcome of a simulation when the 'link value' parameter is fixed at 5%.

Figure 4 - Industry and labour market dynamics for high levels of the 'link value' parameter



As can be seen in the graphs above, some of the dynamic patterns are common to the ones identified for intermediate levels of the 'link value parameter': once again we have an initial period during which many firms enter the market and are able to survive and grow for a number of periods, and during which individuals are changing jobs frequently; after that, some firms are able to grow above the others, attracting a high number of workers, and causing a shake-out in the number of incumbent firms. But the similarities with the previous case stop here. In fact, by comparing the graphs it can be noticed that the proportion of job changes in the initial period has decreased. This means that, as could be expected, interpersonal links start to influence individuals' job decision since the early evolution of the industry; as a result, individuals more easily 'get stuck' in a firm (which explains why the proportion of links external to the individuals' own employing firms is even lower than before - see chart in the bottom-right quadrant).

Consequently, firms which perform well enough in the early stage are more likely to survive, even if their performance levels decrease afterwards – since they can rely on the influence of interpersonal links among its employees to prevent poaching from competitors. The 'first-mover advantages' are not limited to the ability in retaining present employees: firms that enter the market early and which maintain high levels of performance for a while are more able to attract individuals with high expected skills (and retain them in their ranks afterwards).

However, such 'first-mover advantages' are not absolute. As illustrated in Figure 4, even firms which attempt to enter the industry after the shake-out episode may be able to grow and survive. This is because the successful incumbents tend to reduce their performance levels as they grow; just as in the case where interpersonal links were irrelevant (see Figure 1), growth is a source of risk to firms, since in order to grow firms have to hire individuals whose skills may be lower than the firms' current average (and in fact this can be expected to happen after some point, since firms start by hiring those individuals whose expected skills are highest). But in the present case, the 'risk of growth' is not as high as before, since firms can rely on the network of interpersonal links. That is, market leaders can afford to have lower performance levels than competitors. Therefore, as long as their entrepreneurs are highly skilled and have good links to other workers, late-comers may still achieve a considerable competitive position.

But this is true only up to some point. After a number of periods the network of interpersonal links inside the firms is so dense that it becomes virtually impossible for prospective entrants to attract workers to their ranks. Every attempt by an entrepreneur to launch a new venture is doomed to failure (and those individuals tend to go back to their former employing firm, where the number of interpersonal links among the employees is highest).

If we increase even more the level of the 'link value' parameter, the result is that the average number of incumbents will increase even more: interpersonal links will start influencing the results even earlier in the industry's evolution, and firms will more easily retain employees, in spite of their relatively low performance. This also means that successful entry becomes more probable in later periods, since there will be more incumbent firms with low levels of performance, which can be challenged by 'late-comers'.

4.3. Robustness issues

The complexity of the model presented in this paper was deliberately kept at a relatively low level. Its development aimed at illustrating the possibility and usefulness of considering the coupled dynamics of industry structures and labour mobility – something that has been absent from most models available in the relevant literature. Therefore, in order to focus on that aim and avoid unnecessary complications, the number of parameters and behavioural equations were kept to the minimum.

In spite of this option for a parsimonious approach to modelling, the space of parameters in the present model is virtually infinite (as is often the case with simulation models). In fact, the results presented in the preceding sections are based on the exploration of variations in the value of a single parameter, α. It is then worth to discuss the criteria behind the choice of parameterisation used, and the possible implications of changes in the parameter values.

4.3.1. The choice of parameter values

In what regards the choice of parameter values, three different cases can be distinguished.

First, there are those parameters in which the choice of values was determined by the constraints imposed by the software used for the analysis of the results. These were: |N| (the number of specialists), |T| (the number of simulation steps) and |M| (the number of entering firms, which is attached to the value of |T| – see section 3), all of which were fixed at 250. An arbitrary choice of |T| (and, consequently, |M|) could be problematic if the dynamics of the system for t>|T| would lead us to modify the main inferences emerging from the analysis. However, the discussion above was basically centred on the mechanisms leading to an initial rise in the number of incumbents followed by a shake-out the industry structure (for moderate and high levels of parameter α) and the value of |T| is more than enough to study those effects. On the other hand, changes in |N| (the total number of specialists) lead to variations in the number of incumbent firms, but, as could be expected, do not modify the general dynamic patterns of the system.

A second case regards those parameters that determine the limits to firms' growth. These include (see equation 3): λ (which determines the maximum initial size of firms), and γ and δ (which determine the maximum number of specialists a firm can recruit in each later period), as a function of its size in the previous iteration. Here the choice of parameter values was done on the basis of empirical data; namely, I have used Portuguese annual data on knowledge-intensive business services (KIBS) firms during the period 1991-2000.[18] In what concerns parameter λ, I have simply computed the average size those firms in their first year of life – which was 3,13 (and, accordingly, the value of λ was fixed at 3). In order to fix the values of γ and δ I have proceeded as follows: first, I have computed the maximum growth, *MG*, which was observed for each firm size from one year to the next, during the whole period covered in the dataset – this was taken as the empirical counterpart of variable MC^t_q in equation 3; second, I estimated the empirical model $MG^t_q = a + b * N^{t-1}_q + \varepsilon^t_q$ where N^t_q represents the size of

[18] For a definition of KIBS see EMCC (2005). For a description of the official database which was used in the present context, «Quadros de Pessoal» (organised by the Portuguese Ministry of Labour and Social Solidarity) see, for example, Cabral and Mata (2003).

firm q at time t; the estimated coefficients were a=22,33 and b=1,309. These results give us a linear approximation to the relation between the size of a firm in one year and its potential maximum size in the year after; it is, however, improbable that the year, as a time unit, constitutes the most adequate empirical counterpart of the simulation steps in the present model. In fact, simulation steps represent in this context the moments in which the labour market opens up and new job matches are obtained. It is reasonable to think that, in reality, this will take place at time periods shorter than one year, such as quarters or months. Therefore, assuming that the maximum potential annual growth of all the firms in the database would be obtained according to the function $MC_q^t = 22{,}33 + 1{,}309 * N_q^{t-1}$, I have computed the quarterly and monthly equivalents of such growth pace, and estimated new empirical models in order to obtain the coefficients relating firms' size and firms' potential growth at those shorter time spans. The estimated coefficients were a^Q=2,174 and b^Q=1,07 for quarterly changes, and a^M=1,295 and b^M=1,023 for monthly changes. The values for parameters γ and δ that were used in the simulations discussed above (to recall, γ=2 and δ=1.05) are in between the quarterly and monthly estimated coefficients in the potential growth equation.

The third case regards two remaining parameters of the model: the standard deviation of that distribution, σ (its value was fixed at 0.25; the mean of the distribution of specialists' real skills, μ, was simply normalised to 1); and parameter β in equation 2 (the autocorrelation factor, determining the way expectation of specialists' skills are formed in the market – which was fixed at 0.9). The problem with these parameters is that it is hard to identify measurable empirical counterparts that can guide us in fixing their values, and therefore the decision regarding the values to be used in the simulations was essentially arbitrary.[19] It is thus advisable to analyse the extent to which the main results obtained above would change in case of different parameter values.

[19] Regarding β , its high value was somehow inspired in what seems to be the practice in the type of industries that have inspired the development of this model (see section 2.5). A simple inspection of equation 2 elucidates the role played by this parameter: the value of β varies between 0 and 1; if β=1, the expected value of an individual's skills would never change (actually the expected skills of all individuals would be the same and, therefore, the evolution of the market would not lead no any information updating); if β=0 the only thing that matters for forming an expectation about individual i's expected skills at t is the performance of the firm for which i's has worker in t-1. A value of β=0.9 means that the market attaches a great importance to the past trajectory of individuals (with the weight attached to more recent periods being higher than more distant ones).

4.3.2. Sensitivity analysis (in relation to parameter values)

In order to perform a sensitivity analysis of the model in relation to changes in the value of the parameters I have generated 25 independent random combinations of values of the later 5 parameters referred to above, that is: λ, γ, δ, σ, and β. In the case of the first four parameters, the random values were drawn from normal distributions in which the mean was equal to values used in the simulations above and the standard deviation was equal to half of that mean.[20] In the case of parameter β, the random values used in the sensitivity analysis were drawn from a uniform distribution over the whole possible range of values, that is, the interval]0,1[. Each of the 25 random combinations of parameters thus generated was run 30 times, in order to check for the robustness of each combination. Since the discussion in sections 4.1 and 4.2 was centred on the effects of changes in the link value parameter on the behaviour of the system, the same procedure was repeated for 3 different values of parameter α: 0, 0.01 and 0.05 (in order to check to what extent similar comparative outcomes would ensue).

The tables in annex A.2 display some informative statistics of the simulation outcomes for each of the 25 random combinations of parameters. It can be seen that there are two types of situations in which the outcomes of the model clearly diverge from the general patterns discussed in section 4.1 and 4.2 above. The first is when the value of the parameters that determine the potential maximum growth of firms strongly constrain their initial pace of growth (see parameterisations 8, 19, and 21 – after 10 simulation steps, the maximum size that entering firms can achieve in these 3 parameterisations is lower than any other of the 25 alternative parameterisations, and about half of the maximum size allowed in the parameterisation used in sections 4.1 and 4.2); in this cases firms' growth is so slow that no firm can become dominant and the number of incumbents rises until there are no more specialists to allocate among firms. The second type of situation that diverges from the general results discussed in the previous sections is also an extreme one: it consists in those cases in which the standard deviation of the specialists real skills (parameter σ) is close to zero (see parameterisations 7, 12, and 25); in such cases, differences in performance among firms are so small that, as soon as

[20] The following restrictions are imposed in order to assure that the maximum potential growth is positive and decreasing with size: $\lambda \geq 1$, $\delta > 0$ and $\gamma \geq 1$. Since σ consists in a standard deviation (determining the heterogeneity among the agents in the model) we must also impose $\sigma \geq 0$.

specialists start to attach a positive value to interpersonal links (see tables A.2.2 and A.2.3), the tendency for a small number of incumbents to become dominant will be lower than otherwise.

In sum, from the sensitivity analysis preformed in relation to the value of the parameters it can be concluded that only in extreme situations will the outcomes of the simulation strongly diverge from the ones discussed in section 4.1 and 4.2 above.

4.3.3. Changes in the functional form of the 'link function'

One can also question to what extent would the outcomes of the simulations change significantly if marginal variations to some structural aspects of the model were introduced. Given the centrality of the 'link function' (see equation 5) for the discussion of the simulation outcomes in sections 4.1 and 4.2, I will focus the discussion here on the consequences of changing the basic form of such function.

The results that have been presented and discussed in section 4.2 refer to simulations in which a linear version of the 'link function' was used. This means, for example, that if the 'link value' parameter is fixed at 1%, an additional link with some of the firm's employees increases the value of that firm to the individual by exactly 1% of the performance level, no matter how many acquaintances the individual already has among that firm's employees. Of course, this is not the only conceivable way for interpersonal links to influence individual job decisions. Given the centrality of this function in the model, it is worth discussing how the outcomes of the model would change if other functional forms were adopted.

For example, two alternative versions of the 'link function' would be an exponential form and a logarithmic form. In the case of the exponential 'link function' the value attached to any additional acquaintance working for some firm would increase with the number of links a specialist already has in that firm. On the contrary, in the case of a logarithmic 'link function' the first few acquaintances are much more important that the additional ones.[21]

While the general patterns do not change as those alternative forms of the 'link function' are adopted (this is especially true for the exponential case), some interesting differences that result from the logarithmic case are worth noting (see the coefficients of variation presented in table A.3, in annex). In both the linear and the exponential cases, as the 'link value' increases, there is a smooth transition from a stable monopoly (or quasi-monopoly), through different degrees of stable, relatively symmetric oligopolies (with decreasing levels of concentration), and finally to rather un-concentrated, stable industry structures. On the contrary, the logarithmic case is much more unstable and rather unpredictable for levels of 'link value' in the upper-bound of region II in Figure 2; in such cases, the same parameterisation can give rise to very diverse results, which include: stable and unstable monopolies, oligopolies of different degrees (usually not totally stable) with or without a dominant firm, changes from one type of structure to another at different moments in the evolution of the industry, etc. The reason that explains such instability has to do with one crucial factor: since the first few links within a firm can have a significant impact in individuals' job decision, it becomes much easier for an entrepreneur to enter the market successfully, even after the 'shake-out' episode (as long as her expected skills are not too low, the entrepreneur just needs to be linked to a few highly skilled specialists to be able to compete with the incumbent firms). This clearly illustrates how the factors determining the job decisions of individuals can be crucial not only to the patterns of job mobility, but also to the evolution of industry structures.

[21] One possible way to rationalise these alternative functional forms of the link function is the following. In the exponential case interpersonal links are relevant for reasons of power: having few links in a firm does not alter one's career prospects, while having many links in a firm grants an easier access to promotion and other benefits. In the logarithmic case, individuals are motivated by the pleasure of working with acquaintances; arguably, one's emotional comfort increases much more when switching from a job situation where he has no interpersonal links with other workers, to one in which there is one or two links, than when an individual already works with dozens of acquaintances and makes an additional emotional link among his colleagues.

5. DISCUSSION AND CONCLUSIONS

The model presented in this paper was built in order to analyse the interdependencies between labour market dynamics and the evolution of industries' structure, in situations where individuals' job decisions are influenced by interpersonal links among workers. One crucial motivation for its development was the scarcity of models of industrial dynamics suitable to industries that strongly depend on highly skilled workers, and in which labour mobility can have significant impacts on the patterns of the industry's evolution.

I argued in the introduction that the existing models of industry evolution and of job mobility, to the extent that they ignore the co-evolution of the product and the labour markets, tend to miss some relevant elements of the industries mentioned above. It is now time to illustrate how the model put forward in this paper can contribute to the analysis of such contexts.

In section 2.2 I have presented the basic ingredients of Klepper's (1996) theory of industry life-cycles, which are essentially related with the cost-advantages obtained through investments in process innovations by firms that enter the market at an early stage. As was shown in section 4, for all but the most extreme sets of parameters, the model proposed here gives rise to the same regularities in the evolution of industries which were identified in section 2.2, but it does that on the basis of quite different mechanisms. As in Klepper (1996), there are in my model some 'first-mover' advantages, but these are now related more with the dynamics of the network of interpersonal links than with any kind of durable superior performance; in fact, firms that perform well enough in the early stage are more likely to survive, even if their performance levels decrease afterwards (since they can rely on the influence of interpersonal links among its employees to attract new specialists and to prevent poaching by competitors). However, and again contrarily to Klepper's model, such 'first-mover advantages' are not permanent in the present case: as was shown, even firms which attempt to enter the industry after the shake-out episode may be able to grow and survive; this is because the established firms tend to reduce their performance levels as they grow (the paradoxical 'risk of success'), giving the opportunity for new firms to poach their employees. Still, such successful entries by late-comers become increasingly difficult, and this is explains the fact (also present in Klepper's model) that the industry structure tends to stabilise after the shake-out.

The present model is also able to propose explanations for the most commonly observed patterns of job mobility that were presented in section 2.1, which are different from the ones in Jovanovic's (1979) model. The short duration of many jobs is here related to two phenomena. First, they are a direct consequence of the entry and exit of firms in the first stage of the industry evolution (and of the indirect effects related to the vacancy chains). Second, they derive from the fact that, in the initial stage of the industry evolution, individuals are mainly driven by the will to work for high performing firms; but job mobility in this period is a self-reinforcing mechanism – the more individuals change jobs in the search for higher financial rewards, the more firms change their position in the ranking of performance, creating the conditions for further mobility. However, as the industry evolves, a growing number of interpersonal links is established, and individuals' choices are increasingly influenced by them. The longer an individual stays in a firm, the higher the number of links she establishes with her colleagues and the less likely becomes the poaching by other firms.

While the discussions above are intended to be essentially illustrative, by emphasising a number of causal mechanisms that could help explaining some regularities often found in the data (and which could show to be more adequate to some types of industries than the prevailing theories) the model put forward in this paper may stimulate the development of studies on both the empirical and the theoretical front.

On the empirical side, it would be interesting to assess the validity of the implications of this model. Some of those implications can be tested using more or less available data; this includes propositions such as: job mobility and industry turbulence are highly correlated; job mobility will be higher in younger industries, even after controlling for turbulence; firms often reduce their performance levels as they grow. In other cases one would probably need to collect data specifically for that purpose, as would be the case with the following propositions emerging from the present model: people tend to observe longer tenures in firms in which they have a higher number of acquaintances among their colleagues; in social contexts where people do not attach much value to working with individuals they are acquainted with, the same industries will be more turbulent than otherwise, monopolies will rarely occur, and low performing firms will more easily survive; firms whose initial entrepreneurs have more and better links within the available labour force will show lower hazard rates.

On the theoretical front, the present model can be extended in several directions, in order to analyse other interesting dimensions of the interdependency between industry dynamics and labour mobility, including the following: the impact of labour turnover in changing the internal demographic composition of firms (and the way these changes feedback into the structure of industries through its impact on the relative performance of firms); the role of labour mobility in defining the opportunities for learning within and between organisations (and its welfare implications); the impact of alternative human resource management practices on the patterns of industry dynamics and worker mobility; the role of social networks in the determining the patterns of entry and post-entry performance; the impact of different costs related to turnover – costs of searching, screening, recruiting, training, firing – on the industry's structure; among others.

Hopefully this paper was able to demonstrate the opportunity for, and the usefulness of, such developments.

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A.1. RECRUITMENT DECISIONS AND FIRMS' SURVIVAL

The present model assumes that the goal of firms is to maximize the duration of survival, and that in order to fulfil that goal they hire as many specialists as possible at each period. However, one may question if this is the best strategy available to firms, given the general structure of the model. In particular, it is shown in section 4.1 that as a firm grows above a certain level it will necessarily start to hire specialists whose skills are below the average of its employees' skills, and therefore the firm's performance will start to decrease – with irreversible negative impacts on the its survival. As such, it can be questioned whether firms would not be able to prolong survival by imposing some threshold on the expected skills of the employees they decide to recruit.

In order to test this hypothesis I have modified the model by introducing such recruitment thresholds, and by letting firms differ in the threshold level. Recruitment thresholds were defined as a percentage of each firm's performance (e.g., a 90% threshold means that a firm will not recruit specialists whose expected skills are more than 10% lower than the performance of the firm in the previous period), and were identically and independently distributed among firms, varying between 0 and 100% according to a sinusoidal distribution (this makes higher thresholds more frequent than smaller ones). I ran the simulation 50 times for different levels of the 'link value parameter' (corresponding to the three regions identified in figure 2), recording information about several characteristics of firms, as well as on their life duration.

Then, this information was used to estimate Cox-regressions of the firms' hazard rates.[22] The results of the regressions are shown in the table below.

[22] For an overview of statistical methods for survival analysis see Jenkins (2004)

A.1.1. Results of the Cox-regression for firms' hazards

Link value	Firms' characteristics (regressors)	Coef.	p-value
0	Time of entry	,011	,000
	Reputation at entry	-4,511	,000
	Minimum threshold for recruitment	1,525	,000
0.01	Time of entry	,043	,000
	Reputation at entry	-2,223	,000
	Minimum threshold for recruitment	2,232	,000
0.05	Time of entry	,046	,000
	Reputation at entry	,389	,468
	Minimum threshold for recruitment	1,104	,000

As can be seen in the table, the hazard rates of firms are always positively (and significantly) related to the recruitment threshold used by firms in order to decide the minimum level of expected skills of the specialist they recruit. In other words, whatever the relevance of interpersonal links for individuals' job decisions, firms that are less demanding in what concerns the expected skills of the specialists they recruit – that is, firms that grow as much as they can in each period, as the present model assumes – will tend to survive longer.

The table above also illustrates other relevant features of the model. Namely, it shows that 'first-mover advantages' increase as the value of interpersonal links for individuals' job decisions gets higher. It also shows that reputation at entry (which is determined by the expected skills of the firms' entrepreneurs) strongly increases the survival chances of firms when social networks are absent or have a modest value for individuals' job decisions (as can be seen in the table, for higher levels of the 'link value' parameter, reputation at entry becomes statistically insignificant in explaining the survival chances of firms).

A.2.1. OUTCOMES OF THE SIMULATION FOR DIFFERENT RANDOM COMBINATIONS OF PARAMETER VALUES (LINK VALUE = 0)

	Parameters					Outcome statistics							
Parameterisation No.	β	σ	λ	δ	γ	Final Incumbents	Average incumbents	Coef. var. incumbents	Average C4 ratio	Coef. var. C4 ratio	Average job changes 0-50[1]	Average job changes 100-150[1]
1	0,80	0,18	2,2	1,1	1,052	11,4	12,2	24,4	69,6	19,8	0,44	0,35
2	0,51	0,41	2,3	1,9	1,014	10,4	11,4	18,8	68,3	14,0	0,43	0,37
3	0,71	0,23	4,7	2,2	1,034	8,5	9,5	19,6	73,4	14,0	0,42	0,40
4	1,00	0,34	4,2	1,7	1,062	7,7	8,8	25,4	80,4	14,6	0,38	0,34
5	0,86	0,11	2,7	3,2	1,072	6,9	7,4	21,3	86,2	10,0	0,39	0,34
6	0,85	0,31	1,4	2,4	1,047	8,5	9,5	21,3	79,1	12,9	0,40	0,35
7	0,72	0,05	0,6	1,3	1,078	10,0	10,8	25,0	78,2	15,6	0,40	0,32
8	0,29	0,27	4,6	0,7	1,048	42,0	36,3	30,9	15,5	112,0	0,38	0,52
9	0,06	0,30	2,0	2,8	1,043	8,1	8,9	19,6	79,2	12,0	0,39	0,38
10	0,56	0,22	5,2	0,8	1,040	12,1	12,5	20,8	59,8	21,1	0,46	0,42
11	0,01	0,48	1,4	1,2	1,044	12,6	12,9	25,9	68,5	21,3	0,43	0,32
12	0,18	0,01	5,4	1,7	1,101	7,6	8,5	22,3	79,9	13,2	0,40	0,39
13	0,97	0,27	2,2	2,7	1,060	7,4	8,3	21,7	82,9	11,5	0,37	0,37
14	0,20	0,37	3,7	2,1	1,052	8,5	9,5	20,2	75,1	13,7	0,41	0,40
15	0,47	0,20	2,5	1,9	1,032	10,2	10,4	19,2	70,4	14,7	0,43	0,39
16	0,99	0,32	2,5	1,9	1,019	9,7	10,2	19,3	71,5	14,4	0,42	0,38
17	0,96	0,27	0,9	3,4	1,054	7,3	8,1	20,0	83,7	10,3	0,39	0,40
18	0,06	0,40	1,9	2,6	1,041	8,0	9,4	19,5	77,8	12,3	0,40	0,38
19	0,01	0,33	1,8	0,0	1,000	84,0	60,9	45,2	12,5	147,5	0,18	0,49
20	0,79	0,58	0,7	2,4	1,071	7,7	8,9	21,6	82,2	11,8	0,39	0,35
21	0,34	0,13	1,4	0,9	1,017	125,0	73,7	54,9	12,0	155,9	0,33	0,49
22	0,35	0,18	5,3	2,5	1,023	9,1	9,8	18,7	71,6	13,6	0,43	0,41
23	0,98	0,44	1,9	2,8	1,045	7,8	8,5	20,3	81,0	11,8	0,41	0,37
24	0,69	0,14	2,3	3,3	1,083	6,9	7,5	21,5	87,1	9,6	0,38	0,35
25	0,25	0,06	3,4	1,5	1,047	10,5	11,4	22,2	71,4	16,9	0,41	0,38
Reference[2]	**0,90**	**0,25**	**3,0**	**2,0**	**1,050**	**8,6**	**9,2**	**21,7**	**77,8**	**13,9**	**0,40**	**0,36**

[1] «Average job changes 0-50» gives the average value from t=1 to t=50 of the proportion of specialists that have changed jobs in each period; «Average job changes 100-150» gives the same average for the period t=100 to t=150.

[2] This corresponds to the parameterisation used in sections 4.1 and 4.2.

A.2.2. OUTCOMES OF THE SIMULATION FOR DIFFERENT RANDOM COMBINATIONS OF PARAMETER VALUES (LINK VALUE = 0.01)

	Parameters					Outcome statistics							
Parameter-isation No.	β	σ	λ	δ	γ	Final Incumbents	Average incumbents	Coef. var. incumbents	Average C4 ratio	Coef. var. C4 ratio	Average job changes 0-50[1]	Average job changes 100-150[1]
1	0,80	0,18	2,2	1,1	1,052	1,2	5,1	92,9	90,3	21,3	0,31	0,01
2	0,51	0,41	2,3	1,9	1,014	1,3	6,5	58,5	89,0	17,3	0,34	0,03
3	0,71	0,23	4,7	2,2	1,034	1,2	4,0	75,5	94,2	14,0	0,26	0,01
4	1,00	0,34	4,2	1,7	1,062	1,7	4,3	67,1	94,5	13,6	0,28	0,01
5	0,86	0,11	2,7	3,2	1,072	2,3	4,0	48,5	97,5	7,9	0,15	0,01
6	0,85	0,31	1,4	2,4	1,047	1,1	4,5	69,3	94,5	12,7	0,29	0,01
7	0,72	0,05	0,6	1,3	1,078	7,1	8,7	27,2	73,0	12,2	0,14	0,01
8	0,29	0,27	4,6	0,7	1,048	42,0	36,3	31,0	15,5	112,0	0,22	0,43
9	0,06	0,30	2,0	2,8	1,043	1,1	3,9	71,1	95,5	10,8	0,26	0,01
10	0,56	0,22	5,2	0,8	1,040	1,2	5,4	83,7	87,9	23,9	0,31	0,01
11	0,01	0,48	1,4	1,2	1,044	1,6	6,9	75,9	86,9	23,0	0,37	0,02
12	0,18	0,01	5,4	1,7	1,101	3,7	5,3	36,5	93,3	9,7	0,14	0,01
13	0,97	0,27	2,2	2,7	1,060	1,3	3,7	69,3	96,4	10,0	0,24	0,01
14	0,20	0,37	3,7	2,1	1,052	1,0	4,2	73,4	94,0	13,3	0,29	0,01
15	0,47	0,20	2,5	1,9	1,032	1,4	4,4	75,0	93,4	15,5	0,26	0,01
16	0,99	0,32	2,5	1,9	1,019	1,3	4,8	70,5	92,2	16,1	0,31	0,01
17	0,96	0,27	0,9	3,4	1,054	1,3	3,7	63,4	96,9	8,6	0,24	0,01
18	0,06	0,40	1,9	2,6	1,041	1,2	4,4	70,0	94,4	11,8	0,29	0,01
19	0,01	0,33	1,8	0,0	1,000	84,0	60,9	45,2	12,5	147,5	0,11	0,34
20	0,79	0,58	0,7	2,4	1,071	2,9	5,9	44,8	93,0	11,5	0,33	0,09
21	0,34	0,13	1,4	0,9	1,017	125,0	73,7	54,9	12,0	155,9	0,17	0,49
22	0,35	0,18	5,3	2,5	1,023	1,4	4,1	71,8	94,5	13,8	0,23	0,01
23	0,98	0,44	1,9	2,8	1,045	1,3	4,3	60,1	95,4	10,8	0,28	0,02
24	0,69	0,14	2,3	3,3	1,083	1,9	3,7	56,3	97,3	7,6	0,17	0,01
25	0,25	0,06	3,4	1,5	1,047	8,4	9,8	22,2	64,6	13,5	0,13	0,01
Reference[2]	0,9	0,25	3	2,0	1,05	1,2	3,9	76,2	94,9	13,0	0,25	0,01

[1] «Average job changes 0-50» gives the average value from t=1 to t=50 of the proportion of specialists that have changed jobs in each period; «Average job changes 100-150» gives the same average for the period t=100 to t=150.

[2] This corresponds to the parameterisation used in sections 4.1 and 4.2.

A.2.3. OUTCOMES OF THE SIMULATION FOR DIFFERENT RANDOM COMBINATIONS OF PARAMETER VALUES (LINK VALUE = 0.05)

	Parameters					Outcome statistics							
Parameter-isation No.	β	σ	λ	δ	γ	Final incumbents	Average incumbents	Coef. var. incumbents	Average C4 ratio	Coef. var. C4 ratio	Average job changes 0-50[1]	Average job changes 100-150[1]
1	0,80	0,18	2,2	1,1	1,052	10,5	11,8	20,8	54,2	17,9	0,12	0,01
2	0,51	0,41	2,3	1,9	1,014	4,8	6,8	36,2	83,6	14,1	0,16	0,01
3	0,71	0,23	4,7	2,2	1,034	8,4	9,6	17,0	65,1	11,3	0,10	0,01
4	1,00	0,34	4,2	1,7	1,062	5,3	6,8	28,6	83,5	11,1	0,13	0,01
5	0,86	0,11	2,7	3,2	1,072	9,4	10,1	14,6	66,4	9,6	0,07	0,01
6	0,85	0,31	1,4	2,4	1,047	4,9	6,5	32,0	86,7	10,5	0,14	0,01
7	0,72	0,05	0,6	1,3	1,078	14,6	15,1	18,4	48,9	21,0	0,09	0,01
8	0,29	0,27	4,6	0,7	1,048	42,1	36,4	31,0	15,5	112,0	0,12	0,22
9	0,06	0,30	2,0	2,8	1,043	6,8	8,0	18,6	76,4	8,9	0,11	0,01
10	0,56	0,22	5,2	0,8	1,040	11,3	12,2	18,6	48,3	21,1	0,11	0,01
11	0,01	0,48	1,4	1,2	1,044	5,1	7,7	49,7	78,9	19,2	0,21	0,01
12	0,18	0,01	5,4	1,7	1,101	10,5	11,2	15,7	59,7	12,7	0,08	0,01
13	0,97	0,27	2,2	2,7	1,060	6,1	7,4	20,3	81,3	8,4	0,10	0,01
14	0,20	0,37	3,7	2,1	1,052	5,8	7,3	24,3	81,0	10,4	0,13	0,01
15	0,47	0,20	2,5	1,9	1,032	9,3	10,3	17,5	60,3	13,6	0,10	0,01
16	0,99	0,32	2,5	1,9	1,019	5,9	7,4	25,8	76,8	11,8	0,13	0,01
17	0,96	0,27	0,9	3,4	1,054	6,1	7,3	19,3	82,9	7,4	0,11	0,01
18	0,06	0,40	1,9	2,6	1,041	5,0	6,6	26,9	86,3	9,5	0,13	0,01
19	0,01	0,33	1,8	0,0	1,000	84,0	60,9	45,2	12,5	147,5	0,09	0,36
20	0,79	0,58	0,7	2,4	1,071	1,6	3,8	71,1	96,3	10,6	0,19	0,01
21	0,34	0,13	1,4	0,9	1,017	125,0	73,7	54,9	12,0	155,9	0,09	0,46
22	0,35	0,18	5,3	2,5	1,023	9,9	10,7	15,9	59,0	13,4	0,09	0,01
23	0,98	0,44	1,9	2,8	1,045	2,6	4,4	49,7	96,3	10,2	0,15	0,01
24	0,69	0,14	2,3	3,3	1,083	8,9	9,7	14,4	68,1	9,1	0,08	0,01
25	0,25	0,06	3,4	1,5	1,047	14,5	15,0	18,4	46,7	22,1	0,09	0,01
Reference[2]	**0,90**	**0,25**	**3,0**	**2,0**	**1,050**	**7,2**	**8,4**	**19,8**	**73,1**	**9,9**	**0,11**	**0,01**

[1] «Average job changes 0-50» gives the average value from t=1 to t=50 of the proportion of specialists that have changed jobs in each period; «Average job changes 100-150» gives the same average for the period t=100 to t=150.

[2] This corresponds to the parameterisation used in sections 4.1 and 4.2.

A. 3. OUTCOMES OF THE SIMULATION FOR DIFFERENT FORMS OF THE 'LINK FUNCTION'(*)

		Outcome statistics						
Functional form	**Link value**	**Final incumbents**	**Average incumbents**	**Coef. var. incumbents**	**Average C4 ratio**	**Coef. var. C4 ratio**	**Average job changes 0-50[1]**	**Average job changes 100-150[1]**
Linear	low	7,2	8,3	25,4	82,9	13,8	0,38	0,26
		23	*5*	*8*	*2*	*6*	*10*	*13*
	intermediate	1,2	3,9	76,2	94,9	13,0	0,25	0,01
		41	*9*	*12*	*1*	*5*	*10*	*25*
	high	7,2	8,4	19,8	73,1	9,9	0,11	0,01
		21	*14*	*16*	*9*	*12*	*9*	*21*
Log	low	7,6	8,3	26,2	83,3	14,1	0,35	0,28
		21	*4*	*12*	*2*	*8*	*9*	*10*
	intermediate	3,0	5,3	52,7	92,6	13,2	0,16	0,03
		59	*26*	*32*	*6*	*8*	*14*	*38*
	high	6,8	8,3	24,5	76,7	12,1	0,10	0,02
		38	*22*	*38*	*16*	*16*	*12*	*45*
Exp	Low	6,7	8,8	23,7	80,3	14,0	0,40	0,30
		22	*4*	*10*	*3*	*7*	*8*	*13*
	intermediate	2,1	6,0	49,5	90,6	14,5	0,38	0,03
		47	*9*	*19*	*2*	*7*	*8*	*44*
	high	7,0	8,2	19,9	75,5	9,9	0,11	0,01
		17	*12*	*21*	*10*	*8*	*8*	*48*

(*) The numbers in the upper part of each cell are the average values of the corresponding statistics, and the smaller numbers in italic underneath are the corresponding coefficients of variation.

Chapter 3

Labour mobility and firm survival

1. INTRODUCTION

In many industries the performance of firms is strongly related with their ability to manage human capital. This is particularly true for industries that rely on a highly specialised labour force, and in which the growth of firms depends on their capacity to recruit skilled workers and to avoid poaching by competitors (see, for example, Baron 2004, on hi-tech firms, and Mamede 2002, for IT consultancy). In such contexts, if not in others, one can expect to observe a systematic relation between the patterns of worker turnover and the post-entry performance of firms, and in particular their survival prospects.

In the last two decades the studies on the determinants of firm survival have proliferated. Firm survival has been found to be robustly related with firm-specific variables such as size and age (e.g., Dunne et al., 1989; Mata and Portugal, 1994; Audretsch and Mahmood, 1995; Wagner, 1999), and less robustly related with other industry-specific and macroeconomic variables. However, evidence on the relation between firm survival and labour mobility is rather scarce. While it is possible to find occasional evidence on such a link in the existing literature – as in the studies of worker and job flows by Lane et al. (1996) – this is only enough to encourage further investigations about the way the inflows and outflows of heterogeneous workers may impact on the hazards of firms.

In this paper I use data collected by the Portuguese Ministry of Employment and Social Solidarity on 9.996 firms and 50.283 workers in knowledge-intensive business services (KIBS) industries (from 1991 to 2000), in order to analyse the impact of labour mobility on firm survival. KIBS industries are particularly well-suited to the analysis of such relation: they consist of companies that provide inputs to the business processes of other organisations, and which are heavily based on advanced technological or professional knowledge embedded in their employees (EMCC, 2005)[1]; furthermore, these are industries which have grown significantly during the 1990s, with their pace of growth

[1] This includes firms that provide services in such domains as information technology consultancy, research and development, architecture and engineering, legal activities, accounting and auditing, market research, management consulting, advertising, among others. See technical annex for a detailed presentation of the industries included in the analysis.

being often hampered by the availability of labour resources (Rubalcaba-Bermejo, 1999). As such they can be considered as the ultimate example of industries in which worker turnover is crucial for the performance and survival of firms.

The paper is organised as follows. I start by discussing the theoretical issues underlying the hypotheses to be tested. Section 3 presents the data and some descriptive statistics, and section 4 introduces the method used in the estimation. Section 4 presents and discusses the results, and section 5 concludes de paper.

2. THEORETICAL ISSUES AND HYPOTHESES

It has been noted for a long time that worker turnover has both positive and negative consequences for firms. In a paper that influenced many later developments in organisation studies, Staw (1980) discussed in detail the main costs and benefits of turnover to organisations. Those costs include: selection, recruitment and training costs (which are specially high for complex jobs in the context of tight labour markets, in particular for firms which cannot rely on dedicated departments and/or internal mobility); operational disruption (particularly when turnover affects central functions in the context of highly interdependent structures); and de-moralisation of organisational members (when turnover affects group cohesion). While the organisational costs of worker mobility are often emphasised, turnover may also be beneficial to the performance of organisations in several ways, such as: new hires can be associated with more motivated, more competent, and more educated workers; the exit of workers (in the form of either fires or quits) is one of the possible solutions to entrenched organisational conflict; worker turnover (both inwards and outwards) can lead to a diversification of the external links of organisations, with benefits in terms of access to various types of resources.

The idea that turnover can have deleterious consequences (which, to some extent, are anticipated by firms and reflected in their personnel policies) has provided the basis for explaining labour market related phenomena. For example, efficiency wage theories (Akerloff and Yellen, 1986) incorporate the idea that employee turnover is reduced by increasing current and (expected) future wages and other benefits. In cases when reducing turnover rates is beneficial to the firm (e.g., increasing productivity by promoting investments in firm-specific capital, and/or reducing the costs of searching and recruitment), that idea explains why wages are often higher than expected, or why incentive regimes are particularly generous in rewarding tenure (as found, for example, by Møen, 2005, in the case of technical staff in R&D-intensive firms, where the wage-tenure profile is particularly steep).

The fact that firms respond to the risks posed by employee turnover resorting to internal incentive systems may suggest that, ultimately, the mobility of workers is rendered irrelevant (in the sense that the levels of turnover would result from firms' optimal choices). While it has been shown that firms are characterised by a persistent and heterogeneous propensity for turnover (e.g., Burgess et al., 2000; Lane et al., 1996), one could explain such heterogeneity by arguing that firms chose different optimal levels of turnover because the relevant factors underlying the optimal choice of personnel policy mix differ form firm to firm – and have little to do with persistent differences in firms' ability to avoid the costs of turnover.

However, preliminary results on the relation between worker turnover and firm survival seems to suggest otherwise. In their study of churning flows (understood as the flows of workers in and out of firms in excess of what would be necessary to accommodate net changes in total employment), Lane et al. (1996) have used a hazard rate model in order to test the prediction that high churning firms will have lower survival rates; the results obtained strongly support that prediction. Although using alternative estimation methods, Burgess et al. (2000) have reached similar conclusions concerning the relation between job churning and firm survival. These results reinforce the argument that worker turnover may not be optimising for firms, specially in those cases in which the proportion of employees that either enter or leave a firm is much higher than what would be necessary to accommodate net employment changes associated with the expansion/contraction of firms (or, to use the expression put forward by Lane et al., 1996, when churning is high).

The arguments presented above suggest a number of ways in which labour mobility can be related to firm survival, and which can guide empirical investigations of the subject.

As is often the case, some of the variables establishing that causal link may be hard to measure directly on the basis of the data available in the present context (for example, the direct costs of selection, recruitment, and training; the potential for organisational disruption or conflict resolution; or the establishment of relevant external links). Still, we can expected to identify the following relations on the basis of the available data: (i) churning rates will be positively related with firms' survival chances; (ii) job match dissolutions will be more deleterious to firms when they involve workers with high human capital (using, e.g., educational attainment as a proxy), rather than low human capital; and, inversely, (iii) new hires will be especially beneficial if they imply the firms' access to more skilled workers. This relations are expected to hold even when other variables which were systematically found to be relevant for firm survival are taken into account.

3. DATA AND DESCRIPTIVE STATISTICS

The data used in this paper was collected by the Portuguese Ministry of Employment and Social Solidarity (MTSS), on the basis of an annual survey that started in 1982 (presently, the data available for research covers the period 1985-2002). This survey is compulsory for all firms employing paid labour in Portugal, and includes questions related to the characteristics of both firms (e.g., total employment, industry classification, location, legal status, ownership, number of plants, etc.) and their employees (gender, date of birth, educational background, professional category, type of contract, etc.).

Both firms and workers are identified by their social security numbers, which in principle should allow to follow them over time. In practice, however, while firms are clearly identifiable over the years on the basis of such number, some problems arise in what concerns the longitudinal analysis of workers. To start with, data on workers were not collected in 1990 and after 2000, restricting the availability of continuous series to the periods 1985-1989 and 1991-2000. Second, the quality control of data related to employees has been increasing over the years; while it is possible to have reliable data on individual trajectories in more recent periods, it seems reasonable to renounce to the use of the data corresponding to years before 1990.

Thus, the database used in the present analysis includes all firms in the MTSS's files that comply with two criteria: (i) they were founded between 1991 and 2000 (including the limiting years)[2], and (ii) they are considered as KIBS firms on the basis of their industry classification code (see technical annex). This criteria leads to the inclusion of 9.996 firms in the dataset and, after the necessary data quality checks, of 50.283 individuals employed by those firms.[3]

Drawing on the information available in the MTSS's files, the following variables were computed for each firm at each period: total employment, proportion of graduates among the workforce (as a proxy of human capital), churning rates[4], proportion of hires by level of education (e.g., the number of people with basic education accessing the firm divided by the total employment), proportion of separations by level of education (e.g., the number of people with higher education leaving the firm divided by the total employment).

The tables presented below give information about the main features of the data which will be used in the analysis. Table 1 shows the dynamics of entry and exit of the firms included in the database. It is possible to see in this table that the number of firms entering and exiting the market tends to increase over the decade, reflecting the growth in KIBS industries during that period. Furthermore, both entry and exit denote to some extent the evolution of the business cycle: particularly noteworthy is the fact that the data for 1993 (the only year during the 1990s in which Portugal experienced a negative growth in the GDP) reveal a significant decrease in entries and a substantial increase in the number of exiting firms.

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[2] Restricting the scope of the analysis to new firms allows to keep track of each firm in the database since its foundation until its death or, alternatively, until the year 2002, thus avoiding the problem of left-censoring in the estimation of the empirical model of survival – see section 4 below.

[3] Further issues and problems that arise in preparing the longitudinal series, and the way they were dealt with in the present context, are discussed in more detail in the technical annex.

[4] Following Lane et al. (1996), churning flows are computed at each period as the difference between total worker turnover (i.e., the sum of hires and separations occurring in that period) and the absolute value of net job changes. I.e., $CF=WF-|H-S|$, where CF are the churning flows, WF are the total worker flows, H are the hires, and S stand for the separations in the period. To obtain the corresponding rates, the churning flows of each firm were simply divided by its total employment.

Table 1 – Firm entry, and firm exit
(number of firms by entry cohort)

		Year of exit[#]												Total
		1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	entry
Year of entry	1991	176	81	74	40	20	17	8	7	8	18	9	159	617
	1992		166	129	65	42	18	12	9	9	14	13	189	666
	1993			201	62	31	23	12	15	9	11	15	187	566
	1994				213	71	57	49	29	34	25	30	321	829
	1995					151	90	53	43	40	34	44	318	773
	1996						136	78	61	49	62	51	417	854
	1997							169	88	64	65	81	494	961
	1998								193	111	91	106	674	1.175
	1999									196	111	163	724	1.194
	2000										521	359	1.481	2.361
	Exits	176	247	404	380	315	341	381	445	520	952	871	-	-

[#] For 2002 it is not possible to distinguish between real exists and right-censoring.

The data shown in table 1 also shows that a significant proportion of firms in each cohort exits the market during their first few years: in fact, the percentage of firms that exit after the first year is always higher than 15%, and the number of exits after two years is in no case smaller that 25%. This confirms the idea that the probability of survival is particularly low for younger firms. Finally, the data in table 1 allows one to infer the importance of right-censoring in the 1991-2000 sample (which will be used in the regression)[5]: the average proportion of censored cases is 58,4%, varying between 27,2% for the 1991 cohort and 77,9% for the 2000 cohort.

Table 2 gives information about the average sizes of firms with different ages. In this respect, the growth patterns of the firms in this database are not different from what has been found in other contexts – that is, firms typically enter the market at the lower size classes, and then they either grow and survive, or they exit the market. As a result, the size of firms typically increases monotonically with firms' age.

[5] Since the period under analysis ends in 2000, the information relative to 2001 and 2002 can be used to check whether the firms that were registered in 2000 survived after that year (i.e., are right censored) or they exited the market in that year.

Table 2 – Relation between firm size and firm age
(average sizes by entry cohort)

		Number of years since entry									
		1	2	3	4	5	6	7	8	9	10
Year of entry	1991	3,8	5,9	6,3	12,6	17,6	18,9	22,7	34,3	22,0	34,3
	1992	3,5	4,3	4,7	4,9	6,3	7,6	8,2	9,1	10,1	
	1993	3,4	4,7	5,3	5,7	7,1	8,0	8,0	8,3		
	1994	3,2	4,9	6,4	7,9	11,2	14,1	14,4			
	1995	2,8	4,1	5,9	8,2	10,7	13,4				
	1996	3,1	4,6	5,5	5,8	8,0					
	1997	3,1	4,0	4,7	5,1						
	1998	3,3	4,8	6,3							
	1999	3,4	4,6								
	2000	3,1									
	Total	3,2	4,6	5,7	6,9	10,0	12,6	13,3	16,8	15,7	34,3

Finally, table 3 displays information on the other side of the labour market of KIBS industries – more specifically, on the demographic characteristics of the individuals in the database. We can see in the table that the growth of KIBS industries during the 1990s has benefited from the inflow of new workers to the labour market; even in the last year of the period under analysis, workers in these industries who had never been registered in the MTSS's files represented ¼ of KIBS's employees. It is also clear from the table that the rate of worker turnover is significant: the annual proportion of workers who have stayed in the same firm since the previous year is always smaller than one half. Finally, table 3 contains information about the level of education attainment of KIBS's workers; for example, in the year 2000, 18% of these individuals held an university degree, 36% had completed between 10 and 12 years of schooling, 29% achieved no more than the compulsory level of schooling (it was 6 years until the early 1990s and 9 years after that), and 9% had at most the very basic level of formal education (4 years). When these figures are compared with the ones concerning all the workers that are registered in the MTSS database, it becomes clear the knowledge-intensive character of the KIBS industries in the Portuguese context: in 2000, the proportions for the complete set of workers, from the highest to the lowest level of education, were 6,2%, 17,4%, 40,4% and 36,1%.

Table 3 – Demographic characteristics of the individuals in the database

	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000
% of stayers	-	34%	36%	26%	37%	34%	33%	32%	31%	33%
% of movers	-	24%	33%	38%	31%	36%	35%	36%	44%	42%
% of labour market entrants	-	42%	31%	36%	32%	30%	31%	31%	25%	25%
% holding university degree	13%	12%	13%	14%	14%	16%	17%	19%	20%	18%
% 10 to 12 years of shooling	32%	29%	29%	31%	32%	34%	34%	34%	37%	36%
% 6 to 9 years of shooling	36%	34%	33%	33%	31%	33%	32%	32%	29%	29%
% < 4 years of schooling	21%	18%	18%	15%	14%	14%	14%	11%	11%	9%
Total number of individuals	4410	6658	8137	10402	13201	15435	18959	23496	26117	30528

4. METHOD

The relation between labour mobility and firm survival is here investigated using a piecewise-constant exponential hazard model, a semi-parametric type of approach to the statistical analysis of duration data (Jenkins, 2004; Lancaster, 1990). Statistical models of duration data (or survival time data) are particularly adequate to analyse situations in which individuals can change between states with the passage of time. In the present case, a survival model is used in order to understand the factors determining the survival prospects of firms.

A central concept in this type of analysis is the *hazard function*. In the present context, the hazard function corresponds to the instantaneous probability of a firm exiting the industry at time t, given it stayed in the market until t. Formally,

$$h(t) = \lim_{\Delta t \to 0} \frac{P(t \leq T < t + \Delta t \mid T \geq t)}{\Delta t} = \frac{f(t)}{1 - F(t)} = \frac{f(t)}{S(t)},$$

where $f(t)$ is the probability density function, $F(t)$ is the distribution function, $S(t)$ is the survival function (i.e., the probability that a firm will survive after t).

One model that has been often used in this context is the Proportional Hazards (PH) model. Such framework is characterised by its satisfying a separability assumption:

$$(2) \qquad h(t;X) = h_0(t)\, e^{X'\beta}$$

where $h_0(t)$ is a 'baseline hazard' function which depends on t, and $e^{X'\beta}$ is a firm-specific non-negative function of covariates X which does not depend on t. This property greatly simplifies the estimation of the model; it implies that: (i) the pattern of 'duration dependence' is monotonic and common to all firms (i.e., the probability of survival is monotonically increasing or monotonically decreasing); and (ii) the role of firms' characteristics and other covariates (such as industry characteristics, or macroeconomic conditions) is to scale up or down the survival-duration profile.

The assumption of the 'baseline hazard' being monotonically dependent on t is frequently presented as a crucial shortcoming of the PH approach. In fact, the idea of a monotonic duration dependence is often not consistent with what is observed in the data: for example, the survival chances of firms may actually decrease in the early phases of their life (as initial resources are being exhausted and returns are only starting to take-off) and start to increase afterwards (since the surviving firms are the ones who were able to achieved high performance levels and assure regular returns).

One way to overcome this problem is to use a parametric approach, in which the shape of the hazard function is assumed to follow a certain distribution (the parameters of which have themselves to be estimated empirically), which can assume a number of different patterns. The model used in this paper constitutes an alternative to such parametric models, since the problem of the monotonic duration dependence inherent to the PH model is here solved without having to completely characterise the shape of the hazard function (as is the case with the parametric approach).

The basic idea underlying the piecewise-constant hazard model is the following. The time axis is partitioned into a number of intervals using cut-points (which are chosen by the researcher – in the present case, each interval corresponds to one year), and it is assumed that the baseline hazard is constant within each interval, but it may differ between intervals. Then, the hazard function becomes:

$$(3)\qquad h(t;X)=\begin{cases} h_1\, e^{X'\beta_1} & 0<t\le c_1 \\ h_2\, e^{X'\beta_2} & c_1<t\le c_2 \\ \ldots & \\ h_K\, e^{X'\beta_K} & c_{K-1}<t \end{cases}$$

where the time axis is divided into K intervals by points c_1, c_2 ..., c_{K-1}. Besides the already mentioned flexibility concerning the shape of the hazard function (note that there will be one baseline hazard for each interval), this specification provides a relatively simple way to incorporate time-varying covariates – a relevant feature in the context of the present paper, where the aim is to study the impact of changing patterns of labour mobility on the survival prospects of firms

Regarding the Likelihood function, it is worth noting that we are dealing with annual data. This means that we do not know the exact time T at which firms exit the market, we only know the year interval in which exit (or censoring) occurs. Let $\{c_k\}$ represent, as before, the end points of the K intervals into which the data is grouped (with $c_0=0$ and $c_K=\infty$).[6] Thus, the individual contribution to the Likelihood will be:

$$(4)\qquad L_i=\prod_{k=1}^{K}\left[f(c_k)^{\delta_i}.S(c_{k-1})^{1-\delta_i}\right]^{d_{ik}},$$

with

$$\begin{cases} d_{ik}=1 & \text{if} \quad \text{firm i's exit or censoring happen in the interval}\,]c_{k-1},c_k] \\ d_{ik}=0 & \text{otherwise} \end{cases}$$

and

$$\begin{cases} \delta_i=1 & \text{if} \quad \text{firm i exits in the interval}\,]c_{k-1},c_k] \\ \delta_i=0 & \text{if} \quad \text{firm i is censored in the interval}\,]c_{k-1},c_k] \end{cases};$$

[6] In the present case the intervals that determine the baseline hazards basically coincide with the intervals into which the data is originally grouped. This, however, is not necessarily the case in this type of applications.

Noting that $f(c_i)$, the probability that firm i exits during the interval, corresponds to

$$f(c_k) = \Pr(c_{k-1} \le T < c_k) = S(c_{k-1}) - S(c_k)\,,$$

each firm's contribution to the Likelihood becomes

$$(6) \qquad L_i = \prod_{k=1}^{K} \left\{ \left[S(c_{k_i-1}) - S(c_{k_i}) \right]^{\delta_i} . S(c_{k_i-1})^{1-\delta_i} \right\}^{d_{ki}} = \prod_{k=1}^{K} \left\{ \left[1 - \frac{S(c_{k_i})}{S(c_{k_i-1})} \right]^{\delta_i} .S(c_{k_i-1}) \right\}^{d_{ki}}$$

It is possible to show (see Lancaster, pp.176-181) that the elements of equation (6) above can be expressed in terms of the hazard function presented in (5) as follows:

$$\frac{S(c_{k_i})}{S(c_{k_i-1})} = \begin{cases} \exp\left\{-h_k\, e^{X_i'\beta}(c_k - c_{k-1})\right\} & \text{if} \quad k = 1, 2, \ldots, K-1 \\ 0 & \text{if} \quad k = K \end{cases}$$

$$S(c_{k_i-1}) = \exp\left\{ -\sum_{l=1}^{k-1} h_l\, e^{X_i'\beta}(c_l - c_{l-1}) \right\}, \qquad k = 2, \ldots, K$$

5. RESULTS AND DISCUSSION

At the end of section 2 it was suggested that the following relations between labour mobility and the hazards of firms were expected to hold in the context of industries such as KIBS: (i) churning rates will be positively related with firms' survival chances; (ii) job match dissolutions which involved individuals with more human capital will increase the hazard rate of firms; and, inversely, (iii) hiring better workers will decrease the hazard rates of firms. This relations should hold even when other variables which were systematically found to be relevant for firm survival are taken into account.

I start by discussing the role of churning rates in determining the hazard rates, on the basis of the results presented in table 4.

Table 4 – Churning as a determinant of hazard rates

	(1)	(2)	(3)	(4)	(5)
Firm age = 10	-2.34101**	-2.26488**	-2.15943**	-1.70070**	-1.79066**
Firm age = 9	-2.23825**	-2.16478**	-2.05083**	-1.53777**	-1.63261**
Firm age = 8	-2.79801**	-2.73441**	-2.62516**	-2.06434**	-2.06182**
Firm age = 7	-2.61881**	-2.56348**	-2.45111**	-1.89613**	-1.89308**
Firm age = 6	-2.32804**	-2.27359**	-2.16519**	-1.63256**	-1.66554**
Firm age = 5	-2.22835**	-2.17862**	-2.07502**	-1.56979**	-1.65163**
Firm age = 4	-2.06494**	-2.02434**	-1.92299**	-1.45624**	-1.50706**
Firm age = 3	-1.94939**	-1.91516**	-1.81796**	-1.41774**	-1.43860**
Firm age = 2	-1.81030**	-1.78148**	-1.68713**	-1.28731**	-1.28064**
Firm age = 1	-1.19950**	-1.17681**	-1.11305**	-.704226**	-.702404**
Current size		-.007101**			
Initial size			-.028787**	-.030466**	-.031617**
Growth since birth			-.027023**	-.025533**	-.027356**
GDP growth				-.134363**	-.133880**
Churning at t	.448784**	.462358**	.477089**	.464354**	.451298**
Churning at t-1					.241270**
Churning at t-2					.278241**
Churning at t-3					.286462 *
Churning at t-4					-.487675
Churning at t-5					-.132620
Churning at t-6					-.067304
Churning at t-7					.630331
Churning at t-8					-.200507

** significant at a 5% level
* significant at a 10% level

In regression (1) only the current churning rate was included among the regressors (the other 10 coefficients correspond to the 'baseline hazards' of each interval). The coefficients are all significant and their values are as expected: the hazard rate is positively related with churning, and is typically decreasing with firms' age (the hazard-age relation is not entirely monotonic – the probability of hazard decreases from the first to the eight year, but increases slightly in the subsequent years).

This results does not change dramatically when one controls for other variables which have often found to be relevant in determining firms' survival chances. Regression (2) and (3) have considered the role of firm size. In the former case, the current size was included in the regression without changing the previous results; the value of its coefficient is also significant and has the expected sign (i.e., bigger firms have higher survival chances), but is impact is small. Its has been argued before that current size is often not a sufficient statistic for predicting survival (contrarily to what is suggested by some models of firms' growth, as the one by Jovanovic, 1982), and it is therefore advisable to consider the effects of both the size of firms at entry and their rate of growth afterwards (see, e.g., Mata et al., 1995). Thus, this two variables replace current size in regression (3); the previous results do not change considerably, and the value of the coefficients of the new regressors are as expected – they are both negative and their absolute value is nearly for times higher than the one found in regression (2) (confirming the idea that both initial and current size matter for predicting survival).

Regression (4) adds annual GDP growth to the vector of independent variables. The results of this regression confirm the suspicion that was raised when discussing the contents of table 1, concerning the influence of the business cycle in the dynamics of KIBS industries. The sign of the GDP coefficient shows that the hazards of firms decrease with the improvement in the macroeconomic environment, while the remaining results are not substantially altered. In particular, it is noteworthy that the impact of current churning is a strong and significant predictor of firms' hazards in all the regressions from (1) to (4).

The interpretation of this robust impact of churning on survival is not straightforward. As was explained before, churning consists in those hires and separations of workers that exceed what would be necessary to accommodate the changes in firms' sizes (see footnote 4). Then, one possible way to interpret the results related to the churning coefficient in regressions (1) to (4) is to suggest (in line with the discussion in section 2) that high churning firms are more prone to organisational disruption and, therefore, have lower survival chances. However, the causality could be reversed by noticing that many workers anticipate the downfall of their employing firms, and quit before the dissolution of those firms. Regression (5) tries to analyse this issues by including several lags of the churning variable. The results show that hazard rates are significantly (and positively) related to churning up to the second lag (up to the third, at a 10% level of significance). While this does not demonstrate that churning actually causes the dissolution of firms (both aspects can be determined by a third cause, such as incompetence at the managerial level), it does reinforce the notion that high churning precedes (and probably affects) the exit of firms.

Although the results presented up to this point add to the scarce evidence on the relation between worker turnover and firm survival, they essentially confirm the patterns that were identified in other studies (see Lane et al., 1996; and Burgess et al., 2000). Notwithstanding their importance (which is considerable, given the scarcity of studies on this type of subject), the results concerning the impact of churning on firm survival are not very informative about the relevance of the characteristics of those individuals involved in the labour flows. In fact, one should not expect that workers' hires and separations have similar impacts on firms regardless of the individuals who are actual accessing or leaving the firm. More specifically, the impact of hires and separations is probably higher when more human capital is involved.

The MTSS's database allows an approximation to this problem by providing information about educational background of individual workers. Regression (6) incorporates this kind of information by including as independent variables the proportion of workers accessing and leaving each firm at each level of education (as a percentage of total employment), as well as the current proportion of graduates (see table 5).

Table 5 – Educational level of hires and separations as determinants of hazard rates

	(6)	
Firm age = 10	-1.81409	**
Firm age = 9	-1.73352	**
Firm age = 8	-2.18230	**
Firm age = 7	-2.02029	**
Firm age = 6	-1.73691	**
Firm age = 5	-1.70247	**
Firm age = 4	-1.57455	**
Firm age = 3	-1.49460	**
Firm age = 2	-1.33840	**
Firm age = 1	-.741832	**
Current Size	-.006715	**
Proportion of graduates	-.246085	**
GDP growth	-.128148	**
Churning at t	.304911	**
% Basic education hires	.413100	
% Compulsary education hires	-.307998	
% Secundary education hires	-.288021	**
% Graduate hires	-.542528	**
% Basic education separations	-.140589	
% Compulsary education separations	.247358	**
% Secundary education separations	.489103	**
% Graduate separations	.565893	**

** significant at a 5% level
* significant at a 10% level

The results displayed in table 5 confirm the relevance of the characteristics of turnover individuals in relation to firm survival. The values of the coefficients presented in the table show that the impact on the hazard rates increases (in absolute terms) from the lower to the higher levels of education, both for hires and separations. Furthermore, the coefficients are particular significant at the highest educational levels, suggesting that the relation between educational background of individual 'movers' and firms' survival is specially robust in those cases.

Again, one can revert the direction of causality, and suggest that: (i) firms' with good survival prospects can more easily attract highly skilled workers than dying firms; and (ii) skilled workers are the first to leave firms with low survival chances (because they can more easily find alternative jobs). Once more, in order to investigate deeper those alternative explanations, I have estimated another regression which includes two-year lags of hires and separations for different educational levels, controlling for the effect of the initial proportion of graduates. The results are presented in table 6.

Table 6 – Educational level of hires and separations as determinants of hazard rates

	(7)	
Firm age = 10	-1.84386	**
Firm age = 9	-1.77497	**
Firm age = 8	-2.21283	**
Firm age = 7	-2.03951	**
Firm age = 6	-1.77134	**
Firm age = 5	-1.71948	**
Firm age = 4	-1.55353	**
Firm age = 3	-1.48336	**
Firm age = 2	-1.35321	**
Firm age = 1	-.748821	**
Current size	-.006898	**
Initial proportion of graduates	-.212170	**
GDP growth	-.127789	**
Churning at t	.299673	**
Churning at t-1	.275829	**
Churning at t-2	.146774	
Graduate hires at t (as % of size)	-.639891	**
Graduate hires at t-1 (as % of size)	-.704161	**
Graduate hires at t-2 (as % of size)	-1.61505	**
Graduate separations at t (as % of size)	.664308	**
Graduate separations at t-1 (as % of size)	.832396	**
Graduate separations at t-2 (as % of size)	.974968	**
Secondary school hires at t (as % of size)	-.267919	**
Secondary school hires at t-1 (as % of size)	-.793641	**
Secondary school hires at t-2 (as % of size)	-.418454	*
Secondary school separations at t (as % of size)	.597214	**
Secondary school separations at t-1 (as % of size)	.355873	**
Secondary school separations at t-2 (as % of size)	.362088	**

** significant at a 5% level
* significant at a 10% level

The results of regression (7) clearly suggest that the hire and separation of highly educated employees precedes the closure of firms in at least two years. It is particularly interesting to observe that, in the case of hires and separations of individuals holding a university degree, the strength of the impact increases for more distant years, which further reinforces the idea that the mobility of highly qualified workers affects the survival chances of firms in these industries. This is true even after controlling for the initial proportion of graduates among the firms' employees (which is itself significantly related with firms' survival prospects). That is, increasing or decreasing the percentage of highly educated employees in the workforce has a significant and durable impact on the employing firm's performance, regardless of its initial workforce composition.

6. CONCLUSIONS

The idea that the mobility of workers in the labour market and the dynamics of firms and industries are not entirely independent phenomena is not surprising. Many studies have measured the impact of firms' entry exit, expansion and contraction on the creation and destruction of jobs (for a survey, see Davis and Haltiwanger, 1999). Others have pointed out that industry turbulence affects the labour markets not only in a direct way, but also indirectly through the vacancy chains that are opened and closed by firms' growth/founding and contraction/failure (e.g., by Haveman, 1995). Until now, however, very few studies have focused their attention on the reverse type of effect – that is, the role of labour mobility in determining the dynamics of firms and industries.

This paper intended to contribute to fill that gap in the literature, by studying the labour mobility determinants of firm survival in the context of knowledge-intensive business services industries. These industries typically rely on a highly specialised labour force, and the competition among firms is strongly based on their ability to recruit highly skilled workers and to avoid poaching by competitors – and, in this sense, they are obvious candidates for the type of causal relationship under investigation.

The results of the regressions confirm the initial suspicions. Even after controlling for the usual determinants of firm survival (namely, initial and current size of firms, firms' age, initial and current human capital, and general economic conditions), the impact of several labour mobility variables on the hazards of firms is statistically significant and has the expected direction. The negative relation between firm survival and current and past churning rates (which had been identified in a couple of previous studies) was confirmed. Furthermore, it was shown that the characteristics of the individuals involved in worker turnover is not irrelevant to the firm: the survival prospects of firms systematically increase when they hire educated individuals, and systematically decreases when educated employees separate from the firms ranks. These results hold even when labour mobility variables are introduced in the regression with time lags, which reinforces the notion that worker turnover may actually affect the survival chances of firms (specially when highly educated individuals are involved) – and does not simply reflect an anticipation of firms' dissolution by their employees.

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8. Technical Annex

The database used in this paper includes all firms in the MTSS files that comply with two criteria: (i) they were founded between 1991 and 2000 (including the limiting years), and (ii) they are considered as KIBS firms on the basis of their industry classification code.

The most obvious way to control for the first criterion it to identify the first year a firm was included in the files. It happens, however, that this not guarantee that the firm is actually a new one, due to three possible situations: (i) the firm already existed but was not officially registered, (ii) it was registered with a different name and/or social security number, or (iii) the information about the firm was incorrectly introduced. The MTSS database allows to overcome this problem by taking advantage of different variables. First, firms are given a sequential number as identification code, which means that if t is the first year the firm appears in the files, its code number cannot be lower than the highest number among the firms that firstly appeared in the files in year $t-1$. Second, information about individuals includes a question on tenure – and individuals working for new firms cannot have a tenure higher than one year (or two, if one allows for late official registry). Finally, I have arbitrarily decided to exclude firms that had more than 100 employees at start (they represent 0.01% of the universe considered in the present paper), for that is a rather improbable size for new Portuguese firms to start operations.

A related question concerns the identification of the time of exit. Since the period under analysis was 1991-2000, and the MTSS files include information on firms until 2002, firms were considered as ceasing to exist in the year after they have been reported for the last time. Again, this does not assure that exit dates are correctly identified: a firm that was reported for the last time in 2000 may reappear in the 2003 files. In fact it is possible to find a few cases of firms that were temporarily absent from the files. However, cases in which firms are absent from the files for two years in a raw are quite exceptional in the complete database, so checking for the presence of the firm in 2001 and 2002 will assure a correct classification of exit dates in virtually every case of KIBS firms.

Concerning the second selection criterion, the use of the industry classification code to identify KIBS firms is not totally straightforward, since the Portuguese classification of economic activities (CAE) has changed between 1994 (CAE rev.1) and 1995 (CAE rev.2).[7] Thus, the set of industries to include in the database had to be defined for each of the two classification systems. From 1991 to 1994, the following industries were classified as KIBS (the number in parenthesis corresponds to the CAE rev.1 code): legal services (8321); accounting and auditing (8322); data processing (8323); engineering, architecture and other technical services (8324); advertising (8325); other business services (8329); general research (9114); and scientific and research institutes (932). From 1995 to 2000, the following industries were classified as KIBS (the number in parenthesis corresponds to the CAE rev.2 code): computer and related activities (72); research and development (73); legal services (7411); accounting, book-keeping and auditing (7412); market research and public opinion polling (7413); business and management consulting (7414); engineering, architecture and other technical consultancy (742); technical testing and analysis (743); advertising (744); labour recruitment and provision of personnel (745); investigation and security activities (746); secretariat and translation (7483); other business services (74842); telecommunications (64200); and news agencies (924).[8]

In the original MTSS files there are 21.108 firms which were: (i) at least once classified in one of the industries mentioned above, (ii) reported for the first time after 1990, and (iii) reported for the last time until 2000. The following cases have been excluded from the sample used in the present paper: firms that present discontinuities in the series (18,7%), firms that were not always classified as KIBS (12,6%), or firms whose founding date is not consistent with the first inclusion in the files after all the checks mentioned above (32%). This leads to a total number of firms of 9.996 in the dataset used for analysis.

[7] These are equivalent to the International Standard of Industrial Classifications (ISIC) rev.2 and rev.3, respectively.

[8] These criteria for the selection of KIBS industries does not coincide entirely with the other criteria that have been used in related literature. The need to minimise the mismatches in the definition of KIBS between the two classification systems led me to discard some sub-industries and to include one – news agencies – which is usually left aside.

The next step consisted in preparing the longitudinal series of workers. Like in the case of information on firms, in the original MTSS files the data on individual workers were not consolidated over the years. But unlike the case of firms, it is often not possible to clearly identify individuals' trajectories over time. There are two types of reasons for this. First, while the data quality control procedures were quite rigorous in the case of firms, the same did not happen for individuals (the huge number of which – together with the recurrent lack of resources in the Ministry – prevented a thorough quality check); as a result, in many cases some data about individual workers was incorrectly introduced or not introduced at all, which is particularly problematic for the present purposes when it implies the impossibility to unequivocally identify each worker. A second is raised by the fact that it may happen that two different individuals are registered with the same identification code – which may be a consequence of the previous mentioned lack of data quality control, or of the fact that the Portuguese regional centres of Social Security have used for sometime relatively autonomous, and possibly overlapping, sequences of identification codes. In sum, in the original annual files one often finds individual records with duplicate identification codes, or without any individual identification at all. Therefore, if one hopes to build a longitudinal dataset of individual workers, and number of cleansing procedures are required.

The first step was to eliminate those records which do not allow an unequivocal identification of individuals in each annual files. It resulted that this problem was less severe for more recent periods (in which quality checks of data input were significantly improved), than for earlier ones. Together with the total absence of individual data in 1990, this led to the decision to fix 1991 as the starting year of the analysis – in this year, 87% of the individual records included a non-duplicate, valid identification number.

However, one further problem with the data became evident in the process of consolidating the annual files: even if in each year only the records with non-duplicate, valid code numbers are included, this does not guarantee that the records that have the same identification number in different years correspond in fact to the same person (what is to be expected given the problems mentioned above). By comparing the value of variables such as gender or date of birth for different years it is possible to identify those cases in which having the same ID code does not mean being the same person. About 13% of individual records were further eliminated as a result of this problem.

The third step consisted in identifying the individuals that were employed by some of the 9.996 firms in the database at some point. This was relatively easy, since the information on individuals is actually provided by their employers, which means that each individual record (in spite of other possible problems) is unequivocally attach to a firm. This led to the identification of 63.989 KIBS workers.

Finally, some of the individual records presented discontinuities in the longitudinal series. While such discontinuities may be related with the problems of data quality there were mentioned above, they may also result from one of the steps mentioned before: in fact, the decision to eliminate all the records with duplicated identification numbers implies that all the workers that have worked for two firms in the same year will be erased from the files (since there will be two records for each of those individuals). Taking this problem into consideration, I have adopted the following solution: when the gaps in individual records affect two subsequent years, these records were erased from the files; in the case of discontinuities affecting only one year, I assumed that the corresponding workers have moved between firms in that year (thus, if there is no information about worker i at t but there is information at t and $t-1$, it is assumed that i's employer at t is the same as the one at $(t+1)$. After this third step it is possible to unequivocally identify a total of 50.283 individuals working for KIBS firms.

Java/Repast Code
of the simulation model
(Chapter 2)

```java
  package simulation;

  import java.util.ArrayList;
  import java.util.Hashtable;
  import java.awt.Color;

  import uchicago.src.sim.engine.*;
  import uchicago.src.sim.gui.*;
  import uchicago.src.sim.space.*;
  import uchicago.src.sim.analysis.*;
  import uchicago.src.reflector.*;



public class Simulation extends SimpleModel{

  public LabourMarket labourMarket;
  public Statistics simStatistics;
  public Show simShow;

  public int iterationNum;                          //number of iterations per run
  public int currentIteration;                      //current step's number
  private long simulationDelay;
  private boolean simulationStarted;

  public int incumbents;                            //#incumbent firms per period (stat.)
  public double firmShareTurb;                      //turbulence of firms' share ranking (stat.)

  private int incumbentsAcumulator;                 //accumulates the sum of #incumbents over the runs
  private int HHIAcumulator;                        //accumulates the sum of HHI over the runs
  private int CR4Acumulator;                        //accumulates the sum of CR4 over the runs
  private int simRunNum;                            //number of current simulation run

  private DataRecorder recStep;                     //file with data of each step
  private DataRecorder recSize;                     //file with firms' size data
  private DataRecorder recPerform;                  //file with firms' performance
  private DataRecorder recLinks;                    //file with firms' n. of links
  private DataRecorder recJobs;                     //file with individuals' jobs data
  private DataRecorder recNet;                      //file with network data
  private DataRecorder recRuns;                     //file with data of each run

```

```java
private OpenSequenceGraph GraphShareTurb;       //runtime graph of share turbulence
private OpenSequenceGraph GraphIncumbents;      //runtime graph of #incumbent firms

public boolean showGraphs = true;               //false = runtime graphs are not shown
public boolean manyRuns = false;                //false = only one run

public Simulation(){

      this.simRunNum = 0;
      getHashtables();
}



/***********************PREPARING THE MODEL FOR A NEW RUN **********************/


public void setup() {

      super.setup();

      this.simulationStarted = false;
      this.currentIteration = 0;
      this.simulationDelay = 0;
      this.labourMarket = new LabourMarket();
      this.simStatistics = new Statistics(this);

      if (!manyRuns)
            this.simShow = new Show();

      this.iterationNum = this.labourMarket.maxNumOfFirms+1;

      if(this.showGraphs){
            this.GraphShareTurb = new OpenSequenceGraph ("Turbulence of firms' share rank", this);
            this.GraphIncumbents = new OpenSequenceGraph ("#Incumbents", this);
}

      this.schedule = new Schedule();

      if(this.showGraphs){
            this.GraphIncumbents.dispose();
```

```
                this.GraphShareTurb.dispose();
        }

        this.simRunNum++;
    }



    /************* ACTIONS TO PREFORM AT THE BEGGINING OF EACH RUN ****************/


    public void begin() {

        this.simulationStarted = true;
        this.setStoppingTime((long)this.iterationNum);

        this.labourMarket.init();                          //Initialization of firms and individuals
        this.simStatistics.init();                         //Initialization of statistics

        openFiles();

        buildModel();
        buildSchedule();

        if(this.showGraphs){
            GraphShareTurb.display();
            GraphIncumbents.display();
        }

        recNet.record();
        recNet.writeToFile();
    }


        public void openFiles() {                                      //Opening files to save data

          if (!manyRuns) {

            recStep = new DataRecorder ("./stepData.txt", this);
            recSize = new DataRecorder ("./firmSize.txt", this);
```

```
                recPerform = new DataRecorder ("./firmPerform.txt", this);
                recLinks = new DataRecorder ("./firmLinks.txt", this);
                recJobs = new DataRecorder ("./indJob.txt", this);
                recNet = new DataRecorder ("./network.txt", this);

                recStep.addObjectDataSource("FileStep", new FileStep(this));
                recSize.addObjectDataSource("FileFirmSize", new FileFirmSize(this));
                recPerform.addObjectDataSource("FileFirmPerform", new FileFirmPerform(this));
                recLinks.addObjectDataSource("FileFirmLinks", new FileFirmLinks(this));
                recJobs.addObjectDataSource("FileIndJob", new FileIndJob(this));
                recNet.addObjectDataSource("FileNetwork", new FileNetwork(this));
            }

            recRuns = new DataRecorder ("./runsData.txt", this);
            recRuns.addObjectDataSource ("FileRuns", new FileRuns(this));
        }


        public Schedule getSchedule() {
        return this.schedule;
    }


    public void buildModel(){

        if(this.showGraphs) {
            GraphShareTurb.addSequence ("Turbulence", new GraphShareTurb(this));
            GraphShareTurb.setYRange (0.0,(double)1.1);
            GraphIncumbents.addSequence ("#Incumbents", new GraphIncumbents(this));
            GraphIncumbents.setYRange (0.0,(double)this.labourMarket.maxNumOfFirms/10);
        }
    }


    public void buildSchedule () {
        this.schedule.scheduleActionBeginning(0,this,"step");            //to do from the first step
        this.schedule.scheduleActionAtEnd(this, "generateStatistics");   //to do at the last step
    }
```

```java
/***************** ACTIONS TO PREFORM AT EACH SIMULATION STEP ******************/


 public void step() {

        currentIteration++;

        try{
              Thread.sleep(this.simulationDelay);
        }
        catch(InterruptedException e){
              System.exit(0);
        }

        this.labourMarket.doIteration();                          //crucial method in labourMarket

        this.simStatistics.getStepStatistics();                   //computing statistics at each step
        if(currentIteration == iterationNum)
              simStatistics.getRunStatistics();                   //computing run's statistics at last step


        incumbents = simStatistics.incumbents[currentIteration-1];        //inputs for runtime graphs
        firmShareTurb = simStatistics.firmRankTurb[currentIteration-1];



        if (!manyRuns) {                                                  //saving the data into files
              recStep.record();
              recStep.writeToFile();
              recSize.record();
              recPerform.writeToFile();
              recPerform.record();
              recSize.writeToFile();
              recLinks.record();
              recLinks.writeToFile();
              recJobs.record();
              recJobs.writeToFile();

        }

```

```
		if(this.showGraphs){						//updating the runtime graphs
			GraphShareTurb.step();
			GraphIncumbents.step();
		}
	}



	/**************** ACTIONS TO PREFORM AT THE END OF EACH RUN ******************/


	public void generateStatistics(){					//Computing statistics at the last step

		recRuns.record();
		recRuns.writeToFile();

		if (!manyRuns)							//Displaying some final statistics
			System.out.println (simShow.getResults(this));
	}




	/********************************* MAIN METHOD *********************************/


	public static void main(String[] arguments) {

		System.out.println("Starting Simulation...");

		SimInit init = new SimInit();
		Simulation sim = new Simulation();
		if(arguments.length > 0){				//run from a batch file
			sim.manyRuns = true;
			sim.showGraphs = false;
			init.loadModel(sim,arguments[0],true);
		}
		else{							//run from here
			init.loadModel(sim,null,false);
		}
	}
```

```
}
```

```java
    package simulation;

    import java.util.Random;
    import java.util.Arrays;


public class LabourMarket{

    private Random random;
    private Math math;


    //Market Agents storage arrays

    public Individual[] ourIndividuals;              //creates an array of Individuals
    public Firm[] ourFirms;                          //creates an array of Firms



    //Market Parameters

    public int numOfIndividuals = 250;               //Number of Individuals in the market
    public int maxNumOfFirms = 250;                  //Max number of Firms in the market

    public double skillsMean = 1;                    //mean of individuals' real skills
    public double skillsSD = 0.25;                   //std. deviation of individuals' real skills

    public int initContracts = 3;                    //#initial contracts of new firms (initial scale)
    public double maxGrowthRate = 1.05;              //firm's max growth rate per period
    public double fixedGrowth = 2;                   //factor determining disproportionate growth

    public double acfExpSkills = 0.9;                //autocorr. factor of individuals' expected skills

    public int jobMatchRegime = 0;                   //0=simple; 1=with min. thresholds

    public int linkFunction = 0;                     //0=linear; 1=logarithmic; 2=exponential
    public double linkValue = 0.03;                  //the value of a link for individuals' job decision
```

```java
private double[] reputationRank;
private int[] controlRankF;
private double[] skillsRank;
private int[] controlRankI;

public int numOfEnteredFirms;
public int maxTotalContracts;


public LabourMarket(){
      this.random = new Random();
      this.numOfEnteredFirms = 0;
}




/******************************************************************************
*********************************INITIALIZING**********************************
*******************************************************************************/



public void init(){ /*Initialization of firms and individuals*/


      this.ourIndividuals = new Individual[this.numOfIndividuals+1];
      this.ourFirms = new Firm [this.maxNumOfFirms+1];

      this.initializeIndividuals();
      this.initializeFirms();
      if (this.initialNetworkType>0)
            this.initializeNetwork();
      }



/**********INITIALIZING (AND BUILDING ARRAYS OF) FIRMS AND INDIVIDUALS**********/


private void initializeFirms() {
```

```java

        /*In the beginning firms expect the skills of every individual to be equal to
         *the mean of the skills' distribution.*/

        double rnd = 0;
        for (int i = 0;i < this.maxNumOfFirms + 1;i++) {
            do {
                rnd = (random.nextGaussian()*this.skillsSD)+this.skillsMean;
            } while (rnd > 1);
            Firm firm = new Firm(i,
            this.skillsMean,
            rnd
            );

            this.ourFirms[i] = firm;
        }
    }


    private void initializeIndividuals() {

    /*Individuals' real skills are i.i.d. randomly distributed, following a normal
     *density function with parameterized mean and standard deviation. By default, in
     *the beginning, each individual expects the skills of every other individual and
     *the performance of every firm to be both equal to the mean of the skills'
     *distribution.*/


        for (int i = 0;i < this.numOfIndividuals+1;i++) {
            Individual individual = new Individual(
                                        this.numOfIndividuals,
                                        this.maxNumOfFirms,
                                        i,
                                        (random.nextGaussian()*this.skillsSD)+this.skillsMean,
                                        this.skillsMean
                                        );

            this.ourIndividuals[i] = individual;
        }
    }

```

```java
/*****************************************************************************
 ******************** METHODS TO RUN AT EACH ITERATION **********************
 ****************************************************************************/


public void doIteration(){

      for (int i=1; i<this.numOfEnteredFirms+1;i++) {            //firms with only one employee exit
            this.ourFirms[i].resetFirm();                        //the market
            if (this.firmsLearning == 1)
                  this.ourFirms[i].updateThreshold(this.bestThreshold,
                  this.learningFactor);
      }

      this.updateNumOfEnteredFirms();
      this.updateMaxContracts();

      for (int i = 0; i<this.numOfIndividuals+1; i++) {
            this.ourIndividuals[i].resetIndividual(this.numOfIndividuals);
            if (!this.ourFirms[this.ourIndividuals[i].pastEmployingFirmId].incumbent)
            this.ourIndividuals[i].pastEmployingFirmId = 0;
      }

      this.updateSocialNetwork();

      this.allocateEnterpreneurs();
      this.foundingAttributes();

      this.updateExpectedSkills();
      this.updateExpectedValues();

      this.updateFirmsRankForInd();
      this.updateIndividualsRank();

      this.simpleJobMatch();

      this.updateFirmAttributes();
```

```
}



/***************************ENTRY AND GROWTH OF FIRMS*************************/


private void updateNumOfEnteredFirms() {

/*Each period a new firm enters the market. The 'numOfEnteredFirms' is the
 *total number of firms that entered until the current run (including those
 *that have already exited).*/


      if (this.numOfEnteredFirms+this.numOfNewFirms < this.maxNumOfFirms+1)
            this.numOfEnteredFirms += this.numOfNewFirms;
      else {
            this.numOfEnteredFirms = this.maxNumOfFirms;
            this.numOfNewFirms = 0;
      }
}



private void updateMaxContracts() {

/*The maximum number of individuals an entering firm can recruit is fixed by
 *the parameter 'initContracts'. Incumbents potential growth rate (in terms of
 *number of employees) is a decreasing function of current size.*/


      this.maxTotalContracts = 0;

      for (int i=1; i<this.numOfEnteredFirms-this.numOfNewFirms+1; i++) {

            if (!ourFirms[i].incumbent)
                  ourFirms[i].maxContracts = 0;
            else {
                  double maxGrowth = this.fixedGrowth +
                                    (this.maxGrowthRate *
                                    (double)ourFirms[i].pastNSpecialists);
```

```
                    ourFirms[i].maxContracts = (int)(maxGrowth);
                }
        }

        for (int i=this.numOfEnteredFirms-this.numOfNewFirms+1; i<this.numOfEnteredFirms+1; i++)
              ourFirms[i].maxContracts = this.initContracts;

        for (int i=1; i<this.numOfEnteredFirms+1; i++)
              this.maxTotalContracts += ourFirms[i].maxContracts;
}



/**********************UPDATING NETWORK OF INDIVIDUALS************************/


private void updateSocialNetwork() {

/*Each period a link between every pair of individuals working for the same firm
 *may be established. The probability of two not yet linked colleagues becoming
 *linked (conceptualized as a Bernoulli trial) is a decreasing function of the
 *size of the employing firm. (The intuition is that as firms get bigger it gets
 *harder for personal contacts among any two of its employees to be established.)
 *A link between any two individuals will hold regardless of their future job
 *trajectories.*/


        for (int i=1; i<this.numOfIndividuals+1; i++)
          for (int j=i+1; j<this.numOfIndividuals+1; j++){


              if (this.ourIndividuals[i].pastEmployingFirmId>0
                & this.ourIndividuals[i].pastEmployingFirmId
                ==this.ourIndividuals[j].pastEmployingFirmId
               & !this.ourIndividuals[i].linkedWith[j]) {

                    int n = this.ourFirms[this.ourIndividuals[i].pastEmployingFirmId].pastNSpecialists;
                    double rnd = random.nextDouble();

```

```java
                    if (rnd < (1/(double)n)){
                        this.ourIndividuals[i].linkedWith[j] = true;
                        this.ourIndividuals[j].linkedWith[i] = true;
                    }
                }
            }
    }




    /******************** ATTRIBUTES OF NEW ENTERPRENEURIAL FIRMS *******************/


    private void allocateEnterpreneurs() {

    /*Every period one randomly picked individual (the enterpreneur) is allocated to
     *the new firm entering the market in that period. The reputation of the new firm
     *will correspond to the (updated) expected skills of the enterpreneur.*/


        for(int k=this.numOfEnteredFirms-this.numOfNewFirms+1;k<this.numOfEnteredFirms+1;k++){

            int i = 0;

            do {
                i = (random.nextInt(this.numOfIndividuals))+1;

                if (this.ourIndividuals[i].employingFirmId==0) {

                    this.ourIndividuals[i].employingFirmId = k;
                    this.ourFirms[k].enterpreneurID = i;

                  if (this.ourIndividuals[i].pastEmployingFirmId>0)
                    this.ourFirms[k].reputation =
                            this.ourIndividuals[i].expectedSkills*this.acfExpSkills
                          + this.ourFirms[this.ourIndividuals[i].pastEmployingFirmId].reputation
                          *(1-this.acfExpSkills);
                  else
                    this.ourFirms[k].reputation = this.ourIndividuals[i].expectedSkills;

```

```
                        this.ourIndividuals[i].expectsPerfomanceOf[k]=this.ourFirms[k].reputation;
                    }
                    else
                        i = 0;

                } while (i == 0);

                this.ourFirms[k].incumbent = true;
            }
    }


    private void foundingAttributes() {

    /*The aim here is to register the initial attributes of new firms, including
     *the initial number of links of the entrepreneur, the sum of the skills of
     *the entrepreneurs' friends at the time of entry, and the initial reputation
     *of the firm.*/


            for(int k=this.numOfEnteredFirms-this.numOfNewFirms+1; k<this.numOfEnteredFirms+1;k++){

                int i = this.ourFirms[k].enterpreneurID;
                int countLinks = 0;
                double sumSkills = 0;
                double sumLags = 0;

                for (int j=1; j<this.numOfIndividuals+1; j++)
                  if (i!=j & this.ourIndividuals[i].linkedWith[j]) {

                        sumSkills += this.ourIndividuals[j].realSkills;
                        countLinks++;
                  }

                this.ourFirms[k].foundingNLinks = countLinks;
                this.ourFirms[k].foundingLinkSkills = sumSkills/(double)countLinks;
                if (countLinks == 0)
                        this.ourFirms[k].foundingLinkSkills = 0;
                this.ourFirms[k].foundingReputation = this.ourFirms[k].reputation;
            }
    }
```

```java



/********************** UPDATING EXPECTATIONS OF AGENTS **********************/


private void updateExpectedSkills() {

/*Every period each individual's expected skills are updated. The skills expected
 *by the market are a weighted average of last period's expected skills and of
 *the reputation of the firm the individual has worked for in the previous period.
 *The weight is given by a autocorrelation factor, which is a parameter of the
 *model.*/


      for (int i=1; i<this.numOfIndividuals+1; i++)
        if (this.ourIndividuals[i].pastEmployingFirmId>0) {

            this.ourIndividuals[i].expectedSkills =
                          this.ourIndividuals[i].expectedSkills*this.acfExpSkills
                        + this.ourFirms[this.ourIndividuals[i].pastEmployingFirmId].reputation
                        *(1-this.acfExpSkills);
        }
}


private void updateExpectedValues() {

/*Every period the expectations held by individuals on firms are updated.
 *In assessing the value of working for each firm, individuals consider not
 *only the reputation of the firm, but also the number of links he has in
 *that firm.*/


      for (int i=1; i<this.numOfIndividuals+1; i++) {
        for (int k=1; k<this.numOfEnteredFirms+1; k++)
          if (this.ourFirms[k].incumbent) {

            int count = 0;

            for (int j=1; j<this.numOfIndividuals+1; j++) {
```

```
                if (i!=j & this.ourIndividuals[j].pastEmployingFirmId==k
                        & this.ourIndividuals[j].linkedWith[i])
                    count++;
                }

            if (this.linkFunction==0)
                this.ourIndividuals[i].expectsPerfomanceOf[k] =
                                                this.ourFirms[k].reputation
                                              *(1+(this.linkValue*count));
            if (this.linkFunction==1)
                this.ourIndividuals[i].expectsPerfomanceOf[k] =
                                                this.ourFirms[k].reputation
                                              *(1+math.log((double)count+1)*this.linkValue);
            if (this.linkFunction==2)
                this.ourIndividuals[i].expectsPerfomanceOf[k] =
                                                this.ourFirms[k].reputation
                                              *(1+math.exp(math.sqrt((double)count))*this.linkValue);
        }
    }
}



/****************UPDATING INDIVIDUALS' AND FIRMS' RANKINGS********************/


private void updateFirmsRankForInd() {

/*Each individual ranks the incumbent firms according to the value he attaches
 *to each of them.*/


      for (int i=1; i<this.numOfIndividuals+1; i++) {

            this.reputationRank = new double[this.numOfEnteredFirms];
            this.controlRankF = new int [this.numOfEnteredFirms];

            for (int k = 0; k<this.numOfEnteredFirms; k++) {
                  reputationRank[k] = this.ourIndividuals[i].expectsPerfomanceOf[k+1];
                  controlRankF[k] = 0;
            }
```

```java

            Arrays.sort(reputationRank);

            for (int k = 1; k<this.numOfEnteredFirms+1;k++) {
                  int x = 0;
                  for (int j=0; j<this.numOfEnteredFirms; j++)
                    if (controlRankF[j] == 0)
                      if (ourIndividuals[i].expectsPerfomanceOf[k]==reputationRank[j]){

                        ourIndividuals[i].rankedReputationOf[k]=
                        this.numOfEnteredFirms-j;
                        x = j;
                      }
                  controlRankF[x] = 1;

                  if (k>this.numOfEnteredFirms-this.numOfNewFirms
                      & ourIndividuals[i].employingFirmId == k)
                            ourIndividuals[i].rankedReputationOf[k]=-1;

            }
            ourIndividuals[i].rankedReputationOf[0] = -1;
      }
}


private void updateIndividualsRank() {

/*Individuals are ranked by the market on the basis of their expected skills.*/


      this.skillsRank = new double [this.numOfIndividuals];
      this.controlRankI = new int [this.numOfIndividuals];

      for (int i = 0; i<this.numOfIndividuals;i++) {
            skillsRank[i] = this.ourIndividuals[i+1].expectedSkills;
            controlRankI[i] = 0;
      }

      Arrays.sort(skillsRank);

      for (int i=1; i<this.numOfIndividuals+1; i++) {
```

```java

            int x = 0;

            for (int j = 0; j<this.numOfIndividuals; j++)
            if (controlRankI[j] == 0)
            if (this.ourIndividuals[i].expectedSkills == skillsRank[j]){
                  this.ourIndividuals[i].rankedSkills = this.numOfIndividuals - j;
                  x = j;
            }

            controlRankI[x] = 1;

            for(int k=this.numOfEnteredFirms-this.numOfNewFirms+1;k<this.numOfEnteredFirms+1;k++)
              if (this.ourIndividuals[i].employingFirmId == k)
                  this.ourIndividuals[i].rankedSkills = -1;
      }

      this.ourIndividuals[0].rankedSkills = -1;
}



/********************************MATCHING PROCESS*********************************/


//Simple Match


private void simpleJobMatch() {

/*Firms are willing to hire the individuals with the highest possible expected
 *skills, and individuals are willing to work for firms they value the most.
 *Thus, every period the matching is done in the following way: starting from
 *the first individual in the ranking, workers will be placed in order of
 *expected skills on the firm they value the most among the firms which still
 *have vacancies left to fill. As the matching process develops, some firms
 *will have hired the maximum number of individuals they can in the current
 *period; therefore, the individuals with the lowest expected skills are less
 *likely to be placed in the firms they value the most.*/


```

```java
        int[] countContracts = new int [this.numOfEnteredFirms+1];

        for (int i=0; i<this.numOfEnteredFirms+1; i++)
              countContracts[i] = 0;

        for (int i=1; i<this.numOfIndividuals+1; i++)
         for (int j=1; j<this.numOfIndividuals+1; j++)
          if (this.ourIndividuals[j].rankedSkills == i) {

              out:
              for (int k=1; k<this.numOfEnteredFirms+1;k++)
               for (int l=1; l<this.numOfEnteredFirms+1; l++)
                if (this.ourIndividuals[j].rankedReputationOf[l]==k) {


                    if (this.jobMatchRegime == 1 &
                        this.ourIndividuals[j].expectedSkills <
                        this.ourFirms[l].recrThreshold*this.ourFirms[l].reputation)
                                countContracts[l]=this.ourFirms[l].maxContracts;

                    if (countContracts[l]<this.ourFirms[l].maxContracts) {
                          this.ourIndividuals[j].employingFirmId = l;
                          countContracts[l]++;
                          break out;
                    }
              }
        }
  }



  /***********************EX-POST UPDATING OF ATTRIBUTES***********************/


  private void updateFirmAttributes(){

  /*After the matching process the size of the firm (i.e., the number of
   *employees) is updated, as well as its reputation (which will correspond
   *to the average real skills of its employees).*/
```

```
        double bestReputation = 0;

        for (int k=1; k<this.numOfEnteredFirms+1; k++) {

              int countSpecialists = 0;
              double sumSkills = 0;

              for (int i=0; i<this.numOfIndividuals+1; i++) {
                if (this.ourIndividuals[i].employingFirmId == k) {

                    sumSkills += this.ourIndividuals[i].realSkills;
                    countSpecialists++;
                }
              }

              this.ourFirms[k].nSpecialists = countSpecialists;

              if (this.ourFirms[k].nSpecialists > 0){

                    this.ourFirms[k].reputation = sumSkills/(double)this.ourFirms[k].nSpecialists;
              }
              else
                    this.ourFirms[k].incumbent = false;

              if (this.ourFirms[k].incumbent &
                    this.ourFirms[k].reputation > bestReputation &
                    this.ourFirms[k].incumbent)

                          this.bestThreshold = this.ourFirms[k].recrThreshold;
            }
        }
  }
```

```
package simulation;

public class Firm{

        public int identifier;
        public int maxContracts;            //max job positions to fill each period
        public int nSpecialists;            //total number of employees
        public int pastNSpecialists;        //total number of employees last period
        public double reputation;           //dependent on performance and past reputation
        public double recrThreshold;        //min skills (as % of reputation) for recruitment


        public int enterpreneurID;
        public int foundingNLinks;          //#links of the entrepreneur at founding
        public double foundingLinkSkills;   //Avg skills of the entrepreneur's links at founding
        public double foundingReputation;   //Expected skills of the entrepreneur at founding

        int rankedReputation;
        int rankedShare;
        int pastRankedShare;
        double marketShare;
        int nFriendships;
        int nLinks;

        boolean incumbent;
        int duration;

  public Firm(int identifier, double skillsMean, double threshold){

        this.identifier = identifier;
        this.reputation = skillsMean;
        this.recrThreshold = threshold;
        this.initThreshold = threshold;
  }

  public void resetFirm(){

        if (this.incumbent)
              this.duration += 1;

        if ((this.pastNSpecialists==1 & this.nSpecialists==1)
```

```
            | (this.pastNSpecialists>0 & this.nSpecialists==0)) {
                this.incumbent = false;
                this.reputation = 0;
        }



        this.pastNSpecialists = this.nSpecialists;
        this.pastRankedShare = this.rankedShare;
        this.rankedReputation = 0;
        this.rankedShare = 0;
        this.nFriendships = 0;
        this.nLinks = 0;
    }
}
```

```
package simulation;

public class Individual{

        public int          identifier;
        public double       realSkills;
        public double       expectedSkills;
        public int          employingFirmId;
        public int          pastEmployingFirmId;
        public int          rankedSkills;
        public int          jobDuration;
        public int          jobChanges;
        public int          changedJob;

        public boolean[]  linkedWith;



        public double []  expectsPerfomanceOf;
        public int []     rankedReputationOf;


  public Individual(int nInd, int nFirm, int id, double rSk, double expSk){

        this.identifier = id;
        this.realSkills = rSk;
        this.expectedSkills = expSk;

        this.friendOf = new boolean [nInd+1];
        this.expectsPerfomanceOf = new double [nFirm+1];
        this.rankedReputationOf = new int [nFirm+1];

        for (int k=1; k<nFirm+1; k++)
              this.expectsPerfomanceOf[k] = expSk;
        }


  public void resetIndividual(int numInd){

        if (this.employingFirmId>0) {

```

```java
                if (this.pastEmployingFirmId==this.employingFirmId) {
                    this.jobDuration += 1;
                    this.changedJob = 0;
                }
                else {
                    this.jobDuration = 0;
                    this.changedJob = 1;
                    this.jobChanges++;
                }
            }
            else {
                this.jobDuration = 0;
                this.changedJob = 0;
            }


            this.pastEmployingFirmId = this.employingFirmId;
            this.employingFirmId = 0;
    }
}
```

```java
package simulation;

import java.util.Arrays;

public class Statistics {

   private Simulation sim;
   private Math math;

   public int [] employment;
   public double [] propJobChanges;
   public double [] avgJobDuration;
   public int [] incumbents;
   public double [] HHI;
   public double [] CR4;
   public double [] monopoly;
   public double [] incumbTurb;
   public double [] firmRankTurb;
   public double [] avgLinks;
   public double [] netDensity;
   public double [] firmDensity;

   public double employmentAvg;
   public double propJobChangesAvg;
   public double propJobChangesAvg1;
   public double propJobChangesAvg2;
   public double propJobChangesAvg3;
   public double avgJobDurationAvg;
   public double incumbentsAvg;
   public double HHIAvg;
   public double CR4Avg;
   public double incumbTurbAvg;
   public double incumbTurbAvg1;
   public double incumbTurbAvg2;
   public double incumbTurbAvg3;
   public double firmRankTurbAvg;
   public double firmRankTurbAvg1;
   public double firmRankTurbAvg2;
   public double firmRankTurbAvg3;
   public double avgLinksAvg;
   public double avgLinksAvg1;
```

```
    public double avgLinksAvg2;
    public double avgLinksAvg3;
    public double netDensityAvg;
    public double firmDensityAvg;

    public double employmentCVar;
    public double propJobChangesCVar;
    public double propJobChangesCVar1;
    public double propJobChangesCVar2;
    public double propJobChangesCVar3;
    public double avgJobDurationCVar;
    public double incumbentsCVar;
    public double HHICVar;
    public double CR4CVar;
    public double incumbTurbCVar;
    public double incumbTurbCVar1;
    public double incumbTurbCVar2;
    public double incumbTurbCVar3;
    public double firmRankTurbCVar;
    public double firmRankTurbCVar1;
    public double firmRankTurbCVar2;
    public double firmRankTurbCVar3;
    public double avgLinksCVar;
    public double avgLinksCVar1;
    public double avgLinksCVar2;
    public double avgLinksCVar3;
    public double netDensityCVar;
    public double firmDensityCVar;

    public double monopPeriods;
    public double monopolyFinal;
    public double monopolyStart;
    public boolean monopolyPhase;

    public double initialAvgThreshold;
    public double finalAvgThreshold;
    public double avgThreshold;
    public double avgThreshold10;


    public Statistics(Simulation sim){
```

```
        this.sim = sim;
    }

    public void init(){
        this.employment = new int [sim.iterationNum];
        this.propJobChanges = new double [sim.iterationNum];
        this.avgJobDuration = new double [sim.iterationNum];
        this.incumbents = new int [sim.iterationNum];
        this.HHI = new double [sim.iterationNum];
        this._CR4 = new double [sim.iterationNum];
        this.monopoly = new double [sim.iterationNum];
        this.incumbTurb = new double [sim.iterationNum];
        this.firmRankTurb = new double [sim.iterationNum];
        this.avgLinks = new double [sim.iterationNum];
        this.netDensity = new double [sim.iterationNum];
        this.firmDensity = new double [sim.iterationNum];
    }


    void getInitialValuesS() {
        monopolyPhase = false;
    }


    public void getStepStatistics() {

        this.getinitialAvgThreshold();
        this.getJobMobilityStep();
        this.getConcentrationStep();
        this.checkMonopoliesStep();
        this.getTurbulenceStep();
        this.getNetworkStep();
    }


    public void getRunStatistics() {

        this.getJobMobilityRun();
        this.getConcentrationRun();
        this.getIncumbTurbRun();
        this.getFirmRankTurbRun();
```

```java
        this.getAvgLinksRun();
        this.getFinalAvgThreshold();
}



/**************************************************************************
 ******************* Compute main statistics for each step ********************
 **************************************************************************/


/******************** Labour Market Statistics for each step ******************/


void getinitialAvgThreshold() {

        if (sim.currentIteration == 1) {

                double sum = 0;

                for (int i = 1;i < sim.labourMarket.maxNumOfFirms + 1;i++)
                        sum += sim.labourMarket.ourFirms[i].recrThreshold;

                initialAvgThreshold = sum/(double)sim.labourMarket.maxNumOfFirms;
        }
}


void getJobMobilityStep() {

        int sum = 0;
        int _sum1 = 0;

        for (int i = 1;i < sim.labourMarket.numOfIndividuals + 1;i++)
          if (sim.labourMarket.ourIndividuals[i].employingFirmId> 0) {
                sum += sim.labourMarket.ourIndividuals[i].jobDuration;
                sum1 += sim.labourMarket.ourIndividuals[i].changedJob;
                employment[sim.currentIteration - 1]++;
        }

        avgJobDuration[sim.currentIteration-1] = (double)sum
```

```
                                           /(double)employment[sim.currentIteration - 1];
      propJobChanges[sim.currentIteration-1] = (double)_suml
                                           /(double)employment[sim.currentIteration - 1];

}


/********************* Product Market Statistics for each step *****************/


void getConcentrationStep() {


      double[] shareRank = new double[sim.labourMarket.numOfEnteredFirms + 1];
      double[] controlShareF = new double[sim.labourMarket.numOfEnteredFirms + 1];
      double rankChanges = 0;

      for (int i = 1;i < sim.labourMarket.numOfEnteredFirms + 1;i++) {

        if (sim.labourMarket.ourFirms[i].nSpecialists > 0)
              incumbents[sim.currentIteration - 1]++;

        sim.labourMarket.ourFirms[i].marketShare = ((double)sim.labourMarket.ourFirms[i].nSpecialists
                                             / (double)employment[sim.currentIteration - 1])*100;

        HHI[sim.currentIteration - 1] += sim.labourMarket.ourFirms[i].marketShare
                                      *  sim.labourMarket.ourFirms[i].marketShare;

        shareRank[i] = sim.labourMarket.ourFirms[i].marketShare;
        controlShareF[i] = 0;
      }

      Arrays.sort(shareRank);

      for (int i = 1;i < sim.labourMarket.numOfEnteredFirms + 1;i++) {

            int x = 0;

            for (int j = 1;j < sim.labourMarket.numOfEnteredFirms + 1;j++) {

              if (controlShareF[j] == 0)
```

```
                if (sim.labourMarket.ourFirms[i].marketShare == shareRank[j]){
                 sim.labourMarket.ourFirms[i].rankedShare = (sim.labourMarket.numOfEnteredFirms + 1) -
                 x = j;
               }
             }
             controlShareF[x] = 1;
        }

        for (int i=1; i<sim.labourMarket.numOfEnteredFirms+1; i++) {

             if (sim.labourMarket.ourFirms[i].rankedShare < 5)
                  CR4[sim.currentIteration - 1] += sim.labourMarket.ourFirms[i].marketShare;

             if (sim.labourMarket.ourFirms[i].nSpecialists>0 &
                 sim.labourMarket.ourFirms[i].rankedShare !=
                 sim.labourMarket.ourFirms[i].pastRankedShare)

                  rankChanges += sim.labourMarket.ourFirms[i].marketShare
                              *  sim.labourMarket.ourFirms[i].marketShare;

        }

        firmRankTurb[sim.currentIteration - 1] = rankChanges
                                               /incumbents[sim.currentIteration-1];
}


void checkMonopoliesStep() {

      if (incumbents[sim.currentIteration - 1] == 1)
           monopoly[sim.currentIteration - 1] = 1;
      else
           monopoly[sim.currentIteration - 1] = 0;

      if (incumbents[sim.currentIteration - 1] == 1 & !monopolyPhase
        & sim.currentIteration < (sim.iterationNum - 6)) {
           monopolyPhase = true;
           monopolyStart = sim.currentIteration - 1;
      }

      if (incumbents[sim.currentIteration - 1] != 1) {
```

```
                monopolyPhase = false;
                monopolyStart = 0;
            }
    }


    void getTurbulenceStep() {

            int sumEntry = 0;
            int sumExits = 0;

            for (int i = 1;i < sim.labourMarket.numOfEnteredFirms+1;i++) {

                    if (sim.labourMarket.ourFirms[i].nSpecialists>1
                      & sim.labourMarket.ourFirms[i].pastNSpecialists==0)
                          sumEntry++;

                    if (sim.labourMarket.ourFirms[i].nSpecialists==0
                      & sim.labourMarket.ourFirms[i].pastNSpecialists>1)
                          sumExits++;
            }

            incumbTurb [sim.currentIteration - 1] = (double)(sumEntry+sumExits)
                                                  / incumbents[sim.currentIteration-1];
    }


    /********************* Network Statistics for each step ************************/


    void getNetworkStep() {

            int netDensity = 0;
            int firmDensity = 0;
            int links = 0;
            int count = 0;

            for (int i=1; i<sim.labourMarket.numOfIndividuals+1; i++)
              for (int j=i+1; j<sim.labourMarket.numOfIndividuals+1; j++) {

                    if (sim.labourMarket.ourIndividuals[i].friendOf[j]) {
```

```

                        netDensity++;

                        if (sim.labourMarket.ourIndividuals[i].employingFirmId !=
                            sim.labourMarket.ourIndividuals[j].employingFirmId) {

                  sim.labourMarket.ourFirms[sim.labourMarket.ourIndividuals[i].employingFirmId].nLinks += 1;

                  sim.labourMarket.ourFirms[sim.labourMarket.ourIndividuals[j].employingFirmId].nLinks += 1;
                  links ++;
                        }

                        if (sim.labourMarket.ourIndividuals[i].employingFirmId ==
                            sim.labourMarket.ourIndividuals[j].employingFirmId
                          & sim.labourMarket.ourIndividuals[i].employingFirmId>0)

            sim.labourMarket.ourFirms[sim.labourMarket.ourIndividuals[j].employingFirmId].nFriendships += 1;
                  }
            }

            for (int k=1; k<sim.labourMarket.numOfEnteredFirms+1; k++) {

                  if (sim.labourMarket.ourFirms[k].nSpecialists > 1) {

                        firmDensity += sim.labourMarket.ourFirms[k].nFriendships
                                     / sim.labourMarket.ourFirms[k].nSpecialists;

                        count++;
                  }
            }

            double totalLinks = sim.labourMarket.numOfIndividuals *
            sim.labourMarket.numOfIndividuals;

            this.netDensity [sim.currentIteration - 1] = 2*(double)netDensity
                                                        /totalLinks;
            this.firmDensity[sim.currentIteration - 1] = (double)firmDensity/count;
            this.avgLinks [sim.currentIteration - 1] = 2*(double)links
                                                      /totalLinks;
      }

```

```java



/*********************************************************************************
 ****************** Compute main statistics for each run ************************
 *********************************************************************************/


/********************** Labour Market Statistics for each run *******************/


void getJobMobilityRun() {

      double sumEmploy = 0;
      double sumEmploy1 = 0;

      double sumDur = 0;
      double sumDur1 = 0;

      double sum00 = 0;
      double sum01 = 0;
      double sum02 = 0;
      double sum03 = 0;

      double sum10 = 0;
      double sum11 = 0;
      double sum12 = 0;
      double sum13 = 0;

      for (int t = 0;t < sim.iterationNum;t++) {

            sumEmploy += (double)employment[t];
            sumDur += avgJobDuration[t];
            sum00 += propJobChanges[t];

            if (t<50)
                  sum01 += propJobChanges[t];
            else if (t<100)
                  sum02 += propJobChanges[t];
            else if (t<150)
                  sum03 += propJobChanges[t];
```

```
        }

        employmentAvg = sumEmploy / (double)sim.iterationNum;
        avgJobDurationAvg = sumDur / (double)sim.iterationNum;
        propJobChangesAvg = _sum00 / (double)sim.iterationNum;
        propJobChangesAvg1 = _sum01 / 50;
        propJobChangesAvg2 = _sum02 / 50;
        propJobChangesAvg3 = _sum03 / 50;

        for (int t = 0;t < sim.iterationNum;t++) {

              sumEmploy1 += (double)((employment[t] - employmentAvg)
                          *(employment[t] - employmentAvg));

              sumDur1 += (double)((avgJobDuration[t] - avgJobDurationAvg)
                        *(avgJobDuration[t] - avgJobDurationAvg));

              sum10 += (double)((propJobChanges[t] - propJobChangesAvg)
                    *(propJobChanges[t] - propJobChangesAvg));

              if (t<50)
                    sum11 += (propJobChanges[t]-_propJobChangesAvg1)
                          * (propJobChanges[t]-_propJobChangesAvg1);
              else if (t<100)
                    sum12 += (propJobChanges[t]-_propJobChangesAvg2)
                          * (propJobChanges[t]-_propJobChangesAvg2);
              else if (t<150)
                    sum13 += (propJobChanges[t]-_propJobChangesAvg3)
                          *  (propJobChanges[t]-_propJobChangesAvg3);
        }

        double stdDevEmploy = Math.sqrt(_sumEmploy1 / (double)(sim.iterationNum-1));
        double stdDevDur = Math.sqrt(_sumDur1 / (double)(sim.iterationNum - 1));
        double stdDev = Math.sqrt(_sum10 / (double)(sim.iterationNum - 1));
        double _stdDev1 = Math.sqrt(_sum11 / 49);
        double _stdDev2 = Math.sqrt(_sum12 / 49);
        double _stdDev3 = Math.sqrt(_sum13 / 49);

        employmentCVar = 100 * stdDevEmploy / employmentAvg;
```

```
        avgJobDurationCVar = 100 * stdDevDur / avgJobDurationAvg;
        propJobChangesCVar = 100 * stdDev / propJobChangesAvg;
        propJobChangesCVar1 = 100 * _stdDev1 / _propJobChangesAvg1;
        propJobChangesCVar2 = 100 * _stdDev2 / _propJobChangesAvg2;
        propJobChangesCVar3 = 100 * _stdDev3 / _propJobChangesAvg3;
    }




    /******************** Product Market Statistics for each run *****************/


    void getConcentrationRun() {

        double sumInc = 0;
        double sumInc1 = 0;

        double sumHHI = 0;
        double sumHHI1 = 0;

        double sumCR4 = 0;
        double sumCR41 = 0;

        double sumMonop = 0;

        for (int t = 0;t < sim.iterationNum;t++) {
            sumInc   += (double)incumbents[t];
            sumHHI   += HHI[t];
            sumCR4   += CR4[t];
            sumMonop += monopoly[t];
        }

        incumbentsAvg = sumInc / (double)sim.iterationNum;
        HHIAvg = sumHHI / (double)sim.iterationNum;
        CR4Avg = _sumCR4 / (double)sim.iterationNum;
        monopPeriods = 100*sumMonop / (double)sim.iterationNum;

        for (int t = 0;t < sim.iterationNum;t++) {

            sumHHI1 += (double)((HHI[t] - HHIAvg) * (HHI[t] - HHIAvg));
```

```java

            sumIncl += (double)((incumbents[t] - incumbentsAvg)
                      * (incumbents[t] - incumbentsAvg));

            sumCR41 += (double)((CR4[t] - CR4Avg) * (CR4[t] - CR4Avg));
        }

        double stdDevInc = Math.sqrt(sumIncl / (double)(sim.iterationNum - 1));
        double stdDevHHI = Math.sqrt(sumHHI1 / (double)(sim.iterationNum - 1));
        double stdDevCR4 = Math.sqrt(sumCR41 / (double)(sim.iterationNum - 1));

        incumbentsCVar = 100 * stdDevInc / incumbentsAvg;
        HHICVar = 100 * stdDevHHI / HHIAvg;
        CR4CVar = 100 * stdDevCR4 / CR4Avg;

        if (monopoly[sim.iterationNum - 1] == 1 & monopolyStart < (sim.iterationNum - 6))
            monopolyFinal = 1;
        else
            monopolyFinal = 0;
    }



    /*************** Survival and Turbulence Statistics for each run ***************/


    void getIncumbTurbRun() {

        double _sum00 = 0;
        double _sum01 = 0;
        double _sum02 = 0;
        double _sum03 = 0;

        double _sum10 = 0;
        double _sum11 = 0;
        double _sum12 = 0;
        double _sum13 = 0;

        for (int t = 0;t < sim.iterationNum;t++) {

```

```
            sum00 += incumbTurb[t];

            if (t<50)
                sum01 += incumbTurb[t];
            else if (t<100)
                sum02 += incumbTurb[t];
            else if (t<150)
                sum03 += incumbTurb[t];
        }

        incumbTurbAvg = _sum00 / (double)sim.iterationNum;
        incumbTurbAvg1 = _sum01 / 50;
        incumbTurbAvg2 = _sum02 / 50;
        incumbTurbAvg3 = _sum03 / 50;

        for (int t = 0;t < sim.iterationNum;t++) {

            sum10 += (double)((incumbTurb[t] - incumbTurbAvg)
                   *(incumbTurb[t] - incumbTurbAvg));

            if (t<50)
                sum11 += (incumbTurb[t]-_incumbTurbAvg1)
                      * (incumbTurb[t]-_incumbTurbAvg1);
            else if (t<100)
                sum12 += (incumbTurb[t]-_incumbTurbAvg2)
                      * (incumbTurb[t]-_incumbTurbAvg2);
            else if (t<150)
                sum13 += (incumbTurb[t]-_incumbTurbAvg3)
                      * (incumbTurb[t]-_incumbTurbAvg3);
        }

        double stdDev = Math.sqrt(_sum10 / (double)(sim.iterationNum - 1));
        double _stdDev1 = Math.sqrt(_sum11 / 49);
        double _stdDev2 = Math.sqrt(_sum12 / 49);
        double _stdDev3 = Math.sqrt(_sum13 / 49);

        incumbTurbCVar = 100 * stdDev / incumbTurbAvg;
        incumbTurbCVar1 = 100 * _stdDev1 / _incumbTurbAvg1;
        incumbTurbCVar2 = 100 * _stdDev2 / _incumbTurbAvg2;
```

```
        incumbTurbCVar3 = 100 * _stdDev3 / _incumbTurbAvg3;
    }


    void getFirmRankTurbRun() {

        double sum00 = 0;
        double sum01 = 0;
        double sum02 = 0;
        double sum03 = 0;

        double sum10 = 0;
        double sum11 = 0;
        double sum12 = 0;
        double sum13 = 0;

        for (int t = 0;t < sim.iterationNum;t++) {

            sum00 += firmRankTurb[t];

            if (t<50)
                sum01 += firmRankTurb[t];
            else if (t<100)
                sum02 += firmRankTurb[t];
            else if (t<150)
                sum03 += firmRankTurb[t];
        }

        firmRankTurbAvg = sum00 / (double)sim.iterationNum;
        firmRankTurbAvg1 = sum01 / 50;
        firmRankTurbAvg2 = sum02 / 50;
        firmRankTurbAvg3 = sum03 / 50;

        for (int t = 0;t < sim.iterationNum;t++) {

            sum10 += (double)((firmRankTurb[t] - firmRankTurbAvg)
                *(firmRankTurb[t] - firmRankTurbAvg));

            if (t<50)
                sum11 += (firmRankTurb[t]- firmRankTurbAvg1)
                      * (firmRankTurb[t]- firmRankTurbAvg1);
```

```
			else if (t<100)
				sum12 += (firmRankTurb[t]- firmRankTurbAvg2)
					* (firmRankTurb[t]- firmRankTurbAvg2);
			else if (t<150)
				sum13 += (firmRankTurb[t]- firmRankTurbAvg3)
					* (firmRankTurb[t]- firmRankTurbAvg3);
		}

		double stdDev = Math.sqrt(sum10 / (double)(sim.iterationNum - 1));
		double stdDev1 = Math.sqrt(sum11 / 49);
		double stdDev2 = Math.sqrt(sum12 / 49);
		double stdDev3 = Math.sqrt(sum13 / 49);

		firmRankTurbCVar  = 100 * stdDev / firmRankTurbAvg;
		firmRankTurbCVar1 = 100 * stdDev1 / firmRankTurbAvg1;
		firmRankTurbCVar2 = 100 * stdDev2 / firmRankTurbAvg2;
		firmRankTurbCVar3 = 100 * stdDev3 / firmRankTurbAvg3;
	}




	/******************** Network Statistics for each run ************************/


	void getAvgLinksRun() {

		double sumN = 0;
		double sumF = 0;
		double sum00 = 0;
		double sum01 = 0;
		double sum02 = 0;
		double sum03 = 0;

		double sumN1 = 0;
		double sumF1 = 0;
		double sum10 = 0;
		double sum11 = 0;
		double sum12 = 0;
		double sum13 = 0;

```

```
        for (int t = 0;t < sim.iterationNum;t++) {

              sumN += netDensity[t];
              sumF += firmDensity[t];

              sum00 += avgLinks[t];

              if (t<50)
                    sum01 += avgLinks[t];
              else if (t<100)
                    sum02 += avgLinks[t];
              else if (t<150)
                    sum03 += avgLinks[t];
        }

        netDensityAvg  = sumN / (double)sim.iterationNum;
        firmDensityAvg = sumF / (double)sim.iterationNum;
        avgLinksAvg    = sum00 / (double)sim.iterationNum;
        avgLinksAvg1   = sum01 / 50;
        avgLinksAvg2   = sum02 / 50;
        avgLinksAvg3   = sum03 / 50;

        for (int t = 0;t < sim.iterationNum;t++) {

              sumN1 += (double)((netDensity[t] - netDensityAvg)
                     * (netDensity[t] - netDensityAvg));

              sumF1 += (double)((firmDensity[t] - firmDensityAvg)
                     * (firmDensity[t] - firmDensityAvg));

              sum10 += (double)((avgLinks[t] - avgLinksAvg)
                     * (avgLinks[t] - avgLinksAvg));

              if (t<50)
                    sum11 += (double)((avgLinks[t] - avgLinksAvg)
                           *(avgLinks[t] - avgLinksAvg));
              else if (t<100)
                    sum12 += (double)((avgLinks[t] - avgLinksAvg)
                           *(avgLinks[t] - avgLinksAvg));
              else if (t<150)
                    sum13 += (double)((avgLinks[t] - avgLinksAvg)
```

```
                            *(avgLinks[t] - avgLinksAvg));
        }

        double stdDevN = Math.sqrt(sumN1 / (double)(sim.iterationNum - 1));
        double stdDevF = Math.sqrt(sumF1 / (double)(sim.iterationNum - 1));
        double stdDev = Math.sqrt(sum10 / (double)(sim.iterationNum - 1));
        double stdDev1 = Math.sqrt(sum11 / 49);
        double stdDev2 = Math.sqrt(_sum12 / 49);
        double stdDev3 = Math.sqrt(_sum13 / 49);

        netDensityCVar = 100 * stdDev / netDensityAvg;
        firmDensityCVar= 100 * stdDev / firmDensityAvg;
        avgLinksCVar = 100 * stdDev / avgLinksAvg;
        avgLinksCVar1 = 100 * stdDev1 / avgLinksAvg1;
        avgLinksCVar2 = 100 * stdDev2 / avgLinksAvg2;
        avgLinksCVar3 = 100 * _stdDev3 / _avgLinksAvg3;
    }


    /************************* Final Average Threshold ****************************/


    void getFinalAvgThreshold() {

        double sum = 0;

        for (int i = 1;i < sim.labourMarket.numOfEnteredFirms + 1;i++) {

            if (sim.labourMarket.ourFirms[i].nSpecialists > 0)
                sum += sim.labourMarket.ourFirms[i].recrThreshold;
        }
        finalAvgThreshold = sum/(double)incumbents[sim.currentIteration - 1];
    }

}
```