Are innovative regions more unequal? Innovation and regional inequality in European regions

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Abstract

Studies of the United States have suggested that the most innovative areas are also the most unequal. There are a number of potential processes that might lead to this. Innovation may raise the return to human capital in ways which can lead to localised inequality. Innovative industries may be subject to greater wage polarisation or offer more erratic returns than other industries. Moreover, the affluent may hire others to work in poorly paid personal service employment nearby. However, while there is some evidence for these processes in the US, whether this applies in the European case is less certain. This paper uses the European Community Household Panel and the Eurostat Regio database to test the link between innovation and wage inequality in a panel of European regions for the period 1996-2001. Two measures of innovation are used: employment in knowledge-based industries and the level of patenting in a region. The results are indicative of a positive link between regional innovation, as measured by patenting, and inequality. In contrast, there is little evidence of a link between knowledge based industries and inequality, with the exception of a positive relationship between employment in Knowledge Intensive Financial Services and inequality.

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1. Introduction

In his book *The Flight of the Creative Class,* Richard Florida (Florida 2005) suggests that the most innovative US cities are also the most unequal. While innovation creates wealth for a few, this prosperity fails to trickle down to others living nearby. Because of this:

> "Not only is Silicon Valley the home of great economic wealth; it's also one of the most innovative and creative regions in the world. If ever a rising tide of prosperity were going to lift all boats, you would expect it to happen here. Yet it doesn't. Instead the opposite occurs."
>
> (Florida, 2005: 186)

Florida provides evidence linking innovation with inequality in a cross-section of US cities. This finding is common to other studies which show that cities with a high-tech industrial base are more unequal (Hale and Galbraith 2004; Donegan and Lowe 2008).

There are a number of reasons why innovation in a city or region may lead to inequality. Individuals working in innovative firms will receive higher wages, while others living nearby may gain in the form of spillovers of new knowledge. Product or process innovation may alter the type of employment in an area, as innovations substitute for particular types of employment (Berman, Bound et al. 1997; Acemoglu 2002). Innovative industries may operate with greater wage dispersion (Faggio, Salvanes et al. 2007). Alternatively, innovation may alter the composition of local labour markets as affluent innovators hire others in personal service occupations (Manning 2004; Florida 2005; Georgiadis and Manning 2007; Autor and Dorn 2008). These factors all vary geographically, as innovation is partly determined by a complex range of spatial factors (Crescenzi, Rodríguez-Pose et al. 2007; Rodríguez-Pose and Crescenzi 2008).

Yet while there has been some evidence linking innovation and inequality in US cities, little research has considered whether this applies in Europe's alternative economic context. European labour markets operate very differently from those in the United States (Freeman 2007), while innovation processes in the two continents differ substantially (Crescenzi, Rodríguez-Pose et al. 2007). This makes the direct transfer of American evidence to the European case problematic.

This paper investigates the link between innovation and inequality in a panel of European regions in the period 1995-2001. It uses the European Community Household Panel (ECHP) to construct 7 different indicators of inequality within the regions, each of which identifies a different shape of the distribution. Alongside this, two different measures of regional innovation are used: the proportion and type of 'knowledge-based' businesses in the region and the level of patenting. The results suggest a relationship between innovation – as measured by patenting – and inequality, with innovative regions displaying increasing levels of inequality according to a number of measures. However, excepting a relationships between Knowledge Intensive Financial Services and inequality there is little link between the proportion of employment in a selection of 'Knowledge-intensive' Industries and inequality.

The link between innovation and regional inequality is of some importance as structural economic change in the European Union has made innovation more important as a driver of economic success (Kratke 2007; van Winden, van den Berg et al. 2007). Moreover, this issue is one of particular policy relevance because stimulating innovation and innovative industries has been an objective of policymakers at a European, national and regional level. In 2000, European member states committed themselves to the Lisbon agenda, which aimed to make the union the "most dynamic and competitive knowledge-based economy in the world". This has provided the justification for sub-national economic development bodies to implement strategies aimed at increasing the level of innovation in regional economies.

Despite this, little research has considered the link between innovation and inequality in sub-national areas. This paper makes a number of contributions to the literature. First, it is the first paper to examine these issues for European regions. Second, most work on this issue has been restricted to cross-sectional techniques whereas this paper uses a panel data model. Third, this paper incorporates a wider range of indicators for both inequality and regional innovation to develop a more nuanced picture of the links between innovation and inequality.

The remainder of the paper is structured as follows. Section two outlines the mechanisms through which innovation may lead to inequality. Section three presents the model and describes the data. Section four discusses the results of a series of fixed effects regression models and presents some robustness checks to test the strength of the relationship. Section five concludes with the implications of the results.

2. Innovation and regional inequality in the European Union

Innovation and inequality

Innovation has been given a central role in explanations of wage inequality (Svizzero and Tisdell 2003). However, relatively little research has investigated its impact on levels of inequality within regions. There are at least five mechanisms through which regional innovation may lead to regional inequality. First, there is a productivity effect as innovative firms or workers benefit from increased productivity in the form of wage gains, although the benefits of new knowledge may also raise productivity for others within the same region. Second, there may be greater dispersion of incomes within innovative sectors which may have decentralised pay structures, irregular systems of labour regulation or highly variable rates of return for particular innovations (Storper and Scott 1990; Faggio, Salvanes et al. 2007). Third, if innovations are diffused locally a process of skill-biased technological change may operate through which innovations either complement or substitute for particular jobs (Breau 2007). Fourth, innovative regions may simply attract highly skilled and highly paid workers. These mechanisms are all likely to lead to increases in innovation, but the distributional impact of a fifth process is more ambiguous: if innovation raises the wages of certain groups it may stimulate employment in service activities reliant on co-location (Manning 2004; Sassen 2006; Autor and Dorn 2008; Glaeser, Resseger et al. 2008). It is unclear, however, whether this will increase demand for labour at the bottom, and so wages, or displace other industries with higher wage rates. The following outlines the rationale for these processes and the evidence behind them.

Innovation, productivity and wages

The first mechanism through which innovation may lead to inequality is through a simple productivity effect. Innovation may raise productivity, which in turn is passed on to workers in the form of higher wages (Van Reenen 1996; Faggio, Salvanes et al. 2007; Pianta and Tancioni 2008). These wage gains will accrue to particular groups, with much of the literature on innovation and wages implying that wages will increase most for the highly skilled. Alongside the direct process of wage gains for those in innovative firms the benefits of innovation may spread locally to other groups through spillovers of knowledge. The distributional impact of these knowledge spillovers is unclear, however. They may benefit those who have the capacity to use such knowledge, who will tend to be highly skilled. Processes of learning may mean the benefits go to those with lower skills, who have a greater range of potential learning partners (Glaeser 1999). Both groups may gain (or lose) but by different amounts.

There is robust evidence linking innovation and wages, but little which considers the wage distribution. For US cities, Echeverri-Carroll and Ayala (2009) estimate that this 'tech-city' premium is around 4.6% on average, but with a higher premium for the highly skilled compared to the low skilled, in which case innovation may increase inequality. At the firm level, innovative firms have been shown to share the rents with their workforces (Van Reenen 1996; Pianta 2003; Faggio, Salvanes et al. 2007). This productivity may be limited to those within particular areas and the distribution of these benefits may be skewed towards particular groups. For example, Dew-Becker and Gordon (2005) find that ICT innovation in the US economy in the late 1990s increased productivity, but that these productivity gains only translated into wage gains for the top 10%.

Innovation and wage dispersion

A second and related mechanism through which innovation may lead to inequality is due to the risky and unpredictable nature of innovations. The gains from particular innovations are assumed to benefit the innovator. However, the returns from innovation are highly variable (Coad and Rao 2008). The literature on this point has tended to focus on the impact of 'superstar' effects, through which small improvements in performance can translate into large increases in income or wages for certain groups. These might occur from ownership of intellectual property rights on a product, such as the patent on an important drug, which can them be mass-produced at a low marginal cost (Rosen 1981). Many innovative products are subject to these properties, ranging from medical advances (with patients willing to pay large premiums for small improvements in their life expectancy) to cultural products (where the most popular album may perform exponentially better than the next most popular). More prosaically, however, there may simply be highly unpredictable returns to investment in innovative activity (Coad and Rao 2008).

This uncertainty and – in some innovative industries – the newness of the industry itself may mean that these industries may be less subject to formal workplace regulation and so more unequal (Storper and Scott 1990). "New industries" may be have higher rates of part-time employment, lower rates of job security and fewer unionised employees (Nord 1990; Card, Lemieux et al. 2003; Autor and Dorn 2008). Industries operating in new markets with less regulation may have higher wage dispersion (Guadalupe 2005). Regions specialising in these industries have greater inequality because of this.

Studies investigating the rate of return on innovations at the firm level have shown considerable variation in the likely return, with a small proportion of firms reporting large gains while other firms make substantial losses (Coad and Rao 2008). Alongside this, there is good evidence suggesting that innovative industries will have greater wage dispersion (Faggio, Salvanes et al. 2007). However, there has been less evidence for the widespread nature of these superstar effects, leading some to question their empirical relevance (Lemieux 2008).

Regional innovation and sorting of the highly skilled

These mechanisms may be complicated by a third, as particular groups migrate into sub-national areas and so change the population balance and measures of inequality. Attention in this area has tended to focus on the mobility of the highly skilled, who will sort themselves into innovative regions in which the returns to their human capital are highest (Glaeser, Resseger et al. 2008; Echeverri-Carroll and Ayala 2009). This means that:

> "people of different skills levels may be drawn to particular areas because of skill-specific economic opportunities. Silicon Valley has a booming computer industry, and it attracts extremely highly skilled engineers. New York City attracts smart people to work in finance. Certainly there is a strong correlation between the skill level of an area and the skill orientation of the industries in the area"
>
> (Glaeser et al., 2008: 19-20).

These returns may lead to cumulative processes of innovative wage growth, as innovative cities attract the highly skilled who then can increase levels of innovative activity (Saxenian 2006).

This sorting effect will skew the distribution of skill levels in a population, and so create local inequality (Glaeser, Resseger et al. 2008). Evidence on skills and inequality suggests important changes. Echeverri-Carroll and Ayala (2009) show that wages are higher for both the highly skilled and the low-skilled in US metros with a high-technology industrial base. But the premium from living in a high-tech city is greater for the highly-skilled, suggesting increased inequality. In his study of US cities, Florida (2005) suggests that the presence of his 'Creative Class' of innovative, creative and highly skilled workers in a city leads to inequality.

Skills biased technological change

Fourth, innovation will interact with skill levels in a process of Skills Biased Technological Change (SBTC), as new technology complements or substitutes for different types of job (Berman, Bound et al. 1997; Acemoglu 2002). This has been one of the most popular explanations for rising inequality in many countries (Krueger 1993; Berman, Bound et al. 1997; Lemieux 2008). In its basic version, the theory suggests that technology would replace low skilled employment but increase the productivity of the highly-skilled. However, this simple version of the theory has been questioned with a significant modification to SBTC being made by Autor et al (2003) in what became known as the Autor-Levy-Murnane (ALM) hypothesis. They argued that rather than a simple high / low skill division, the substitution process would operate in a more nuanced fashion. Technology would complement the labour of the highly skilled, but would be unable to substitute for the manual labour and non-routine cognitive work performed by those with low skills. However, it was likely to substitute for those in the middle of the distribution who performed skilled but routine cognitive labour. Jobs like bookkeeping would be vulnerable to computerisation, whereas employment in service occupations such as cleaning or waitressing would be less so.

There has been some speculation on the relevance of SBTC to innovative cities or regions. For example, Wheeler argues that "the combination of more skilled populations with dense environments may make urban areas a focal point for skill-biased technological change and, thus, earnings inequality" (Wheeler 2005: 333-334). However, despite a wide body of literature on SBTC processes at the national level, there is very little empirical evidence on this exact point. Other results tend to be supportive however, with a number of studies showing that innovations are most likely to diffuse locally, at least initially (Audretsch and Feldman 1996). Thus, technological changes resulting from local innovation will spread locally first and so may imply local SBTC (Storper 2000).

Co-location of personal services

The fifth group of explanations focus on the impact of the high wages in innovative industries on the remainder of the wage distribution. These studies tend to show that employment opportunities available to the low-skilled are increasingly related to their proximity to those with higher skill levels (Manning, 2004). These co-location jobs include food service workers, security guards, janitors, cleaners and gardeners, home health aides, childcare workers and personal appearance and recreational occupations (Autor and Dorn, 2008: 2). It is unclear, however, what the impact of this effect is on wages and so inequality. It is possible that the manufacturing employment which these personal service jobs squeeze out may have higher wages. Alternatively, the process of increased demand for labour may raise wages in these jobs.

A number of studies have shown that these effects apply in US cities and UK regions (Manning, 2004). Research on human capital spillovers in German regions has shown that the presence of the highly skilled leads to employment opportunities for the low skilled (Suedekum 2006). There has been less research on the impact of these processes on wages. Evidence for US cities suggests that wages are increased for the low skilled, although there has been little research to date which investigates whether this is compensation for an increased cost of living (Mazzolari and Ragusa 2007; Autor and Dorn 2008). The impact on inequality overall will depend on the extent to which the wage gains for those with low skills are greater than the wages required for the high skilled.

Inequality in Euopean regions

While a range of studies have suggested that these processes apply in the US case, it remains unclear whether they also apply for European regions. There are substantial differences between innovative processes between the US and Europe, with the European economy lagging levels of innovation. Greater factor mobility in the United States allows individuals, firms and knowledge to sort into locations in which the returns are highest (Crescenzi, Rodríguez-Pose et al. 2007). This can increase overall levels of innovation, but may also lead to increasing geographical specialisation of innovative activities. These processes are less likely to operate in European regions, with the result that lower levels of innovation will not translate into higher wages.

A related issue is the sorting of individuals into particular cities or regions. Population mobility is higher in the United States, both for US citizens moving within the country and with a higher number of foreign immigrants (Freeman 2007). This will mean that the sorting of the highly skilled into particular cities is less likely, but it may also mean that there is reduced supply of low-waged labour who may work in personal service employment. The absence of a large immigrant class has been seen as one region why patterns of employment polarisation identified in US cities have not been replicated in the EU case.

Moreover, European countries operate in a diverse range of institutional environments. Higher taxation will reduce the extent to which wages respond to innovation. Labour markets may have greater unionisation and regulation, meaning that the flexible working patterns seen in some US high-technology industries are less likely to operate. Higher levels of unionisation may mean that within-industry wage compression is greater, and that the benefits from innovation are shared more equitably with the workforce. Higher minimum wages may make low-waged service employment less likely, as potential employees see employment as less likely.

3. The Model and Variables

3. 1 The Model

The basic hypothesis this paper seeks to test is that innovation leads to greater inequality in particular regions. The secondary area of interest is the relationship between innovation and different particular measures of inequality, each of which has an alternative perspective on the distribution. To test this, a series of regressions are presented which investigate the relationship between a variety of regional characteristics and the level of inequality in European regions. It is specified as a fixed effects panel data regression model. The model takes the form:

$$Y_{it} = \alpha + \beta_1 \, GDP_{it} + \beta_1 \, Unemp_{it} + \beta_1 LowSkill_{it} + \beta_1 HigherEd_{it} + \beta_1 WageCoord_{it} + \beta_1 PopDen_{it} + \beta_1 Innovation_{it} \, x_{it} + v_i + \varepsilon_i$$

Where Y represents the dependent variable, one of a group of inequality measures calculated from the European Community Household panel. Subscript 'i' stands for the region, and subscript 't' represents the time period ranging from 1995 to 2001. Unemp is the unemployment rate, LowSkill the proportion of the population with low skill levels, HigherEd the proportion with higher education, WageCoord a measure of centralised wage coordination and PopDen the population density. Innovation stands for one of a series of measures of regional innovation. v accounts for all unobserved region specific characteristics which are time-invariant. The constant is α and the remaining error term is ε_i.

3.2 Variables

Measuring Inequality

The variable of interest, Y_{it} is inequality within the region. This is calculated from the European Community Household Panel which provides individual data for over 100,000 individuals in 89 regions[1]. The measure used here is wage income, calculated as the "Total Net Income from Work" (ECHP Question PI110) for those whose income is greater than nought. This measure includes wages / salaries and bonuses from employment (or self-employment) after tax. Note that results are broadly the same if a wider measure of income is used.

[1] To maintain comparability between the geographical definitions a small number of UK and Italian regions have been combined.

Table 1. Measures of inequality

Domain	Variable	Description	Source
Wage inequality	Wgini	Gini coefficient of wage income for normally working people	ECHP
	Wgen1	Theils generalised entropy measure of inequality for normally working people	ECHP
	Wat05	Atkinsons measure of inequality where α =0.5 (sensitive to the bottom of the distribution)	ECHP
	Wat01	Atkinsons measure of inequality where α =0.5 (sensitive to the top of the distribution)	ECHP
	WP8020	Ratios of wages of the 80th percentile to those of the 20th	ECHP

There are a range of potential measures of inequality, each of which allows subtly different inferences about the shape of the distribution to be made. A key problem in these measurements is a high degree of instability at the top and – to a lesser extent – the bottom of the distribution. Studies of regional inequality using the same data-set have been shown to be highly sensitive to the different measure of inequality which is used (Rodríguez-Pose and Tselios 2007). This limits the potential choices of inequality parameters to those which are less sensitive to these changes. In response, five measures are used.

The standard measure of inequality is the Gini coefficient (Coulter 1989; Glaeser, Resseger et al. 2008). This is calculated as the area under the Lorenz curve, which is given by the cumulative percentage of population ranked by incomes (Shaw, Galobardes et al. 2007). The strengths of the Gini coefficient include its population symmetry, meaning that if two identical population are merged the results remain the same and so are generalisable from a sample of the population to the population as a whole (Coulter, 1989). It is invariant, in that it is unchanging if all numbers are multiplied by a positive constant (Allison 1978). It is directly comparable between units of different size (Hale 2006; University of Texas Inequality Project 2006). However, there are a number of problems with the measure, not least its lack of intuitive understanding (Allison, 1978). Most significantly for this paper, it is sensitive to transfers around the mean of the distribution (rather than those which involve the top and bottom) (Coulter, 1989).

The second measure of inequality is Theil's index of economic inequality, the most commonly used of the generalised entropy measures of inequality. These summarise differences as the natural logarithm of the share of income compared to the share of population (Shaw, Galobardes et al. 2007). While it remains a general measure of inequality, the Theil is more sensitive to changes at the extremes of the distribution than the Gini coefficient, such as superstar effects.

Third, two Atkinson indices are used. These apply the concept of the "equally distributed equivalent income" – the level of income which if equally distributed through the entire population would provide a total level of welfare which is the same as the current distribution. The Atkinson index can be understood as one minus the ratio of the "equally distributed income" to the mean of the actual distribution (Coulter, 1993). The measure uses a sensitivity parameter, α, which assumes the shape of a utility function. If the assumption is that inequality at the bottom of the distribution is more important, this is set lower; if importance is given to the top of the distribution, α is set higher. Here the Atkinson with α = 0.5 ("Atkinson (0.5)") and α = 1 ("Atkinson (1)") are used, where the former will capture effects such as might arise from increased employment in low wage services and the latter may arise from effects increasing incomes at the top of the distribution.

Finally, the 80 / 20 percentile ratio is used, or the ratio of the 80^{th} and the 20^{th} percentiles of the distribution. This is a broad measure of inequality and one of those which is most common in studies of inequality (Wilkinson and Pickett 2009). This is a broad measure of the general spread of the income distribution, and in contrast to the Gini is less sensitive to movements around the median of the distribution.

Measuring regional innovation

Table 2. Innovation variables

Domain	Variable	Description	Source
Innovation	Patents	Patents per 100,000 population in the following three sections.	Eurostat
	High-Tech Patents	The number of patents per 100,000 population for high-technology sectors only. These are: Computer and Automated Business Equipment; Communication Technology; Laser; Micro-organism and genetic engineering; semi-conductors.	Eurostat
	ICT Patents	The number of patents per 100,000 population for ICT Manufacturing and ICT Services.	Eurostat
	Biotech Patents	The number of patents per 100,000 population classified as Biotechnology.	Eurostat
Knowledge intensive industries	HTM	Employment in High Technology Manufacturing as a proportion of total employment. This includes: Manufacture of office machinery and computers (NACE 30); Manufacture of radio, television and communication equipment and apparatus (32).	Eurostat
	KIHTS	Employment in Knowledge Intensive High-Technology Services as a proportion of total employment. This includes: Post and telecommunications (64); Computer and related activities (72); Research and development (73).	Eurostat
	KIFS	Employment in Knowledge-Intensive Financial Services as a proportion of total employment. This includes: Financial intermediation, except insurance and pension funding (65); Insurance and pension funding, except compulsory social security (66); Activities auxiliary to financial intermediation (67).	Eurostat
	KIS	Employment in knowledge intensive services overall. This includes HTKIS, KIFS, along with “Other knowledge intensive services” (Education (80); Health and Social Work (85); and Recreational, cultural and sporting activities (92)) and Knowledge Intensive Market Services (Water transport (61); Air transport (62); Real estate activities (70); Renting of machinery and equipment without operator and of personal and household goods (71); Other business activities (74)).	Eurostat

As with inequality, there are a range of potential measures of regional innovation. Measures of regional innovation are inevitably imperfect, covering only a small proportion of innovative activity at any one time (Crescenzi, Rodríguez-Pose et al. 2007). To address this problem, this paper uses two of the main measures of innovative activity, both of which are used in the literature on innovation. The first of these is the number of patents per 100,000 population. The strength of this measure is that it is an output measure, rather than one which measures the inputs to innovation. Eurostat provide one overarching measure of innovation which can be broken into three sub-categories: high-tech patents, ICT patents and biotechnology patents. Patenting is a useful measure as it is an outcome of innovation and is roughly comparable between regions, and for this reasons is one of the dominant measures of innovation in the literature. However, it lacks any measure of the importance of the innovations each patent represents, or their commercial success. And it fails to account for innovation which is unlikely to be patented, such as process innovation.

The second measure of innovation is sectoral, the proportion of employment in various knowledge-based industries by the Eurostat definition (Vence-Deza and González-López 2008). These sectors are useful in describing innovation in certain sectors which may engage in service innovation or innovation which may not be patented. There is also some descriptive evidence linking them with inequality. In a simple correlation of UK regions against the proportion of employment in knowledge-based industries, Hudson (2006) shows that a greater proportion of knowledge-based industries is correlated with higher inequality. However, the measures are broad and employment within each sector may be very different (for example, it may not be possible to distinguish between the head office of a firm in a particular sector, which may gain more from innovation, and the manufacturing component, which may gain less). Eurostat provide five overlapping measures of knowledge-based industries: Knowledge intensive services (KIS) which is the aggregated category for Knowledge Intensive High-Tech Services (KIHTS), Knowledge Intensive Financial Service (KIFS), both of which are used as variables, along with Other Knowledge Intensive Services which is predominantly the public sector and so likely to have less impact on the distribution and Knowledge Intensive Market Services, which are primarily services which are not seen as of the same class as the 'high-tech' industries[2]. There is also a measure of High Technology Manufacturing (HTM], although the sign on this is not clear as manufacturing is often seen as an industry which is more equal (Bluestone and Harrison 1988).

Independent Variables

A wider group of independent variables are calculated to account for the potential explanatory variables associated with regional inequality. Since the seminal work of Kuznets (1955) the link between economic development and inequality has been a focal point of research in this area. In both the US and the EU, recent economic growth in cities and regions has been linked with reductions in inequality (Wheeler 2004; Rodríguez-Pose and Tselios 2007), and so it is important to control for this. The GDP per capita of each region is used. The distribution of human capital amongst the population is also a key determinant of inequality (Wheeler 2005; Glaeser, Resseger et al. 2008; Tselios 2008; Bacolod, Blum et al. 2009), and two measures are incorporated here both of which are taken from the ECHP. To account for the proportion of the normally working population with high skills we use the Eurostat indicator of the "Recognised third level education (ISCED 5-7)", which is a standardised measure recognising qualification at around degree level. To account for those with low skills a measure for the proportion of the population without qualifications is used. This is derived from the category "Less than second stage of secondary education (ISCED 0-2)" among the normally working, again from the ECHP. This variable may ignore the distinction between 'qualifications' and the

[2] Note that when included in the analysis KIMS is not significant.

broader category of 'skills', such as soft skills around communication, which may be more important in determining labour market outcomes (Gordon and Turok 2005).

Density is a common explanation of inequality, with the theoretical prediction that in denser areas lower skilled individuals may gain more from processes of learning and so inequality will be lower (Wheeler 2004; Glaeser, Resseger et al. 2008). Other studies have found a negative relationship between density and inequality (Wheeler 2004; Rodríguez-Pose and Tselios 2007). Population density, or population per square kilometre, from Eurostat is used here.

Finally, a variable is included to account for changing labour market institutions. There is the possibility that institutional changes, such as the British introduction of the minimum wages in 1999 will alter the distribution. To account for this, a summary measure of wage coordination is introduced at a national level. This varies from 0 to 8 and changes annually. It is taken from the Database on Institutional Characteristics of Trade Unions, Wage Setting, State Intervention and Social Pacts from Jelle Visser at the University of Amsterdam (Visser 2009).

Table 3. Independent variables

Variable	Description	Source
GDPpc	GDP per capita, (ln)	Eurostat
HighSkill	Population of working age with recognised third level education, % (ln)	ECHP
LowSkills	Population of working age with less than second stage of secondary education among normally working people, % (ln)	ECHP
URate	ILO Unemployment as a percentage of the population of working age (ln)	ECHP
PopDen	Population density in population per square kilometre (ln)	Eurostat
WageCoord	A measure of the strength of wage coordination (0 is low, 8 is high)	Visser (2009)

3.3 Estimation issues

The models are estimated using fixed effects panel regression models. As the data is for regions clustered within countries, one potential problem is an unobserved cluster effect derived from institutional or macroeconomic changes within the countries (Wooldridge, 2009). It is unlikely that wages in one region are independent of the wages in other regions (Autor and Dorn 2008). To account for this the standard errors are clustered by country. A Hausman test is used to test for whether fixed or random effects is the most appropriate measure of estimation, and suggests that fixed effect estimation should be used[3]. As there is evidence of heteroskedasticity a number of the independent variables are logged.

The ECHP data is available at the NUTS 1 level for all countries except Portugal, the United Kingdom and Sweden for which NUTS2 regions are available. Data for Denmark and Finland is each given as a single region. One problem with the NUTS regions is that they are administrative rather than functional regions. This means that they do not necessarily reflect the functional boundaries of economic entities (Cheshire 1999).

A further issue is missing data for particular years. In several cases, data is not available for individual years – where it is only a single year which is missing, but data is available for the previous and subsequent years, missing values have been filled using linear interpolation. In the case of population density, it is assumed that regional sizes vary little and so new figures are calculated using the updated population measure.

[3] When using panel data models a choice is made between fixed and random effects. The fixed effects estimates are differences from the regional mean for each time period, while the random effect models also contain information from the region as well as from time periods. Random effect models must be uncorrelated with other independent variables to be efficient estimators (Wooldridge, 2007). The common test between the two types of model is the Hausman test, which tests the hypothesis that the errors are distributed independently of the regions. If this were true, both FE and RE estimators would be possible. In this case a Hausman test reveals that the random effect estimators would be subject to unobserved heterogeneity bias and fixed effects are the appropriate method of estimation (Dougherty, 2006).

4. Results

4.1 Patenting and inequality

TABLE 4

Tables 4 and 5 give the results for patenting against the seven measures of inequality. Table 4 gives the results of patenting variables against the Gini coefficient and the Theil index. The basic model includes the variables for GDP per capita (GDPpc), the unemployment rate (URate), high and low skill levels (HighSkill and LowSkill), population density (PopDen) and the innovation variable. The R-Squared varies between 0.039 and 0.054 which, while low, is comparable with similar studies (e.g. Tselios, 2008). Moreover, the control variables perform well, with the expected negative signs on GDP, unemployment, the low skilled population, the population with degree and the wage coordination measure.

The results are strongly indicative of a relationship between innovation, as measured by patenting, and inequality. These relationships are significant and positive in almost all cases, although Biotechnology patenting is not significant against the Gini and significant only at the 10% level against to the Theil index. High-technology patenting is positive and significant against the Gini but not the Theil. ICT patenting is positive against both Gini and the Theil. Against these measures of inequality, there seems a relatively strong link between innovation and inequality.

TABLE 5

Table 5 gives the results against the Atkinson indices, the Atkinson index with a α = 0.5 (Atkinson (0.5)) and with an α = 1 ("Atkinson (1)"). The former places a higher importance on transfers towards the top of the distribution, while the latter is more sensitive to transfers at the top. The patenting measures perform well against the Atkinson index with the inequality aversion coefficient set to 0.5. The overall patenting measure, alongside the ICT patenting measure are significant and positive here. Against the Atkinson (1) none of the patenting measures are significant. This measure of inequality is more sensitive to movements at the lower end of the distribution. This is consistent with those processes which imply that patenting raises wages at the upper end of the distribution. Otherwise the measures perform slightly worse than in the previous regressions, ranging from only 0.029 and 0.045. The controls are reasonable, however, with the expected performances. The one exception is the measures of wage coordination which is not significant against the Atkinson (0.5) index. It also gives the results for the 80 / 20 ratio. High Technology Patenting, Biotechnology Patenting and ICT Patenting are all significantly related to this ratio but the overall level of inequality is not. The overall performance of the models are relatively good for the 20 / 80 and the 20 / 50 ratios, with R^2 varying between 0.084 and 0.098.

Overall, the results for patenting are strongly suggestive of a link between innovation and wage inequality in European regions. The coefficients are generally significant, but where they are not they tend to be close to standard significance levels. Overall patenting is significant and positive with the three 'composite' measures of the wage distribution, but not the 80 / 20 ratio which only accounts for the range. One explanation is that it accounts for movements within the distribution (for example, by shifting forwards the median of the distribution), and so is not included in the wider percentile ratios. High technology patenting is only significant against the 80/20 ratio, and at a lesser significance level against the Gini coefficient. In contrast, biotechnology is significant against the 80 / 20 and the Theil indices only. There is a clearer relationship between these measures and the Atkinson index (0.5) compared to Atkinson (1), implying that innovation is leading to changes at the bottom of the distribution. This may suggest a movement towards polarisation, as employment with median level wages are squeezed out of these regions.

Little research has considered the impact of different types of patenting on inequality, and the results here suggest there will be some differences according to the context in which innovation is undertaken. One key difference will be between innovation which takes place in the public and the private sector. Biotechnology patenting may be more likely in the public sector, for example, with the rewards less likely to go to the workers than other sectors. This might explain the results for ICT patenting, for example.

4.2 Knowledge Intensive Services and Inequality

TABLE 6

Tables 6 and 7 give results for knowledge intensive industries against the seven measures of inequality. Table 6 shows the impact of innovative industries on the Gini coefficient of wages and the Theil generalised entropy measure. While the model fit is reasonable, the knowledge intensive industries variables perform considerably worse than the patenting variables. High tech knowledge intensive services and high technology manufacturing are negative in each model but never significant. Knowledge intensive services are positively related to inequality as measured by the Theil, but not that measured by the Gini (although the coefficient is positive). In contrast, knowledge intensive financial services are positively related to inequality as measured by the Gini, but not by the Theil (although it comes close to standard significance levels).

TABLE 7

Table 7 shows the same regressions run with two Atkinson indices and the 80 / 20 ratio. The only knowledge intensive industry to impact on these measures is knowledge intensive financial services. this is significant against the Atkinson (0.5) at 10%, the Atkinson (1) at 5% and the 80 / 20 at 1%. The control variables perform reasonably well. GDP is negative and significant in most regressions, although it loses significance when HTMAN is included. Unemployment is negative, as expected, as is the proportion with low skill and the measures of wage coordination and population density. The proportion of the population with degrees is negative, but not always significant.

Overall, the relationship between knowledge intensive industries and inequality seems to be dominated by one sector, Knowledge Intensive Financial Services. While the results are suggestive of a possible relationship between Knowledge Intensive Services overall and Knowledge Intensive Market Services and inequality, the results for both remain weak. That knowledge intensive financial services would lead to inequality is intuitive. Other work on sectoral differences in wage levels has suggested that financial services have higher wages than other sectors . For example, Brewer et al. (2007) show that financial intermediation and “real estate, renting and other business activities” have higher average wages in the UK, overrepresented in the top 0.1% of earners in the UK. Other studies have found similar results for US cities (Chevan and Stokes 2000; Zhong, Clark et al. 2007). It is less clear, however, the extent to which this is due to their innovative nature or merely the positional advantages of access to finance capital.

In contrast, there is less evidence on the other knowledge based industries. Both Knowledge Intensive Services overall and Knowledge Intensive Market services are positive against one measure but no more. This result is contrary to some evidence on this point, such as Taylor (2006) who found greater wage dispersal in high-technology manufacturing, the results indicate less inequality derived from these sectors. It also implies a more complicated picture than that presented in cross-sectional correlations (Hudson 2006). One explanation may be the broadness of the measures of innovation which are used, but it may simply be that alternative measures are important.

The results also shed light on the other measures of inequality. The unemployment rate is consistently negatively associated with inequality. This is the opposite of what might be expected in other studies, which expect a positive sign as wages at the bottom of the labour market are bid down by a large unemployed population. However, given that the indicator which is used here is one of inequality solely among the employed population it may indicate a composition effect as, in the context of European welfare states, for many at the bottom of the labour market as working is not financially viable when weighed against the loss of benefits. Moreover, minimum wages may make some low-wage jobs unaffordable and so constrain the measure of inequality used here.

The effect of the skills of the population is unclear in these models. The proportion of population with low skills is negative in a number of the models, while the results for the proportion with a degree was less clear but also negative. Previous studies have used more sophisticated measures of educational heterogeneity and shown that educational inequality causes inequality more broadly (Alderson and Nielsen, 1997; Rodriguez-Pose and Tselios, 2007).

The consistent negative effect of public administration on inequality is also expected. Other studies have emphasised the equalising nature of public employment, which is seen as subject to lower wage compression, and have used it as a control variable to account for government spending in a region (Volscho, 2007). Yet a high proportion of employment in these industries may also imply that a low proportion of employment in public sector and a weak regional economy and so it is also likely that lagging regions will have high proportions of employment in the public sector.

5 . Conclusions

Table 12. Summary of Results

		Gini	Theil	At 05	AT01	8020
Patenting	**Patents**	**+++**	**+++**	**++**		
	High Tech Patents	**+**				**+++**
	ICT Patents	**+++**	**+++**	**+++**		**+**
	Biotech Patents		**+**			**++**
Innovative Industries	**KIS**		**++**			
	KIFS	**++**		**+**	**+**	**+++**
	HTKIS					
	HTMAN					

Where +++ indicates positive and significant at the 1% level, ++ at the 5% and + at the 10%. --- indicates negative and significant at the 1% level, -- at the 5% and - at the 10%

Despite the increasing importance of innovation to the European economy and the considerable resources devoted to increasing levels of regional innovation, little is still known about the impact of innovation on inequality within European regions. This paper has tested this link for a panel of European regions in the period 1995-2001. It finds inconclusive evidence of a link between innovation and inequality in European regions. The relationship is highly sensitive to the definition of innovation and the to the measure of inequality. While there appears to be only a limited relationship between employment in knowledge based industries and inequality, the evidence is highly suggestive of a link between innovation as measured by patenting and inequality. One explanation for this is the sheer broadness of the measures of knowledge based industries, with the innovative parts of each industry hidden within the general measure. In contrast, the much more specific measure of patenting appears to be related to inequality, with greater levels of innovation leading to greater levels of inequality. The results imply that the impact of innovation on regional inequality is limited to those places which are directly producing innovations, rather than those in which innovative industries are located.

The instability of the results means that any assessment of which of the underlying process is operating can only be made cautiously. However, it appears there is no clear benefits to either end of the distribution, but rather a general process of upgrading with the overall income being stretched upwards. That the Atkinson (0.5) performs better than the Atkinson (1) implies. that this effects are being felt towards the middle of the distribution, with a general upgrading process rather than a specific increase in the upper tail. It is likely that these processes of innovation are increasing wages in the middle of the distribution, with a smaller effect at the bottom of the distribution. This may fit with both the simple productivity effect, the impact of wage dispersion or through the sorting of some skilled individuals into these regions. It appears less clear that the processes benefiting those at the top are operating, but further research is needed on this point.

This paper has only provided a first link in the relationship, and there are a number of caveats to these findings, however. First, the modelling strategy has shown that inequality is difficult to predict, and sensitive to the choice of measures used. Inequality is complicated by a range of social and institutional factors, which will interplay with the dynamics of innovation. Scandinavian economies, for example, manage to combine high levels of innovation and low levels of inequality. Second, while the paper presents data for Europe as a whole, one cost of this approach is that the nature of the regional boundaries used here is not optimal. Third, the evidence is for a relatively short time period, albeit one which covers some of the important changes in inequality across Europe. Further research may want to consider the impact of innovation on the wage distribution, rather than on aggregate measures of inequality.

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TABLES

Table 4

VARIABLES	(1) wgini	(2) wgini	(3) wgini	(4) wgini	(5) wge1_	(6) wge1_	(7) wge1_	(8) wge1_
GDPpc	-0.0557***	-0.0405***	-0.0491***	-0.0454**	-0.0812***	-0.0494	-0.0738*	-0.0725**
	(0.0149)	(0.0128)	(0.0145)	(0.0152)	(0.0232)	(0.0337)	(0.0343)	(0.0289)
URate	-0.0210***	-0.0166***	-0.0167**	-0.0173*	-0.0417***	-0.0334*	-0.0353*	-0.0384*
	(0.00592)	(0.00505)	(0.00692)	(0.00864)	(0.0112)	(0.0156)	(0.0188)	(0.0188)
HighSkill	-0.0129**	-0.00889	-0.0115*	-0.0118**	-0.0235***	-0.0148*	-0.0202**	-0.0216***
	(0.00465)	(0.00521)	(0.00568)	(0.00529)	(0.00550)	(0.00700)	(0.00741)	(0.00591)
LowSkill	-0.0213**	-0.0241*	-0.0232*	-0.0253**	-0.0329**	-0.0384***	-0.0354**	-0.0377**
	(0.00968)	(0.0112)	(0.0110)	(0.0114)	(0.0115)	(0.0126)	(0.0123)	(0.0128)
WageCoord	-0.00797***	-0.00749***	-0.00789***	-0.00800***	-0.0286**	-0.0276**	-0.0285**	-0.0287**
	(0.000810)	(0.000929)	(0.00111)	(0.000662)	(0.0111)	(0.0112)	(0.0107)	(0.0115)
PopDen	-0.00852***	-0.00876***	-0.00973***	-0.00894***	-0.00684***	-0.00769***	-0.00916***	-0.00754***
	(0.00111)	(0.000853)	(0.00147)	(0.000742)	(0.00149)	(0.00204)	(0.00293)	(0.00146)
Patent	0.00535***				0.00747***			
	(0.00147)				(0.00236)			
HTPatent		0.00260*				0.00195		
		(0.00143)				(0.00289)		
ICTPatent			0.00472***				0.00721***	
			(0.00107)				(0.00186)	
BioPatent				0.00267				0.00429*
				(0.00185)				(0.00233)
Constant	0.873***	0.732***	0.808***	0.782***	1.061***	0.760*	0.987**	0.995**
	(0.156)	(0.137)	(0.158)	(0.172)	(0.249)	(0.363)	(0.378)	(0.335)
Observations	536	504	505	469	536	504	505	469
R-squared	0.054	0.042	0.050	0.050	0.047	0.039	0.046	0.044
Number of case	89	88	88	86	89	88	88	86

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5

VARIABLES	(1) wat05_	(2) wat05_	(3) wat05_	(4) wat05_	(5) wat01_	(6) wat01_	(7) wat01_	(8) wat01_	(5) wp8020	(6) wp8020	(7) wp8020	(8) wp8020
GDPpc	-0.0355***	-0.0237*	-0.0312**	-0.0292***	-0.0603**	-0.0403	-0.0510*	-0.0514**	-0.0459**	-0.0423***	-0.0393***	-0.0404**
	(0.0102)	(0.0122)	(0.0126)	(0.00970)	(0.0245)	(0.0258)	(0.0253)	(0.0196)	(0.0191)	(0.0127)	(0.0105)	(0.0163)
URate	-0.0140***	-0.0105**	-0.0107*	-0.0111*	-0.0201**	-0.0134***	-0.0128***	-0.0131	-0.00601	-0.00484	-0.00496	-0.00381
	(0.00350)	(0.00376)	(0.00510)	(0.00538)	(0.00683)	(0.00341)	(0.00416)	(0.00878)	(0.00677)	(0.00582)	(0.00453)	(0.00770)
HighSkill	-0.00869***	-0.00582	-0.00760*	-0.00829**	-0.0162**	-0.0128	-0.0150*	-0.0175**	-0.000640	0.000219	0.000599	0.00112
	(0.00269)	(0.00335)	(0.00360)	(0.00309)	(0.00704)	(0.00758)	(0.00809)	(0.00754)	(0.00338)	(0.00350)	(0.00340)	(0.00383)
LowSkill	-0.0141**	-0.0164**	-0.0157**	-0.0167**	-0.0257**	-0.0312**	-0.0310**	-0.0312**	-0.00387	-0.00436	-0.00505	-0.00571
	(0.00556)	(0.00627)	(0.00626)	(0.00625)	(0.0119)	(0.0132)	(0.0138)	(0.0129)	(0.00329)	(0.00344)	(0.00345)	(0.00435)
WageCoord	-0.00524***	-0.00492***	-0.00521***	-0.00532***	0.00271	0.00308	0.00267	0.00224	-0.00296***	-0.00284***	-0.00276***	-0.00285***
	(0.000327)	(0.000459)	(0.000429)	(0.000413)	(0.00884)	(0.00874)	(0.00899)	(0.00834)	(0.000712)	(0.000724)	(0.000749)	(0.000697)
PopDen	-0.00329***	-0.00357***	-0.00422***	-0.00356***	-0.00327*	-0.00368**	-0.00513**	-0.00387***	-0.00885***	-0.00865***	-0.00909***	-0.00888***
	(0.000653)	(0.000600)	(0.00102)	(0.000464)	(0.00175)	(0.00123)	(0.00183)	(0.00118)	(0.000874)	(0.000706)	(0.000447)	(0.000685)
Patent	0.00296**				0.00356				0.00247			
	(0.00112)				(0.00287)				(0.00164)			
HTPatent		0.000940				0.000317				0.00169***		
		(0.00120)				(0.00285)				(0.000519)		
ICTPatent			0.00265***				0.00307				0.00109*	
			(0.000820)				(0.00203)				(0.000556)	
BioPatent				0.00136				0.00136				0.00160**
				(0.000892)				(0.00149)				(0.000603)
Constant	0.453***	0.340**	0.409***	0.395***	0.782***	0.582**	0.676**	0.687***	1.558***	1.527***	1.498***	1.509***
	(0.104)	(0.126)	(0.133)	(0.108)	(0.237)	(0.249)	(0.253)	(0.205)	(0.194)	(0.134)	(0.110)	(0.176)
Observations	536	504	505	469	536	504	505	469	536	504	505	469
R-squared	0.045	0.034	0.041	0.042	0.034	0.029	0.033	0.039	0.098	0.088	0.084	0.088
Number of case	89	88	88	86	89	88	88	86	89	88	88	86

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6

VARIABLES	(1) wgini	(2) wgini	(3) wgini	(4) wgini	(6) Wgini	(8) wge1_	(9) wge1_	(10) wge1_	(11) wge1_	(12) wge1_
GDPpc	-0.0302***	-0.0376***	-0.0301***	-0.0251*	-0.0190	-0.0486**	-0.0681***	-0.0496**	-0.0436*	-0.0243
	(0.00874)	(0.00903)	(0.00804)	(0.0117)	(0.0156)	(0.0209)	(0.0158)	(0.0186)	(0.0222)	(0.0407)
URate	-0.0160***	-0.0168***	-0.0170**	-0.0149**	-0.00659	-0.0330***	-0.0375***	-0.0401**	-0.0361**	-0.0263
	(0.00394)	(0.00450)	(0.00737)	(0.00604)	(0.0123)	(0.0106)	(0.00969)	(0.0163)	(0.0141)	(0.0316)
HighSkill	-0.00941**	-0.00801	-0.0119**	-0.00975*	-0.00942	-0.0156**	-0.0134*	-0.0212***	-0.0185**	-0.0202*
	(0.00428)	(0.00520)	(0.00499)	(0.00536)	(0.00569)	(0.00621)	(0.00752)	(0.00697)	(0.00784)	(0.0111)
LowSkill	-0.0281**	-0.0258**	-0.0300**	-0.0305**	-0.0397***	-0.0417***	-0.0345**	-0.0441***	-0.0446***	-0.0649***
	(0.00944)	(0.0116)	(0.0103)	(0.0116)	(0.00764)	(0.0101)	(0.0153)	(0.0128)	(0.0145)	(0.0138)
WageCoord	-0.00740***	-0.00719***	-0.00775***	-0.00762***	-0.0116***	-0.0279**	-0.0267**	-0.0281**	-0.0278**	-0.0371*
	(0.000904)	(0.00100)	(0.00105)	(0.000976)	(0.00296)	(0.0116)	(0.0105)	(0.0111)	(0.0112)	(0.0198)
PopDen	-0.00835***	-0.00754***	-0.00888***	-0.00981***	-0.0108***	-0.00729***	-0.00300	-0.00642**	-0.00754***	-0.00996**
	(0.00130)	(0.00183)	(0.00171)	(0.00166)	(0.00148)	(0.00209)	(0.00269)	(0.00221)	(0.00245)	(0.00354)
KIS		0.000682					0.00265**			
		(0.000708)					(0.00109)			
KIFS			0.00224**					0.00335		
			(0.000992)					(0.00277)		
HTKIS				-0.00148					-0.000831	
				(0.00328)					(0.00514)	
HTMAN					-0.00500					-0.0116
					(0.00650)					(0.0148)
Constant	0.630***	0.688***	0.624***	0.581***	0.511**	0.753***	0.881***	0.764***	0.708**	0.520
	(0.0908)	(0.0946)	(0.0860)	(0.113)	(0.175)	(0.234)	(0.185)	(0.221)	(0.239)	(0.472)
Observations	555	546	475	493	358	555	546	475	493	358
R-squared	0.041	0.044	0.049	0.045	0.078	0.039	0.048	0.044	0.041	0.072
Number of case	90	90	83	85	70	90	90	83	85	70

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 7

VARIABLES	(1) wat05_	(2) wat05_	(3) wat05_	(4) wat05_	(6) wat01_	(8) wat01_	(9) wat01_	(10) wat01_	(11) wp8020	(12) wp8020	(13) wp8020	(14) wp8020
GDPpc	-0.0281***	-0.0219***	-0.0192**	-0.0126	-0.0553***	-0.0419***	-0.0386**	-0.0307	-0.0359***	-0.0347***	-0.0315**	-0.0412**
	(0.00554)	(0.00618)	(0.00763)	(0.0130)	(0.0132)	(0.0115)	(0.0129)	(0.0209)	(0.0119)	(0.00986)	(0.0112)	(0.0148)
URate	-0.0124***	-0.0115**	-0.00968**	-0.00426	-0.0200**	-0.0142*	-0.00852	0.00191	-0.00461	-0.00377	-0.00302	-0.00563
	(0.00321)	(0.00488)	(0.00397)	(0.00958)	(0.00852)	(0.00794)	(0.00673)	(0.0128)	(0.00490)	(0.00554)	(0.00567)	(0.00758)
HighSkill	-0.00467	-0.00747**	-0.00641*	-0.00720	-0.00864	-0.0146*	-0.0121	-0.0150*	0.000630	0.000280	-0.000496	0.000628
	(0.00329)	(0.00315)	(0.00327)	(0.00425)	(0.00775)	(0.00758)	(0.00744)	(0.00728)	(0.00314)	(0.00339)	(0.00294)	(0.00269)
LowSkill	-0.0153**	-0.0193***	-0.0197**	-0.0275***	-0.0253	-0.0363**	-0.0371**	-0.0505***	-0.00681	-0.00853	-0.00831	-0.00506
	(0.00689)	(0.00615)	(0.00694)	(0.00545)	(0.0144)	(0.0133)	(0.0148)	(0.00997)	(0.00452)	(0.00496)	(0.00532)	(0.00346)
WageCoord	-0.00458***	-0.00518***	-0.00496***	-0.00867**	0.00384	0.00236	0.00319	-0.00684***	-0.00268***	-0.00314***	-0.00293***	-0.00315***
	(0.000451)	(0.000464)	(0.000491)	(0.00309)	(0.00909)	(0.00829)	(0.00873)	(0.00212)	(0.000659)	(0.000501)	(0.000530)	(0.000395)
PopDen	-0.00231*	-0.00332***	-0.00390***	-0.00480***	-0.00170	-0.00361	-0.00485**	-0.00691***	-0.00864***	-0.00821***	-0.00938***	-0.00880***
	(0.00123)	(0.000961)	(0.00101)	(0.00110)	(0.00329)	(0.00211)	(0.00221)	(0.00159)	(0.000686)	(0.000871)	(0.000508)	(0.000920)
KIS	0.000708				0.00117				8.77e-05			
	(0.000540)				(0.00150)				(0.000399)			
KIFS		0.00177*				0.00474**				0.00308***		
		(0.000946)				(0.00201)				(0.000760)		
HTKIS			-0.000224				0.00148				-0.000833	
			(0.00180)				(0.00288)				(0.00247)	
HTMAN				-0.00394				-0.00777				0.00265
				(0.00485)				(0.00735)				(0.00318)
Constant	0.370***	0.319***	0.295***	0.225	0.719***	0.583***	0.548***	0.475*	1.462***	1.442***	1.418***	1.518***
	(0.0609)	(0.0669)	(0.0759)	(0.146)	(0.130)	(0.109)	(0.118)	(0.227)	(0.116)	(0.103)	(0.108)	(0.159)
Observations	546	475	493	358	546	475	493	358	546	475	493	358
Number of case	90	83	85	70	90	83	85	70	90	83	85	70
R-squared	0.041	0.042	0.038	0.068	0.033	0.042	0.035	0.070	0.094	0.108	0.097	0.130

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1