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CESifo Working Paper No. 4391
Category 5: Economics of Education
September 2013

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Abstract

By merging individual data on valuable patents granted in Prussia in the late nineteenth century with county level information on literacy and income tax revenues we show that increases in the stock of human capital not only improved workers' productivity but also accelerated innovative activities which, in turn, evoked an additional rise in the productivity level. Instrumenting the stock of literate people with information on the number of blind and deaf-mute people we also establish the direct causal effect of human capital on income, net of the innovation channel.

JEL-Code: N130, N330, O110, O310.

Keywords: human capital, growth, literacy, innovation, patents, Prussia.

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03 September 2013
Participants at the annual meeting of the Wirtschaftshistorische Ausschuss at Marburg and seminar participants at Cologne, Tübingen, and Ifo Institute provided helpful comments and suggestions.

1. Introduction

Scholars agree on the stylized fact that human capital is one of the decisive factors that explain why some countries are rich and others remain poor (Aghion et al. 2009; Goldin and Katz 2008; Goldin and Katz 1998; Jones and Romer, 2010). Unified Growth Theory even assumes that it was the increase in investment in human capital and the consequent decline in fertility that freed Europe and some of its former colonies from the Malthusian trap in the late nineteenth century (Galor, 2010). However, there is still dissent with regard to the channels through which human capital fosters economic growth. On the one hand, human capital is seen as a substitute for technology: Better educated managers and workers are able to increase production even when the technology they use is constant. On the other hand, human capital is interpreted as an input in the R&D process and therefore rather a complement to technology. According to this view, an increase in human capital will lead to a more efficient adaption of superior technologies thereby shifting the frontier of the production possibility set outwards.

We test both hypotheses for the economic development of more than 400 counties in Prussia in the late nineteenth century, the period in which Prussia as a national economy caught up successfully to the more advanced British economy and even took over the technological leadership in some high-tech sectors like chemicals or electrical engineering (Pierenkemper and Tilly, 2004). Using literacy rate as a proxy for human capital and valuable patents as a measure for innovative activities we demonstrate that the available stock of human capital had a positive and significant influence on the outcome of R&D processes, especially on the creation of firms' high-tech patents that were probably the most important driver of technological progress.

After having established that local human capital played an important role in Prussian counties' innovative activities, in a second step, we explore the direct and indirect influences of human capital on productivity at the county level. Because data on GDP per capita are not available for Prussian counties we use instead information on counties' income tax revenues per capita as a second-best measure.[1] In the late nineteenth century, a Prussian household's income tax was based on its taxable income from capital, immovable property, trade and commerce, and dependent employment. We therefore assume that a Prussian county's income tax revenues reflect the productivity of the economic activities of the county. The productivity level is determined by the capital endowment of the workplaces, the production technology,

[1] Prussia introduced a general income tax in 1891. See Schremmer (1994), p. 151-155.

and the worker's human capital. We can proxy the cross-county variation of the latter variables using valuable patents and literacy rate respectively.

Bils and Klenow (2000) point to the fact that most empirical studies only document correlation between human capital and economic development but do not establish the direction of causation.[2] First, there is the problem of reverse causality. Economically more advanced counties might have had both the need and the financial means to build up a more efficient education system. In this case, economic growth would have fostered human capital formation and not the other way around. Second, omitted variables like a county's formal institutions, its predominant religious beliefs, or its industrial structure might have influenced both economic growth and human capital formation. Under these circumstances, the correlation between human capital and economic growth would just indicate that both variables were determined by the same unknown variable. To establish the direct causal effect of human capital on income we therefore employ statistical information on the number of blind and deaf-mute people as an instrument to predict Prussian counties' literacy rates in a way that is uncorrelated with their growth perspectives.

In the final step of our empirical analysis we use this instrumental variable approach to explore also the influence of human capital on the category of high-tech patents which contains all Prussian patents that the German patent office assigned to the technological classes "chemical processes", "dyes", "electrical engineering" and "scientific instruments". This approach is motivated by the assumption that the availability of human capital was especially important for successful R&D near the technological frontier.

The rest of the paper is organized as follows. Section 2 discusses the role of human capital in economic development on basis of the related literature. In that section, we also develop our research strategy. Section 3 discusses the definition of valuable patents. Section 4 introduces the data. Section 5 presents the empirical results; section 6 establishes the direct causal effect of human capital on income. Section 7 presents evidence which suggests that the impact of human capital on income was the larger the closer a Prussian county was to the technological frontier. Section 8 concludes.

[2] See also Aghion et al. (2009).

2. The Role of Human Capital

Human capital comprises the stock of all competencies and skills that increase an individual's productivity in economic activities. Human capital can be acquired by formal education and learning-by-doing (Arrow, 1962) and therefore accumulates over the life-time of an individual worker or manager (Mincer, 1958). Like physical capital, however, human capital can also be devaluated which occurs especially in the aftermath of technological shocks. Handloom cotton weavers, for example, were highly-paid specialists at the end of the eighteenth century but became soon replaced by unskilled adults and children after Edmund Cartwright had invented the power loom in 1785 (Mokyr, 1990, p. 100). In economic history, exact measures for human capital do not exist. Researchers therefore often rely on imperfect proxies like literacy rate, years of schooling, formal degrees or even the Whipple index which measures the extent of age heaping (Baten and Crayen, 2010).[3]

Mankiw, Romer and Weil (1992, MRW hereafter) suppose that a society's aggregated stock of human capital can serve as a substitute for technology. That is why they augment Solow's classical growth model (Solow, 1956) with the factor human capital which is assumed to increase the workforce's productivity:

$$Y = A \cdot K^{\alpha} \cdot (L \cdot H)^{\beta} \qquad (1)$$

The notation is standard: Y is output, A the level of technology, K capital, L labour, H human capital, whereas α and β are the partial elasticities of production.

Analysing cross-country variation of GDP per capita in 1985 for 98 non-oil producing countries MRW (1992) show that the inclusion of human capital accumulation, measured as the fraction of the population aged 15 to 19 that is enrolled in secondary school, increases the performance of their regression model considerably. As a result, countries with similar technologies, rates of savings, and population growth might still not converge because of enduring differences in national education policies.

Benhabib and Spiegel (1994) raise serious doubts on whether human capital should enter the macroeconomic production function as a separate factor. Following the seminal approach of Nelson and Phelps (1966) they assume instead that human capital is primarily needed to enlarge the level of technology by adapting foreign superior technology or creating own

[3] Age heaping is the phenomenon according to which people approximate their ages with numbers ending in 5 or 0. This is typical for populations with low level of numerical ability.

innovations. In other words, human capital is not a substitute for but a necessary component to technology:

$$Y = A(H) \cdot K^{\alpha} \cdot L^{\beta} \qquad (2)$$

In their empirical approach, Benhabib and Spiegel assume that a country's level of technology is determined by both imitating and innovating activities. A country's capability to innovate is measured by its human capital stock. Its potential to imitate is approximated by the existing gap between the technological level of the productivity leader and its own inferior technological level (Abramovitz, 1986). Analysing the cross-country variation in growth rates of GDP per capita of 79 countries between 1965 and 1985, Benhabib and Spiegel conclude that poorer countries especially rely on adopting foreign technology while richer countries have to create better technology mostly by themselves. For both activities, however, the availability of an appropriate stock of human capital is a necessary precondition.[4]

In a broader sense, human capital enables people to "deal with disequilibria" (Schultz, 1975, p. 827). Only human beings who had reflected about different theoretical concepts and conflicting views of the world during higher education might be able to perceive and adapt to the dynamics of a changing economic and technological environment efficiently. That is why MRW (1992, p. 419) are probably wrong when stating that philosophy, religion and literature are not "intended to yield productive human capital".

A basic problem of all empirical approaches that try to identify the relationship between human capital and economic growth on basis of international comparisons is that countries differ in many idiosyncratic aspects like their institutions, their geography or their culture for which it is difficult to control in regression analysis. This problem can be reduced by looking at different regions within one single country that have most of these characteristics in common. Analysing the development of 452 counties within Prussia we make use of this methodological advantage.

In summary, there are two different channels through which human capital formation is supposed to foster productivity and therefore growth. First, human capital might directly increase the labour productivity of managers and workers. Second, human capital might enable firms and individuals both to imitate superior technologies from abroad and to develop their own innovations thereby increasing the productivity of production processes indirectly. We will start the empirical part of our paper with exploring the first part of the indirect

[4] See also Acemoglu et al. (2006).

channel, that is, whether in late-nineteenth century Prussia education increased significantly innovative activities measured by valuable patents.[5]

3. Valuable Patents

Pure patent counts allocate the same weight to every patent, no matter whether it has a low or a high economic value for the patentee or the society. Using the number of patents as an indicator for innovative activities therefore can lead to a large measurement error.[6] One way to distinguish patents with a high value from those with a low value is to use a patent's lifespan as an indicator for its profitability (Schankerman and Pakes, 1986). The caveat is that this method works only for patent systems with periodical renewal fees. The German patent law introduced in 1877 met this precondition (Seckelmann, 2006, pp. 170-179). It allowed both private persons and firms to apply for patent protection that could last up to fifteen years. To keep a patent granted in force the patentee had to pay an annual renewal fee which grew stepwise from 50 marks in the first and second year to 700 marks in the fifteenth year. Facing the rising expenditures for holding a particular patent a patentee was supposed to decide to renew his patent only when the costs of doing this were lower than the expected future returns of the patent. The assumption that this mechanism worked as intended is supported by the finding that, in the late nineteenth century, 70 per cent of all German patents granted had already been given up after just five years. Only about five per cent of all patents reached the maximum age of fifteen years (Streb et al. 2006, p. 352). We therefore assume in the following that only those long-lived Prussian patents that survived at least ten years can be interpreted as valuable innovations.[7] Our first empirical test will analyse whether the literacy rate of the local inhabitants influenced the probability that valuable patents were created in a Prussian county. In a second step, we explore the relationship between literacy rates and the volume of patenting activities.

The rise of chemicals, electrical engineering, and advanced machine building in the late nineteenth century relied much more on the availability and use of scientific knowledge than the innovations of the First Industrial Revolution in the late eighteenth century. That is one of

[5] Note that we do not have the data necessary to test whether human capital formation facilitated the imitation of (foreign) technology. Richter and Streb (2011), however, show for the German machine tool industry that it was primarily the former imitators that became successful innovators in the late nineteenth century.

[6] For a discussion of the shortcomings of patent statistics see Griliches (1992).

[7] A basic question about the life span approach is how many years a patent had to be in force to be interpreted as a valuable patent. Streb et al. (2006) explain in great detail why they decided to choose the cut-off point of ten years to distinguish patents with a low economic value from those with a high economic one.

the major reasons why, during the nineteenth century, the proverbial ingenious inventor lost ground to a more systematic and science-based research carried out in the newly-founded R&D departments of larger firms. This was especially true in Germany where firms like BASF, Bayer or Siemens profited from the advanced national education and research system.[8] Given this background information one might argue that it was primarily the Prussian "high-tech" firms whose innovative activities benefited from the human capital accumulated in their geographical neighbourhood. To test this hypothesis we estimate the impact of a county's human capital on patents granted to individuals and firms, respectively.

4. The Data

By merging individual data on valuable patents granted in Prussia from 1877 to 1890 with Prussian county level information our project makes use of two different, recently assembled historical data bases.[9] The prime source for the patent data is the annual "Verzeichnis der im Vorjahre erteilten Patente" published by the German patent office since 1877, which lists all patents granted in the preceding year. From these periodical listings, in 2005, the researchers Jörg Baten and Jochen Streb selected all patents that were held for at least ten years and were therefore interpreted as valuable. In this selection, we identified 1740 valuable Prussian patents granted between 1877 and 1890, which will be used as a proxy for the level of successful innovation activities. The information attached to each of these patents comprises the year in which the patent was granted, the technological class of the invention, as well as name and location of the patent holder. The name of the patentee allows us to distinguish whether a patent was held by a single inventor or a firm. The information about the location of the patentee is used to assign the origin of a particular patent to a geographical region. In the original data base the patents were allocated to administrative districts ("Regierungsbezirk"), the middle administrative level of the German states (Streb et al. 2006, p. 365). To get a more disaggregated picture of the geographical distribution of valuable patents we re-assigned them to the rural and urban counties ("Land- und Stadtkreise"), the

[8] See, for example, Murmann (2003) and Grupp et al. (2002). See also Burhop and Lübbers (2010) and Labuske and Streb (2008).

[9] For the patent data, see Streb et al. (2006), Streb et al. (2007), Labuske and Streb (2008), Degner (2009), Richter and Streb (2011). For the Prussian county level information, see Becker and Woessmann (2009), Becker et al. (2010), Cinnirella and Hornung (2011), Hornung (2012), Becker et al. (2012).

lower administrative level of the Prussian state. Figures 1 and 2 show the distribution of valuable patents granted to individuals and to firms respectively across Prussian counties.[10]

[Insert Figures 1 and 2 about here]

Figure 1 reveals that the valuable patents held by individuals were by no means equally distributed across Prussia. Innovative centers were the Ruhr area, the counties neighboring the rivers Rhine and Main, Greater Hannover, the Province of Saxony, Greater Berlin and parts of Silesia, while large parts of Poznán, Pomerania, West- and East Prussia display very low innovativeness. According to Figure 2, the innovative activities of firms were even more concentrated geographically. Clearly, the distribution of firms' valuable patents is not independent from the geographical location of innovative industries. Large chemical firms, for example, settled at the banks of the rivers Rhine and Main, which were not only important navigable waterways, but were also used as a water source and to get rid of effluents.[11] Firms engaged in the field of mechanical engineering were particularly concentrated in the neighborhood of iron and steel producers, namely in the Greater Ruhr area, and near textile manufacturers as in the Province of Saxony. Berlin was the center of German electrical engineering. Since technologically advanced industries increased both the number of valuable patents and the demand for education, neglecting their unequal distribution across Prussian counties would cause a serious omitted-variable problem. In the regression analysis, we explicitly control for the share of people working in highly innovative sectors and with a high propensity to innovate such as mining, metallurgy, and chemistry. To construct these variables we rely on the occupational census in 1882 which provides detailed information on the occupational structure of the Prussian population.[12]

Patenting activity in Germany was relatively expensive, especially if compared to the system adopted in the U.S. (Khan and Sokoloff, 2004). Therefore an established local network of banks and financial institutions providing credit for inventors might have facilitated patenting activities. Also based on the information of the occupational census in 1882, we construct a

[10] For the geographical distribution of patents granted in the US and Great Britain see Sokoloff (1988) and Moser (2011), respectively.
[11] In his seminal paper Sokoloff (1998) provided some evidence that proximity to a river is an important determinant of the location of innovative industries. We also tested this hypothesis but in our case the coefficient becomes insignificant as soon as we control for population. Yet this result is still consistent with Sokoloff's hypothesis that demand was a main driver of innovative activity.
[12] See *Preussische Statistik*, Vol. 76 b., pp. 232-695 and Vol. 76 c., p. 239.

variable indicating the percentage of people working in the banking sector. We will see that this variable is indeed strongly correlated with patenting activity. In addition we also use a control for people employed in other services.[13]

Information on literacy, population size, and religious denomination is provided by the population census in 1871.[14] Literacy rate, which is our proxy for the stock of human capital in the county, is measured as the share of people older than 10 years that were able to read and write. We will also take into account the scale of a county's population that might have affected innovative activity through increasing the absolute supply of new ideas (Galor, 2010, p. 8). Religious precepts can influence the investment in education. Becker and Woessmann (2009) have shown that counties which were dominated by Protestants invested more in education than Catholic counties. That is why, in our regression analysis, we also control for the share of Protestant and Jews in the Prussian counties.

Cinnirella and Hornung (2011) show that large landownership has a negative effect on the accumulation of human capital in nineteenth century Prussia. This finding is consistent with the notion that large landowners were primarily interested in securing a stock of unschooled and cheap farm laborers, and thus opposed the education of the peasants' children. Data on landownership by size is also available for the year 1882. In particular, the Prussian census noted down the number of landholdings for each county and classified them into six size bins: 0-1 hectare, 1-2 hectares, 2-10 hectares, 10-50 hectares, 50-100 hectares, and larger than 100 hectares. We include in the analysis a measure for landownership concentration defined as the number of landholdings larger than 100 hectares divided by the total number of holdings. This variable is bounded between zero and one: The higher the share, the stronger was the concentration of large landholdings in a county and in turn the stronger might have been the opposition to the spread of education.

We also include information on schooling from the education census in 1886, which collected data on both primary and secondary schools.[15] In particular, we construct a variable for the number of schools per 100 students aged 6-14. This variable is often used to measure the quality of education. It is usually assumed that the higher the number of schools per student, the higher is the public expenditure on education, and the higher the quality of education. In our context, this assumption could be misleading. Traditionally, the Prussian school system

[13] This variable comprises trade business, insurance, transport, lodging, and restaurants. It does not include servants and housemaids, nor people working in the public administration and the military.
[14] See Königliches Statistisches Bureau (1874): *Die Gemeinden und Gutsbezirke des Preussischen Staates und ihre Bevölkerung: Nach den Urmaterialien der allgemeinen Volkszählung vom 1. Dezember 1871*. Berlin.
[15] See *Preussische Statistik*, Vol. 101, pp. 2-391.

was dominated by one-class village schools in which quality of education was rather low (Kuhlemann, 1991, p. 194). In the last quarter of the nineteenth century, however, larger schools were established, in which the pupils were assigned to different classes according to their age, and educated by specialized teachers. Therefore a lower number of schools per student can imply a higher number of classes and therefore an improvement in the quality of education.

As already explained above, we will rely on information about income tax revenues when estimating the effect of human capital and innovative activities on economic outcomes. The Prussian Statistical Office published data on income tax revenues and the number of income tax payers averaged over the period 1899-1903 for all Prussian counties.[16] Figure 3 shows the relationship of our income variable (log income tax revenues) with log literacy rate and patents per 10,000 people, respectively. For both cases one can see a positive relationship.

[Insert Figure 3 about here]

Descriptive statistics of the variables used in this analysis are shown in Table 1. There is a large variation in the number of patents in our sample. The average number of valuable patents in a county is 3.8, with 301 counties (66 percent) having zero patents. The city-county of Berlin reached the outstanding number of 464 valuable patents in the period between 1877 and 1890, which is due to the fact that very innovative firms like Siemens and Agfa were located there. Berlin-based inventors might also have profited from their proximity to the Imperial Patent Office which facilitated communication with the members of this highly-centralized administration. To take this effect into account, we also control for the geographical distance to Berlin. However, Berlin clearly constitutes an outlier. Therefore, we show that our results remain virtually the same when excluding the city of Berlin from the regressions.

[Insert Table 1 about here]

[16] The source of the 1901 income tax statistics is: *Festschrift des Königlich Preussischen Statistischen Bureaus zur Jahrhundertfeier seines Bestehens* (Berlin: Verlag des Königlich Preussischen Statistischen Bureaus, 1905).

5. Empirical Results

5.1 The Relationship Between Human Capital and Innovative Activities

We begin our empirical analysis by analyzing the relationship between human capital and innovative activities. First, we estimate the effect of literacy rate on the probability to patent as expressed in equation (3). The dependent variable is a binary variable which takes on value one if at least one valuable patent was granted in county *i* in the period 1877-1890. β is the parameter of interest and X is a vector of control variables, generally measured in 1882. Standard probit estimates are presented in Table 2. In column 1, we show a simple bivariate correlation that reveals a strong positive correlation between literacy rate and the patent binary variable.

$$P(Patent_{1877-1890}) = \alpha_0 + \beta Literacy_{1871} + X_{1882}\lambda + \varepsilon \qquad (3)$$

In column 2, we introduce variables that account for the concentration of landownership, population size, urbanization, religious denomination, distance to Berlin, and the number of schools per 100 student aged 6-14. The first thing to note is that the positive relationship between literacy rates and innovative activities remains highly significant. The coefficient for population size is large and highly significant suggesting the importance of scale effects. Counties with a strong concentration of large landowners tend to be less prone to innovation. This is consistent with the fact that counties with a strong concentration of large landowners were less industrialized. Note that this result is net of the effect of urbanization which has a positive impact on innovation. Religious denomination has no significant impact on the probability to patent, whereas distance to Berlin has a significant positive coefficient. The latter finding can be explained by the fact that some highly innovative industrial areas like the Rhineland are located far away from Berlin (see Figures 1 and 2). Counties with a higher number of schools per pupils tend to be less prone to innovation. As we mentioned above, in this particular historical period a *lower* number of schools per capita should be interpreted as a better educational environment since larger schools with different classes were being established in more urbanized counties. That is why, this finding is not implausible.

In column 3 we include variables that account for the occupational structure of the counties. In particular we control for the percentage of people working in highly-innovative sectors such as mining, metallurgy, and chemistry (Streb et al. 2006). In addition we add a variable for the share of people working in the banking & insurance sector and other services. As expected, those counties with a higher share of people working in mining, metallurgy, and chemistry show a higher patenting activity. The coefficients for banking & insurance and other services are imprecisely estimated and are therefore statistically insignificant. However, despite the large set of control variables, the coefficient for literacy rate remains positive and significant.

[Insert Table 2 about here]

In a second step, we estimate the relationship between human capital and the absolute number of valuable patents granted in the period between 1877 and 1890. The dependent variable is now a count variable that takes on nonnegative integer values. In general, linear models are not well suited for count data since E(y|x) should be nonnegative for all x. In our case, two additional issues need to be taken into consideration: first, over-dispersion, e.g. the (conditional) variance exceeds the (conditional) mean, and, second, the excess number of zeros which is due to the fact that many counties have no valuable patents at all. To deal with these issues we use a particular class of count-data models, the so-called zero-inflated negative binominal models. This type of models assumes that the excess zeros are generated by a separate binary process which is independent from the process that leads to the count data. In our case, we assume that the percentage of people working in manufacturing predicts the excess number of zeros, the hypothesis being that counties with low level of manufacturing were less dependent on innovation and therefore had zero patenting. Hence, in the first step, a logit model is used to estimate whether or not a Prussian county was capable (or willing) to get at least one valuable patent. In the second step, a count model is employed to estimate the number of valuable patents in those counties where the occurrence of valuable patents is conceivable. Note that in the second step of the estimation zero patents are also possible. We have to distinguish counties where nobody tried to get a valuable patent from counties where somebody tried but failed.[17]

[Insert Table 3 here]

[17] More formally, the zero inflated model supplements a count density $f_2(\cdot)$ with a binary process having a density of $f_1(\cdot)$. If the binary process takes on value of 0, with a probability of $f_1(0)$, then y=0. If the binary process leads to value 1 with a probability of $f_1(1)$, then y takes on the count values 0, 1, 2, …, N from the count density $f_2(\cdot)$. Thus the zero-inflated negative binomial model has the following conditional mean: $E(y|\boldsymbol{x}) = \{1 - f_1(0|x_1)\} \times \exp(x_2'\beta_2)$, where $1 - f_1(0|x_1)$ is the probability that the binary process variable equals 1. See Cameron and Trivedi, 2010.

The results of this estimation are presented in Table 3. In the lower part of the table we can see that the percentage of labor force working in manufacturing is a good predictor of the excess zeros: the higher the percentage of people in manufacturing, the lower is the probability of observing a county with zero patents. The upper part of the table can be read as usual. In Column 1 we report the unconditional association between literacy rate and the number of patents. The coefficient is positive and highly significant. The coefficient remains significant when we include the set of controls in Column 2. Many of the variables which affect the probability to innovate have also a significant impact on the intensity of innovative activities. This is true for population size, urbanization, distance to Berlin, and the quality of the educational system, whereas the effect of landownership concentration remains insignificant.

In Column 3 we add the controls for the occupational structure. As a result, the coefficient for literacy rates becomes smaller and insignificant. This seems to suggest that a comparatively large share of literate people were concentrated in highly innovative industrial areas. Metallurgy, but most of all chemistry, is significantly associated with patenting activities. In contrast to the estimates of the probability to patent in Table 2, we now find that a larger banking sector has a significant and substantial impact on patenting activities. Apparently, banks helped to finance innovation. In Column 4 we report the estimates when excluding the city-county of Berlin: The results are virtually unchanged.

The richness of the patent data allows us to distinguish between valuable patents granted to single individuals and granted to firms. Thus we can investigate the relationship between human capital and innovative activity by sub-group. The results are presented in Table 4. In Columns 1 and 4 we include only the first set of controls; in Columns 2 and 5 we additionally control for the occupational structure; in Columns 3 and 6 we estimate the model without Berlin.

[Insert Table 4 here]

Already from the specification without occupational controls (Columns 1 and 4) it appears that the stock of human capital is more relevant for firms' innovation rather than for innovations granted to individuals. The relationship between human capital and the number of patents granted to individuals turns insignificant when accounting for the occupational structure and when excluding the city-county of Berlin (Columns 2 and 3). Instead, in the case of firms' innovation, the coefficient for literacy rate remains significant also when accounting for the occupational structure and when excluding Berlin (Column 5 and 6).

The findings of Table 4 support the hypothesis that it was especially the R&D intensive firms that profited from higher levels of human capital. The coefficients for the industrial sectors are consistent with the results presented so far. The percentage of labor force working in the chemical sector has a very strong impact on the number of patents granted to firms. The financial sector has consistently a strong positive impact on patenting activity across sub-groups. Finally, the scale effect of population and the negative effect of schools per student are confirmed also in the analysis by sub-group.

In general, we do not find any significant effect of landownership concentration. This result might suggest that, at the end of the nineteenth century, large landowners were not opposing innovative activities. The significant negative effect found in Column 2 of Table 2 might simply indicate a low complementarity between extensive agriculture and patenting activities, but not necessarily a general opposition to innovation. This interpretation is consistent with the work of Cinnirella and Hornung (2011) who show that the negative effect of landownership concentration on education decreased almost to zero by the end of the nineteenth century.[18]

We test whether these results are robust to an alternative model, namely to the zero-inflated Poisson model which also accounts for the excess zeros but not for over-dispersion.[19] The estimates presented in Table 5 show a similar pattern: the point estimates suggest that the relationship between the stock of human capital and patenting activity is somewhat stronger for firms.

In sum, this first set of estimates indicates that the level of human capital is positively correlated with innovative activity in a period of rapid technological change such as the last quarter of the nineteenth century in Prussia. Probit estimates indicate that, *ceteris paribus*, counties with a higher level of literacy rates were more prone to innovation. Estimates of count-data models suggest that the level of human capital influenced significantly the intensity of innovative activities of firms. This is consistent with the notion that especially the

[18] This is also consistent with Galor, Moav, and Vollrath (2009) who postulate that by the end of the nineteenth century landowners had gained large stakes in the industrialization process and therefore became less adverse to the spread of education.

[19] Comparing the goodness of fit between different count-data models, we find that the zero-inflated Poisson (zip) model performs almost as good as the zero-inflated negative binomial (zinb).

emerging R&D departments of firms benefited from higher levels of locally available human capital.

[Insert Table 5 about here]

5.2 The Effect of Human Capital and Innovative Activities on Income

After having established the role of human capital as an important determinant of innovative activity, in this section, we explore the separate effects of human capital and innovation on income. Two recent articles have shown that improvements in education fostered economic development in nineteenth century Prussia.[20] These studies do not provide any test, however, on whether human capital increased economic outcomes directly via its effect on labor productivity or rather indirectly by accelerating technological progress.[21] We close this gap using data on income tax revenues per capita that serve as a proxy for income per capita. More formally, we first estimate the following model through OLS:

$$log\ inc.tax\ rev.p.c._{1901} = \beta\ log\ literacy_{1871} + \gamma\ Patents\ p.c._{1877-1890} + X\lambda + \varepsilon \quad (4)$$

where the vector of control variables *X* includes the share of people working in manufacturing and services (1882), landownership concentration (1882), urbanization (1871), religious denomination (1871), the share of young (below 10 years of age) in the population to capture the demographic structure (1871), the share of people born in the municipality, and log population size (1871).

Reverse causality is not a crucial issue given the timing of our variables. However, unobserved heterogeneity might bias the OLS estimates and invalidate any inference on the causal effect of human capital on income. Because we have information on the income levels of male elementary school teachers for 1886 and past income tax revenues per capita for 1877, we can adopt a "value-added" approach and control for initial income (tax) levels. In the next section, we also propose an instrumental variable approach to further address the issue of causality. Here, we will estimate the following model:

[20] See Becker and Woessmann (2009), Becker et al. (2010).
[21] Clearly the two channels are not mutually exclusive.

$$log\ \ inc.tax\ rev.\ \ p.c._{1901} = \beta\ log\ literacy_{1871} + \gamma\ Patents\ p.c._{1877-1890} + X\lambda + \ \delta\ income_{1901-\tau} + \varepsilon \quad (5)$$

where ß and γ indicate whether human capital and innovative activities have a separate effect on productivity levels once accounting for past income levels ($income_{1901-\tau}$).

The estimates are shown in Table 6. In Column 1 we show the unconditional correlation between log literacy rates in 1871 and log income tax revenues in 1901. As expected, we find a strong positive significant coefficient. In Column 2 we run a "horse race" and find that both literacy rate and patents per 10,000 people are positively and significantly correlated with income tax levels. It is interesting to note that these two variables explain 50 percent of the variation in income tax revenues per capita across counties. In Column 3 we include the set of control variables. The coefficients of both literacy rate and patents per 10,000 people become smaller in magnitude but they keep their statistical significance. As expected, we find that counties both with a higher share of manufacturing and services and a higher degree of urbanization have higher income tax revenue levels. The share of Protestants is negatively correlated with income tax revenues, which corroborates the result of Becker and Woessmann (2009) who find no trace of an effect of the supposed Protestant work ethic after controlling for human capital.

The share of young (below 10 years of age) is negatively correlated with income tax revenues and the coefficient is highly significant and robust to different specifications. This finding is consistent with the concept of the quantity-quality trade-off (Becker et al. 2010), namely the negative impact of high fertility on education which in turn has a negative impact on income. The variable for the share of people born in the municipality is expected to capture the effect of short-run migration. We find that the share of people born in the municipality is negatively associated with income tax revenues: counties with a *lower* share of local people (more migrants) present *higher* levels of income.

In Column 4 we account for systematic differences in "initial conditions" by controlling for the log income of male elementary school teachers in 1886. This variable is significantly positively associated with income tax revenues in 1901. The coefficients for log literacy rate and patents per 10,000 people remain positive and highly significant. Income tax statistics are also available at the county level for 1877. Although the share of taxed income and the percentage of household exempted from paying taxes changed substantially between 1877 and 1901, tax revenues in 1877 constitute the best variable at our disposal to control for “initial conditions”. Income tax revenues in 1877 are not available for the 26 city counties and that explains why we only have 426 observations (Column 5).

The coefficient for income tax revenues in 1877 is large, positive, and significant. Importantly, the estimates in Column 5 suggest the existence of a separate effect of log literacy rate and patenting activities on income levels, also after accounting for initial income differences in 1877. Finally, in Column 6 we include both controls for initial income levels: The levels of literacy and patenting activity continue to have a separate positive significant impact on income tax revenues.

[Insert Table 6 about here]

Since both the dependent variable and the stock of human capital are measured in logarithm, the coefficient can be interpreted as elasticity. With respect to the richest specification in Column 6, an increase in the literacy rate by 1 percent is associated with an increase in income tax revenues per capita by about 0.4 percent. It is also interesting to compare the magnitude of the coefficients for human capital and innovative activities. An increase of the log literacy rate by one standard deviation is associated with an increase of the log income tax revenues per capita by 0.14 standard deviations; an increase of patents per 10,000 people by one standard deviation leads to an increase in log income tax revenues per capita by 0.22 standard deviations. The instrumental variable approach proposed in the next section suggests that OLS underestimates the effect of human capital on income tax revenues.

6. The Causal Effect of Human Capital on Income

As literacy is measured in 1871 and income tax revenues are measured in 1901, reverse causality is not an issue in our regression analysis. However, we cannot rule out the existence of an omitted variable which biases the OLS results by influencing both human capital and income. Therefore, it is not advisable to interpret human capital’s coefficient shown in Table 6 as a causal effect. In this section, we introduce a set of instruments which identifies exogenous variation in literacy rates and therefore permits to measure the causal effect of human capital on income, accounting for innovation.[22] In particular, we use the information about the number of blind and the number of deaf-mute people available in the 1871 Prussian census.

Andersen, Dalgaard, and Selaya (2011) hypothesize that regions with a higher incidence of eye disease have lower incentives to invest in human capital and therefore delayed the fertility transition.[23] Following this approach we assume that counties with a relatively higher share of blind and deaf-mute people have a lower number of individuals being able to read and write. Clearly, the share of disabled people in a county has a direct effect on income tax revenues as it reduces the share of people active in the labor market. Therefore, we will have to include a control for the share of active people. To ensure that the share of blind and deaf-mute people is not a proxy for other diseases, we control for the share of people working in the health sector (doctors and nurses). Another variable we use to account for the disease environment is the stillbirth rate. We include also information on the number of people mentally insane reported in the census. Finally, to ensure that blindness, deafness, and muteness are not correlated with geography, which in turn might have an effect on productivity, we add also controls for latitude and longitude of the county centroid.

In Figure 4 we show the relationship of the share of blind people (left panel) and the share of deaf-mute people (right panel) with literacy rates. In accordance with our hypothesis, the relationships are clearly negative. The strength of our instruments is also shown in Table 7 where we present the first stage estimates. A significant negative association between literacy rates and the share of blind people and the share of deaf-mute people holds when accounting for the full set of control variables (Column 1) and when including the additional controls for the health environment and geography to ensure that we are not violating the exclusion restriction (Columns 2-7).

[Insert Figure 4 about here]

[22] Ideally, we would like to have also an identification strategy for patenting activities. Unfortunately we could not find any suitable instrument for it. Especially, we cannot instrument patents with instrumented literacy because then we would violate the exclusion restriction which demands that literacy has no direct effect on economic outcomes. Yet, our conclusions on the causal effect of human capital on productivity are still valid.
[23] Using data on solar ultraviolet radiation, they present cross-country evidence being consistent with their hypothesis.

The corresponding instrumental variables estimates are shown in Table 8. On the bottom of the table we report the first stage F-statistics whose values above the critical value of 10 (with the exception of Column 6) indicate that the instruments are not weak. Since we have two instruments, the share of blind and the share of deaf-mute people, we can also report the over-identification test. This is a test of the joint null hypothesis that the excluded instruments are valid instruments, i.e. a rejection of the test would cast doubt on the validity of the instruments.

In Column 1 we show the instrumental variable estimates of our baseline specification.[24] We find again a strong positive effect of literacy rates on income tax revenues. A one percent increase in literacy rates increases income tax revenues by 2.5 percent. The OLS specification with the same set of controls (Table 6, Column 3) suggested an elasticity of 0.9. The relationship between patents per 10,000 people and income tax revenues remains positive and highly significant. Also in this case, the magnitude of the coefficient is sizable: an increase in the number of patents per 10,000 people by one unit is associated with an increase in income tax revenues by 7.3 percent.

The share of people employed in manufacturing and services as well as urbanization are positively associated with income tax revenues. Interestingly, whereas Protestants show always a negative relationship with income tax revenues, the share of Jews is now significantly positively associated with income tax. Again, counties with a higher share of people born in the municipality (i.e. lower mobility) show a lower level of income.

In the successive columns we sequentially introduce controls which account for channels which might invalidate our instrumentation. In Column 2 we control for the share of active population: this variable has no significant impact on our estimates. In Columns 3 and 4 we include controls for the share of people working in health care and the infant mortality rate to ensure that our instruments do not proxy for an adverse disease environment. Indeed, the point estimate suggests that counties with a higher infant mortality rate have a lower income level, though the coefficient is insignificant. Yet, the effect of literacy rate on income tax revenues is virtually unchanged. The same happens when we control for the share of people mentally insane (Column 5). Controlling for latitude and longitude (Column 6) decreases the precision of our instrumental variables estimates: the standard error of the coefficient for literacy is about the double with respect to the previous column. However, the coefficient is

[24] Since the instruments aim to identify exogenous variation in literacy rates and to account for unobserved heterogeneity, we drop the control for lagged income tax revenues (1877) or the income of male teachers (1886). However, including these variables in the instrumental variable approach does not change our results.

still highly significant, and the magnitude of the effect is almost unaffected. Finally, in Column 7 we include all the controls. Again, the causal effect of literacy on income remains highly significant.

[Insert Table 7 and 8 about here]

7. **The Effect of Human Capital at the Technological Frontier**

The results presented so far strongly suggest that human capital has a direct effect on economic growth, which is not mediated by innovation. Yet, it is possible that the effect of human capital on income (tax revenues) is larger the more innovative the economic environment (Aghion et al. 2009).[25] We can test this hypothesis by using information on high-tech patents, namely patents that were granted in the following technological classes: "chemical processes", "dyes", "electrical engineering" and "scientific instruments".[26] We assume that a county approaches the technological frontier monotonically with the number of patents granted in these technological classes. Based on this assumption, we can test whether the effect of human capital on income varies on the way to the technological frontier by estimating the coefficient of the interaction between literacy rates and the number of high-tech patents per 10,000 people.[27]

The estimates are presented in Table 9. In Column 1 we report the instrumental variable estimates of the baseline model, in this case using the number of high-tech patents per 10,000 people. It is interesting to note that the coefficient for high-tech patents (0.099) has a larger magnitude compared to the estimates of Table 8 where the coefficient for all the patents was 0.073 (Column 1). In Column 2 we include the interaction term between log literacy rates and high-tech patents. The coefficient for the interaction terms is positive, suggesting an additional positive effect of human capital near the technological frontier, but it is not statistically significant. Literacy rates and high-tech patents maintain their positive effect on income tax revenues.

[25] Aghion et al. (2009) assume that, in our days, higher education is needed to make leading-edge innovations, whereas primary education primarily improves the ability to imitate. Note that we only measure the level of primary education. However, it might be reasonable to assume, that, in the late nineteenth century, a county's comparatively high literacy rate is also a good proxy for the quality of its higher education investment.
[26] In the period between 1877 and 1918, patents of these technological classes account for 25 per cent of all valuable patents granted in Germany (Streb et al. 2006, p. 358).
[27] The instrument for the interaction term is the product of (*i*) the share of blind with the number of high-tech patents per 10,000; (*ii*) the share of deaf-mute with the number of high-tech patents per 10,000.

[Insert Table 9 about here]

In the successive columns we estimate our model for the sub-sample of counties with at least one high-tech patent (Column 3) and for counties with zero high-tech patents (Column 4). The coefficient for literacy rates for the sub-sample with at least one high-tech patent is large in magnitude but imprecisely estimated (*p-value*=0.15). This is due to the small number of counties with at least one high-tech patent (*n*=34). In the sub-sample with no high-tech patents, the coefficient for literacy is similar to the baseline estimate and highly significant.

To conclude, there is some evidence that the effect of human capital on growth is larger the closer the county is to the technological frontier. Yet given the small number of counties with at least one high-tech patent, we are not able to provide precise estimates of the additional effect of human capital on income tax revenues near the technological frontier.

8. Conclusion

We analyze the relationship between human capital, innovation, and income at the micro-regional level studying nineteenth century Prussia, which allegedly owed its rise to one of the leading industrial economies to its advanced education and research system. By merging individual data on valuable patents granted in Prussia from 1877 to 1890 with detailed county level data on literacy rates in 1871 and several socio-economic variables in 1882, we show that increases in the stock of human capital contributed significantly to innovative activities. Estimates of probit and count-data models suggest that counties with higher literacy rates had a higher probability to innovate. Especially, firms' patenting was fostered by increases in the stock of human capital. Interestingly enough, we also find that the development of the financial sector which held no patents by itself had also a significant impact on patenting activities. These results are obtained by controlling for a rich set of variables, such as religion, demography, and the occupational structure of the county.

Using data on income tax revenues for 1901 we also provide estimates of the effects human capital and innovation on income. We find that both variables have a sizable and separate positive impact on income. This result holds also when accounting for "initial conditions" such as income levels in 1877.

Instrumenting the stock of literate people with information on the number of blind and deaf-mute people we can establish the direct causal effect of human capital on income, net of the innovation channel. Our instrumental variables estimates suggest that a one per cent increase in literacy rates causes an increase in income tax revenues by about 2 per cent. Finally, we provide some weak evidence that the effect of human capital increases near the technological frontier.

Therefore, in nineteenth century Prussia human capital was both a substitute for and a complement to technology – and an important precondition for sustainable growth.

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Figure 1: Patents granted to individuals

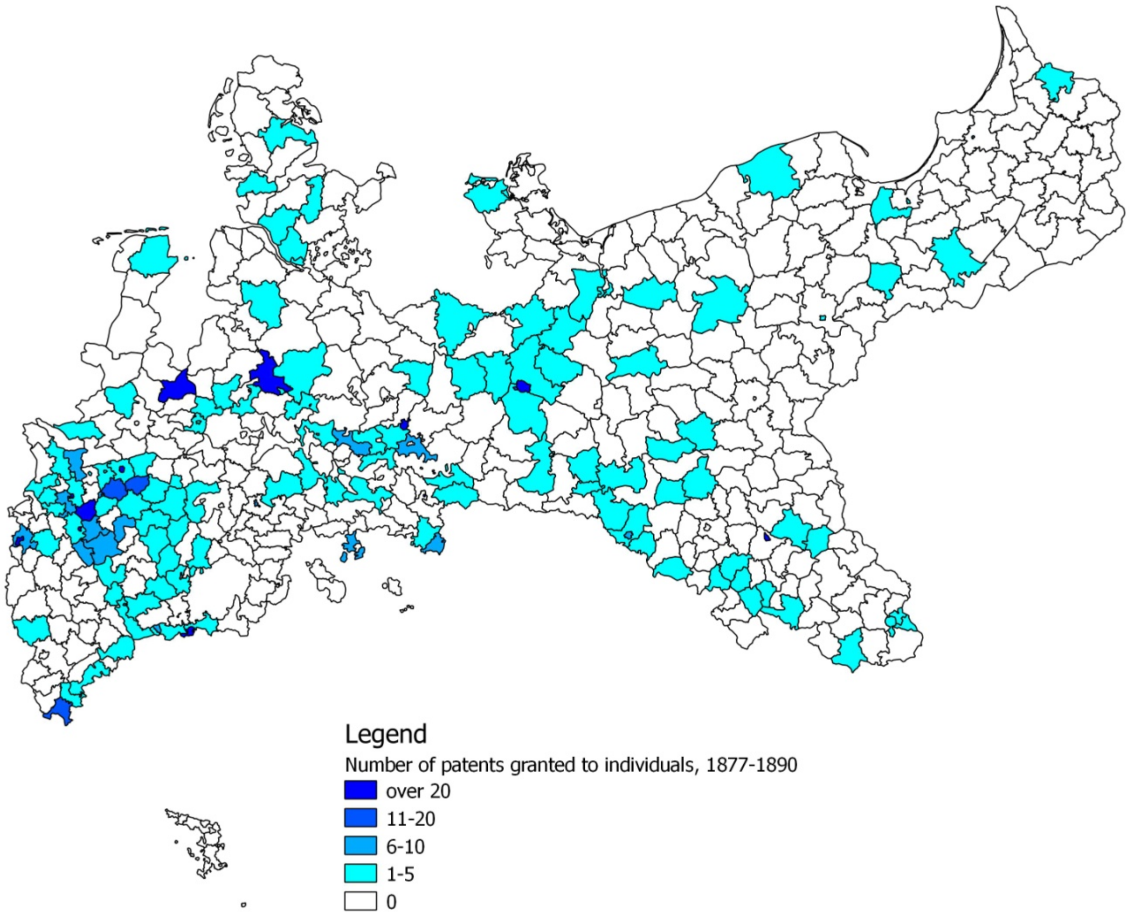

Figure 2: Patents granted to firms

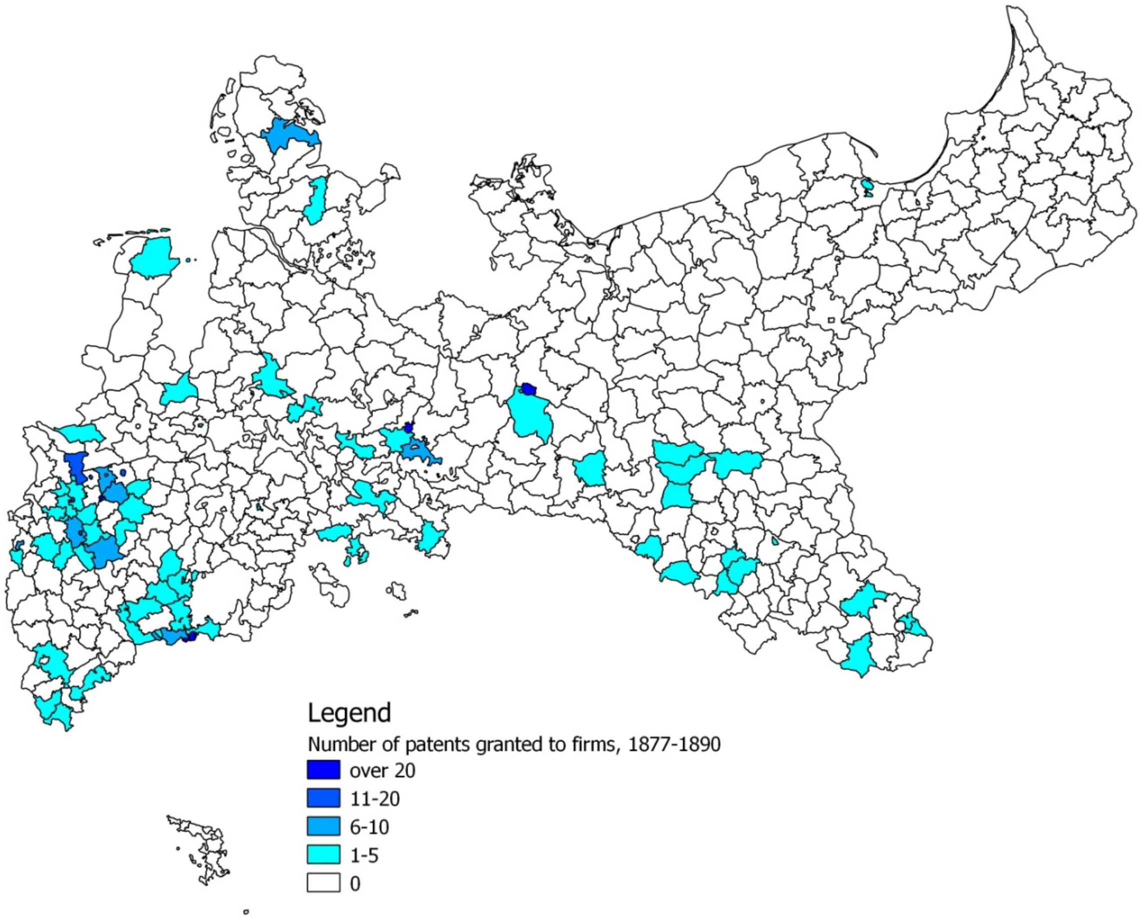

Figure 3: The relationship of income tax revenues with literacy rates and patents

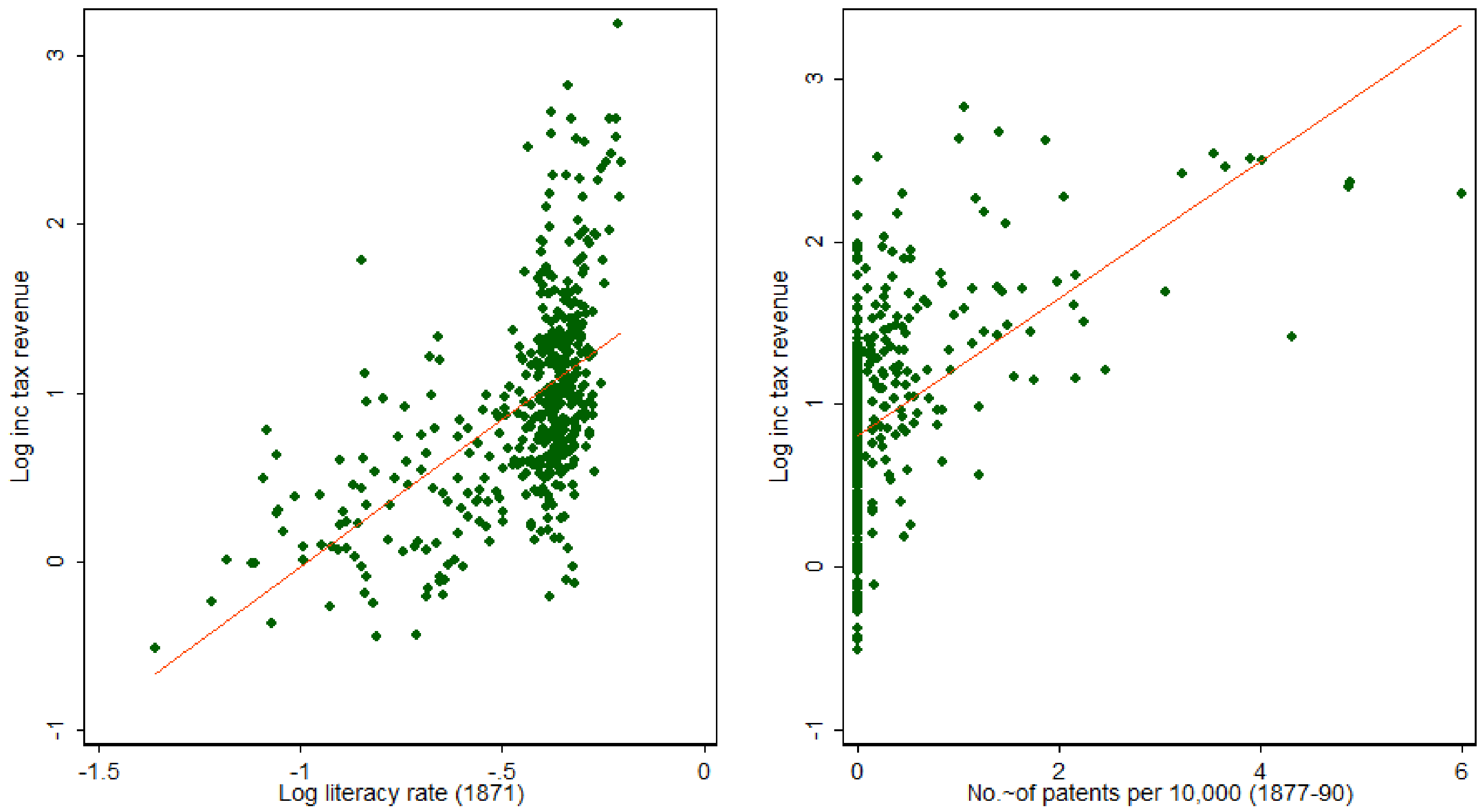

Figure 4: The relationship of literacy rates with the share of blind and deaf-mute people

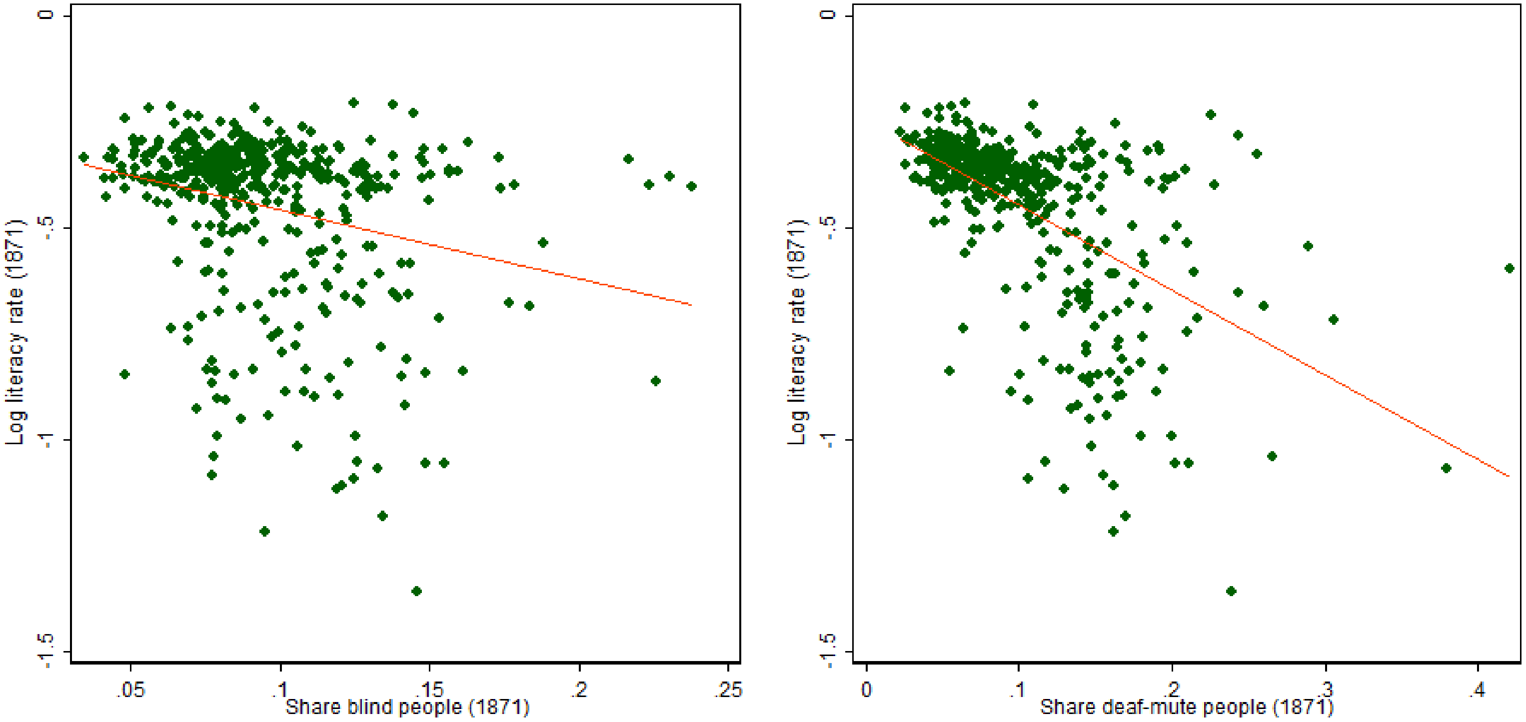

Table 1: Descriptive statistics

Variable	Mean	Std. Dev.	Min.	Max.
Abs. number of patents (1877-90)	3.843	23.988	0	464
Literacy rate (1871)	0.650	0.107	0.256	0.815
Log literacy rate (1871)	-0.448	0.195	-1.362	-0.204
Log income tax revenues p.c. (1901)	0.939	0.612	-0.511	3.194
Landownership concentration (1882)	0.008	0.008	0	0.063
Log population size (1871)	10.804	0.415	9.359	13.625
Perc. urban population (1871)	27.534	21.9	0	100
Perc. Protestants (1871)	64.181	37.831	0.258	99.889
Perc. Jews (1871)	1.139	1.327	0	12.869
Schools per 100 students (1886)	0.666	0.27	0.033	1.493
Distance to Berlin in km	332.897	146.607	1	650.04
Perc. working in mining (1882)	1.011	2.91	0	19.915
Perc. working in metallurgy (1882)	0.997	1.135	0.231	11.916
Perc. working in chemistry (1882)	0.084	0.153	0.002	1.614
Perc. working in banking (1882)	0.02	0.067	0	1.206
Perc. working in other services (1882)	2.679	1.651	0.658	11.233
Perc. young (1871)	24.707	2.478	15.334	29.868
Perc. born in municipality (1871)	58.97	12.386	32.009	87.23
Perc. blind (1871)	0.095	0.031	0.03	0.23
Perc. deaf-mute (1871)	0.101	0.054	0.022	0.42

Source: See text.

Table 2: Human capital and the probability to innovate

Dep. var.: Patent dummy	(1)	(2)	(3)
Log literacy rate (1871)	2.232***	1.960***	1.287*
	(0.437)	(0.660)	(0.687)
Landownership concentration (1882)		-27.036**	-17.612
		(12.682)	(12.575)
Log population size (1871)		1.497***	1.338***
		(0.255)	(0.267)
Perc. urban population (1871)		0.012**	0.002
		(0.005)	(0.007)
Perc. Protestants (1871)		0.002	-0.001
		(0.002)	(0.003)
Perc. Jewish (1871)		-0.051	-0.104
		(0.072)	(0.088)
Distance to Berlin (km)		0.001**	0.000
		(0.001)	(0.001)
Schools per 100 students (1886)		-1.241***	-0.632
		(0.435)	(0.437)
Perc. working in mining (1882)			0.051*
			(0.029)
Perc. working in metallurgy (1882)			0.170
			(0.106)
Perc. working in chemistry (1882)			1.346**
			(0.627)
Perc. working in bank and insurance (1882)			9.508
			(6.284)
Perc. working in other services (1882)			0.099
			(0.087)
Constant	0.526***	-15.563***	-14.607***
	(0.188)	(2.854)	(2.960)
Observations	452	452	452
Pseudo-R2	0.058	0.313	0.342

Note: Probit estimates. Robust standard errors in parenthesis. Significance at * 10, ** 5, *** 1 percent.

Table 3: Human capital and the intensity of innovative activity

Dep. var.: Patents count	(1)	(2)	(3)	(4)
Log literacy rate (1871)	5.264***	2.431***	1.009	1.004
	(1.250)	(0.872)	(1.018)	(1.017)
Landownership concentration (1882)		-0.578	7.012	7.269
		(19.621)	(19.361)	(19.785)
Log population size (1871)		1.624***	1.316***	1.299***
		(0.205)	(0.191)	(0.246)
Perc. urban population (1871)		0.012**	0.004	0.004
		(0.005)	(0.006)	(0.006)
Perc. Protestants (1871)		0.005	0.001	0.002
		(0.004)	(0.004)	(0.004)
Perc. Jewish (1871)		-0.057	-0.295***	-0.295***
		(0.073)	(0.079)	(0.079)
Distance to Berlin (km)		0.004***	0.003***	0.003***
		(0.001)	(0.001)	(0.001)
Schools per 100 students (1886)		-2.103***	-1.267	-1.278
		(0.803)	(0.779)	(0.782)
Perc. working in mining (1882)			0.037	0.037
			(0.024)	(0.024)
Perc. working in metallurgy (1882)			0.114**	0.114**
			(0.046)	(0.046)
Perc. working in chemistry (1882)			0.857***	0.863***
			(0.260)	(0.261)
Perc. working in bank and insurance (1882)			2.984***	2.919**
			(1.098)	(1.155)
Perc. working in other services (1882)			0.176*	0.179*
			(0.097)	(0.098)
Constant	3.833***	-16.715***	-14.429***	-14.267***
	(0.586)	(2.422)	(2.192)	(2.677)
Inflate				
Perc. labor force in manufacturing (1882)	-0.186***	-0.196***	-0.201***	-0.202***
	(0.027)	(0.032)	(0.034)	(0.034)
Observations	452	452	452	451

Note: Zero-inflated negative binomial estimates. Robust standard errors in parenthesis. Significance at * 10, ** 5, *** 1 percent. The manufacturing sector includes mining, construction, and manufacture of metals, machinery, equipment, chemicals, textiles, paper, leather, food products, and wood. In column 4 we exclude the city-county of Berlin.

Table 4: Human capital and the intensity of innovative activity by sub-group

Dep. var.: Patents count	(1) Individ.	(2) Individ.	(3) Individ.	(4) Firms	(5) Firms	(6) Firms
Log literacy rate (1871)	1.569*	0.199	0.197	4.910***	3.291**	3.237**
	(0.921)	(1.066)	(1.067)	(1.225)	(1.601)	(1.595)
Landownership concentration (1882)	2.809	6.662	6.516	-9.677	-1.773	1.356
	(20.988)	(20.242)	(20.585)	(29.495)	(25.695)	(27.191)
Log population size (1871)	1.654***	1.351***	1.350***	1.627***	1.402***	1.319***
	(0.214)	(0.204)	(0.266)	(0.242)	(0.231)	(0.303)
Perc. urban population (1871)	0.014**	0.004	0.004	0.005	0.002	0.002
	(0.006)	(0.006)	(0.006)	(0.006)	(0.008)	(0.008)
Perc. Protestants (1871)	0.005	0.001	0.001	0.006	0.002	0.003
	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)
Perc. Jewish (1871)	-0.121*	-0.321***	-0.321***	0.004	-0.246*	-0.248*
	(0.065)	(0.081)	(0.082)	(0.082)	(0.144)	(0.140)
Distance to Berlin (km)	0.003***	0.002**	0.002**	0.005***	0.005***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Schools per 100 students (1886)	-1.797**	-1.012	-1.010	-2.965***	-1.783**	-1.857**
	(0.879)	(0.882)	(0.883)	(0.718)	(0.770)	(0.762)
Perc. working in mining (1882)		0.037	0.037		0.034	0.035
		(0.024)	(0.025)		(0.038)	(0.038)
Perc. working in metallurgy (1882)		0.149***	0.149***		-0.005	-0.004
		(0.049)	(0.050)		(0.055)	(0.055)
Perc. working in chemistry (1882)		0.435	0.440		1.273***	1.288***
		(0.291)	(0.293)		(0.311)	(0.313)
Perc. working in bank and insurance (1882)		2.212*	2.214*		3.003**	2.876**
		(1.146)	(1.255)		(1.381)	(1.347)
Perc. working in other services (1882)		0.234**	0.235**		0.104	0.115
		(0.092)	(0.093)		(0.150)	(0.150)
inflate						
Perc. labor force in manufacturing (1882)	-0.194***	-0.196***	-0.197***	-0.287***	-0.296***	-0.299***
	(0.036)	(0.037)	(0.037)	(0.072)	(0.072)	(0.073)
Observations	452	452	451	452	452	451

Note: Zero-inflated negative binomial estimates. Robust standard errors in parenthesis. Significance at * 10, ** 5, *** 1 percent. The manufacturing sector includes mining, construction, and manufacture of metals, machinery, equipment, chemicals, textiles, paper, leather, food products, and wood.

Table 5: Human capital and the intensity of innovative activity - Robustness check

Dep. var.: Patents count	(1) Full sample	(2) Individuals	(3) Firms
Log literacy rate (1871)	2.415**	2.031*	2.752*
	(1.197)	(1.223)	(1.605)
Landownership concentration (1882)	15.144	20.577	-45.370
	(14.359)	(13.617)	(34.312)
Log population size (1871)	1.006***	1.083***	1.044***
	(0.246)	(0.260)	(0.308)
Perc. urban population (1871)	0.005	0.002	0.010
	(0.005)	(0.005)	(0.009)
Perc. Protestants (1871)	-0.004	-0.007*	-0.001
	(0.004)	(0.003)	(0.006)
Perc. Jewish (1871)	-0.319**	-0.268***	-0.379***
	(0.125)	(0.100)	(0.120)
Distance to Berlin (km)	0.001	-0.000	0.002
	(0.001)	(0.001)	(0.002)
Schools per 100 students (1886)	-1.856***	-1.966***	-1.120
	(0.605)	(0.709)	(0.984)
Perc. working in mining (1882)	0.058***	0.045*	0.059
	(0.018)	(0.024)	(0.040)
Perc. working in metallurgy (1882)	0.117***	0.154***	0.009
	(0.032)	(0.033)	(0.055)
Perc. working in chemistry (1882)	0.747***	0.153	1.232***
	(0.234)	(0.242)	(0.316)
Perc. working in bank and insurance (1882)	3.185***	1.813**	4.493***
	(0.924)	(0.800)	(0.926)
Perc. working in other services (1882)	0.071	0.121*	0.025
	(0.071)	(0.070)	(0.142)
Constant	-8.507***	-9.297***	-10.494***
	(2.729)	(2.994)	(3.797)
Inflate			
Perc. labor force in manufacturing (1882)	-0.085***	-0.080***	-0.061***
	(0.018)	(0.020)	(0.019)
Observations	451	451	451

Note: Zero-inflated Poisson estimates. Robust standard errors in parenthesis. Significance at * 10, ** 5, *** 1 percent. The manufacturing sector includes mining, construction, and manufacture of metals, machinery, equipment, chemicals, textiles, paper, leather, food products, and wood.

Table 6: Human capital, innovative activity and income (tax revenues)

Dep. var.: Log income tax revenues p.c. (1901)	(1)	(2)	(3)	(4)	(5)	(6)
Log literacy rate (1871)	1.750***	1.473***	0.882***	0.709***	0.426***	0.388**
	(0.118)	(0.104)	(0.165)	(0.169)	(0.158)	(0.161)
No. of patents per 10,000 (1877-90)		0.328***	0.088***	0.072***	0.214***	0.200***
		(0.031)	(0.016)	(0.020)	(0.047)	(0.049)
Log share manufacturing and services (1882)			0.494***	0.396***	0.307***	0.279***
			(0.066)	(0.069)	(0.056)	(0.057)
Landownership concentration (1882)			-3.591	-0.383	-1.110	-0.044
			(2.327)	(2.425)	(2.315)	(2.441)
Perc. urban population (1871)			0.007***	0.005***	0.005***	0.005***
			(0.001)	(0.001)	(0.002)	(0.002)
Perc. Protestants (1871)			-0.001**	-0.001*	-0.001	-0.001
			(0.001)	(0.001)	(0.000)	(0.000)
Perc. Jewish (1871)			0.012	0.013	0.019	0.021
			(0.012)	(0.013)	(0.019)	(0.019)
Perc. young (1871)			-0.024***	-0.027***	-0.027***	-0.029***
			(0.009)	(0.009)	(0.009)	(0.009)
Perc. born in municipality (1871)			-0.010***	-0.008***	-0.005***	-0.005**
			(0.002)	(0.002)	(0.002)	(0.002)
Log population size (1871)			0.086*	0.070	0.091**	0.089**
			(0.044)	(0.043)	(0.045)	(0.045)
Log income male school teachers (1886)				0.007***		0.003
				(0.002)		(0.002)
Log income tax revenues per capita (1877)					0.587***	0.555***
					(0.075)	(0.081)
Constant	1.722***	1.499***	-0.254	-4.855***	-3.153***	-4.739***
	(0.062)	(0.054)	(0.531)	(1.486)	(0.794)	(1.398)
Observations	453	452	452	452	426	426
R-squared	0.312	0.502	0.749	0.765	0.753	0.755

Note: OLS estimates. Robust standard errors in parenthesis. The manufacturing sector includes mining, construction, and manufacture of metals, machinery, equipment, chemicals, textiles, paper, leather, food products, and wood. The service sector includes trade business, insurance, transport, lodging, and restaurants. Significance at * 10, ** 5, *** 1 percent.

Table 7: The causal effect of human capital on income (tax revenues) – First stage estimates

Dep. var.: Log literacy rate (1871)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Perc. blind people (1871)	-0.602***	-0.608***	-0.656***	-0.590***	-0.693***	-0.439***	-0.506***
	(0.164)	(0.164)	(0.155)	(0.163)	(0.159)	(0.148)	(0.146)
Perc. deaf-mute people (1871)	-0.442***	-0.420***	-0.487***	-0.465***	-0.501***	-0.218*	-0.316***
	(0.123)	(0.123)	(0.120)	(0.125)	(0.125)	(0.119)	(0.120)
No. of patents per 10,000 (1877-90)	0.007	0.008	0.004	0.007	0.006	-0.005	-0.002
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Log share manufacturing and services (1882)	0.135***	0.137***	0.127***	0.150***	0.131***	0.092***	0.106***
	(0.018)	(0.019)	(0.018)	(0.018)	(0.018)	(0.017)	(0.018)
Landownership concentration (1882)	0.300	0.169	0.809	0.102	0.558	1.806**	1.569**
	(0.818)	(0.807)	(0.809)	(0.802)	(0.801)	(0.772)	(0.740)
Perc. urban population (1871)	-0.000	-0.000	-0.001*	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Perc. Protestants (1871)	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Perc. Jewish (1871)	-0.018***	-0.018***	-0.018***	-0.016***	-0.017***	-0.020***	-0.019***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Perc. young (1871)	-0.039***	-0.037***	-0.035***	-0.038***	-0.038***	-0.038***	-0.032***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Perc. born in municipality (1871)	0.005***	0.005***	0.006***	0.005***	0.005***	0.003***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Log population size (1871)	-0.034***	-0.034***	-0.029**	-0.038***	-0.033***	-0.009	-0.011
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Perc. active population (1882)		0.002					0.003*
		(0.002)					(0.002)
Perc. working in health care (1882)			0.266***				0.159**
			(0.058)				(0.065)
Infant mortality rate (1871)				-0.450			-0.945***
				(0.363)			(0.344)
Perc. mentally insane (1871)					0.095***		0.040*
					(0.019)		(0.021)
Latitude in radius*100						-0.010***	-0.009***
						(0.003)	(0.003)
Longitude in radius*100						-0.006***	-0.005***
						(0.001)	(0.001)
Constant	0.148	0.031	-0.017	0.166	0.131	1.077***	0.713**
	(0.137)	(0.172)	(0.144)	(0.138)	(0.137)	(0.263)	(0.326)
Observations	452	452	452	441	452	452	441
R-squared	0.80	0.80	0.81	0.81	0.81	0.83	0.84

Note: First stage estimates. Robust standard errors in parenthesis. The manufacturing sector includes mining, construction, and manufacture of metals, machinery, equipment, chemicals, textiles, paper, leather, food products, and wood. The service sector includes trade business, insurance, transport, lodging, and restaurants. Significance at * 10, ** 5, *** 1 percent.

Table 8: The causal effect of human capital on income (tax revenues) – Second stage estimates

Dep. var.: Log income tax revenues p.c. (1901)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log literacy rate (1871)	2.512***	2.514***	2.631***	2.671***	2.420***	2.386**	2.305***
	(0.541)	(0.558)	(0.498)	(0.549)	(0.481)	(0.999)	(0.807)
No. of patents per 10,000 (1877-90)	0.073***	0.072***	0.069***	0.076***	0.074***	0.071***	0.067***
	(0.018)	(0.019)	(0.018)	(0.019)	(0.018)	(0.018)	(0.017)
Log share manufacturing and services (1882)	0.225**	0.223**	0.199**	0.179	0.240**	0.244**	0.197*
	(0.105)	(0.109)	(0.098)	(0.111)	(0.097)	(0.109)	(0.102)
Landownership concentration (1882)	-3.192	-3.112	-2.627	-3.523	-3.330	-2.643	-1.477
	(2.703)	(2.738)	(2.797)	(2.721)	(2.687)	(3.409)	(3.037)
Perc. urban population (1871)	0.008***	0.008***	0.007***	0.008***	0.008***	0.008***	0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Perc. Protestants (1871)	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***	-0.003*	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Perc. Jewish (1871)	0.050**	0.049**	0.051***	0.046**	0.047**	0.049*	0.036
	(0.020)	(0.020)	(0.020)	(0.019)	(0.019)	(0.029)	(0.023)
Perc. young (1871)	0.043*	0.042*	0.052***	0.047**	0.039*	0.039	0.040
	(0.023)	(0.023)	(0.020)	(0.023)	(0.021)	(0.039)	(0.027)
Perc. born in municipality (1871)	-0.018***	-0.018***	-0.018***	-0.019***	-0.018***	-0.018***	-0.017***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)
Log population size (1871)	0.134***	0.134***	0.144***	0.149***	0.131***	0.135***	0.163***
	(0.050)	(0.050)	(0.050)	(0.050)	(0.049)	(0.050)	(0.047)
Perc. active population (1882)		-0.001					-0.001
		(0.005)					(0.006)
Perc. working in health care (1882)			0.315				0.636*
			(0.272)				(0.328)
Infant mortality rate (1871)				-1.876			-1.924
				(1.523)			(1.647)
Perc. mentally insane (1871)					-0.059		-0.204*
					(0.103)		(0.111)
Latitude in radius *100						0.006	0.002
						(0.017)	(0.015)
Longitude in radius *100						-0.003	-0.006
						(0.009)	(0.007)
Constant	-0.209	-0.119	-0.421	-0.123	-0.184	-0.734	-0.484
	(0.582)	(0.717)	(0.636)	(0.584)	(0.581)	(1.788)	(1.510)
Observations	452	452	452	441	452	452	441
1st stage F-stat	16.7	16.3	21.5	16.9	20.9	7.0	10.2

Over-id test	0.33	0.31	0.34	0.28	0.32	0.38	0.28

Note: Instrumental variable estimates. Robust standard errors in parenthesis. The manufacturing sector includes mining, construction, and manufacture of metals, machinery, equipment, chemicals, textiles, paper, leather, food products, and wood. The service sector includes trade business, insurance, transport, lodging, and restaurants. Significance at * 10, ** 5, *** 1 percent.

Table 9: The effect of human capital on income (tax revenues) near the technological frontier

Dep. var.: Log income tax revenues p.c. (1901)	(1)	(2)	(3)	(4)
Log literacy rate (1871)	2.499***	2.571***	8.031	2.562***
	(0.547)	(0.550)	(5.669)	(0.569)
High-tech patents per 10,000 (1877-90)	0.099***	0.319*		
	(0.035)	(0.177)		
Log literacy rate x high-tech patents 10,000		0.793		
		(0.552)		
Log share manufacturing and services (1882)	0.246**	0.234**	1.294**	0.212**
	(0.107)	(0.106)	(0.513)	(0.108)
Landownership concentration (1882)	-3.535	-3.445	9.765	-4.994*
	(2.746)	(2.773)	(10.764)	(2.789)
Perc. urban population (1871)	0.009***	0.009***	-0.001	0.009***
	(0.001)	(0.001)	(0.005)	(0.001)
Perc. Protestants (1871)	-0.003***	-0.004***	-0.007	-0.004***
	(0.001)	(0.001)	(0.006)	(0.001)
Perc. Jewish (1871)	0.045**	0.042*	0.078	0.056**
	(0.021)	(0.023)	(0.089)	(0.027)
Perc. young (1871)	0.044*	0.049**	0.100	0.044*
	(0.023)	(0.023)	(0.167)	(0.024)
Perc. born in municipality (1871)	-0.018***	-0.019***	-0.010	-0.020***
	(0.004)	(0.004)	(0.019)	(0.004)
Log population size (1871)	0.145***	0.146***	-0.026	0.130**
	(0.049)	(0.049)	(0.163)	(0.054)
Constant	-0.399	-0.438	-1.717	0.009
	(0.573)	(0.582)	(2.160)	(0.603)
Observations	452	452	34	418
1st stage F-stat	16.749	8.313	1.277	15.023
Over-id test	0.400	0.395	0.468	0.173

Note: Instrumental variable estimates. Robust standard errors in parenthesis. The manufacturing sector includes mining, construction, and manufacture of metals, machinery, equipment, chemicals, textiles, paper, leather, food products, and wood. The service sector includes trade business, insurance, transport, lodging, and restaurants. Significance at * 10, ** 5, *** 1 percent.