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INSTITUTIONS AND THE ALLOCATION OF TALENT: EVIDENCE FROM RUSSIAN REGIONS[*]

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Strong institutions attract talent to productive activities, whereas weak ones raise the appeal of redistribution and rent-seeking. We propose a theory that develops conditions for the more talented individuals to be particularly sensitive in their career choices to the quality of institutions, and test the responsiveness of individuals' professional choices empirically. First, we use cross-country setting to show that the strength of institutions is positively associated with the share of college graduates with science degrees and negatively associated with the share of those with law degrees. Although these results hold in a variety of specifications, cross-country regressions may suffer from significant endogeneities. In addition, college attendance may be a very crude indicator of talent. To alleviate these concerns we use a unique micro data set describing the choices of fields of studies by newly enrolled university students in Russian regions over 2011-2014. We show that the popularity of sciences and engineering among Russia's youth with higher ability as measured by the Unified State Examination scores increases in the quality of regional investment climate, whereas for law and public administration such link is markedly negative. These findings shed light on the gap between private and public returns to post-secondary education in Russia, and demonstrate that without improving its institutions the country would not be able to rely on investments in human capital as a driver of economic growth. More generally, our results put the link between institutional quality and the allocation of talent on a much firmer empirical footing than has been achieved in the literature so far.

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I. Introduction

Strong impact of institutions on economic growth and welfare is supported by the preponderance of empirical evidence (see e.g. Acemoglu, Johnson, and Robinson 2001; Easterly, Levine 2003; Rodrik, Subramanian, and Trebbi 2004; Besley and Persson 2011). There is also a general consensus about the mechanism linking institutions to economic outcomes: institutions affect the allocation of resources in the economy. Strong institutions protect property and contracts and reward productive activities, whereas under poor institutions unproductive activities rise in their attractiveness and draw resources away from production into redistribution. This includes the deployment of human resources, which is highly sensitive to institutional quality (Baumol 1990; Murphy, Shleifer and Vishny 1993; Mehlum, Moene, and Torvik 2003). However, rigorous empirical support of this conjecture so far has been insufficient, and the present paper partially fills this gap.

We provide evidence that institutional quality strongly affects the allocation of talent measured by the selection of fields of study by university students. We use enrollment in sciences, technology, engineering, and mathematics (STEM) as a proxy for the allocation of talent to productive activities, whereas excessive enrollment in law or law and public administration is viewed as evidence of attractiveness of redistribution. In doing so we follow the seminal paper by Murphy, Shleifer and Vishny (1991) who demonstrated that enrollments in engineering and law are, respectively, positively and negatively associated with economic growth. However, although Murphy et al. (1991) suggested that the allocation of talent depends on the quality of institutions, they and the subsequent literature presented no empirical evidence for this assertion. Moreover, unlike the rest of empirical literature on the allocation of talent, our Russian data allow for the use of much finer indicators of ability than the simple fact of college enrollment or possession of the appropriate degree.

The choice of enrollment or graduation in law and STEM as measures of attractiveness of unproductive and productive activities, while intuitively plausible, warrants explanation. The tradition to link legal profession with rent-seeking has a long pedigree (reviewed in Tollison, 1982, for example) and finds some empirical support (Laband and Sophocleus, 1988; Brumm, 1999). At the same time law obviously plays a critically important role in sustaining productive activities and in particular in protecting property rights. Lawyers are carriers of “legal human capital” (Hadfield, 2007) required to uphold and enforce the rule of law. We have no intent here to engage in the debates about the contribution of the legal profession to economic outcomes (see, e.g., Epp, 1992; Olson, 1992). Rather, we are interested in cross-jurisdictional *variation* of the popularity of education in law among talented individuals and show that it is strongly correlated with the variation of institutional quality. Although our results have to do with what happens at the margin, one can infer that these marginal outcomes are likely to lead to a lopsided allocation of talent well in excess of the "optimal number of lawyers" (Magee, 1992) and thus present evidence of institutional pathologies and failures.

Institutional failures are implied by our results even if the excessive demand for lawyers is not evidence of rent-seeking but has other institutional determinants. De Soto (1989) argues that red tape inflates the demand for legal services, in which case lawyers are not rent-seekers but rather pilots helping their clients to navigate through excessively cumbersome regulatory requirements. Furthermore, when property rights are vulnerable, lawyers help protect their clients' assets from expropriation by rent-seekers, both private and public, so more lawyers substitute for the weakness of the rule of law (Arruñada, 2007; Dezalay and Garth, 1997). In both of these instances our main point holds, i.e. weak institutions increase the demand for legal profession.

As for education in STEM, this is a major activity-specific investment, and enabling institutions provide the necessary confidence that such investment would earn appropriate returns. Furthermore, good institutions support more complex production processes that require a greater intensity of skills (Levchenko 2007). Nunn (2007) shows that good institutions favor contract-intensive industries, nearly all of which are in hi-tech and hence science and engineering areas.

We draw our hypotheses from an equilibrium model, in which an individual can choose between productive activities and redistribution (the latter involves both attempts of rent-seekers to encroach on producers' property rights, and protection from such attempts). An individual selects one of these activities depending on his/her talent, which is a payoff multiplier (irrespective of the chosen activity), and on idiosyncratic preference for redistribution over productive activities shaped by disposition, background, prestige, and other non-pecuniary rewards (Baumol 1990; Acemoglu 1995). Novel features of the model are the inclusion of "offensive" and "defensive" activities as parts of redistribution, and the analysis of the consequences of complementarity between talent and institutional quality.

The model shows that improved protection of property rights causes more individuals to choose productive activities over redistribution. However – and this is perhaps the most important novel feature of the model – such response is uneven across the range of abilities: less talented individuals are not as sensitive to the institutional quality in their occupational choices as those with higher (but not necessarily highest) general abilities. Therefore, assuming that we cannot identify the very top talent, the impact of institutions on the allocation of human capital is more pronounced in the group with higher ability.

To test these predictions empirically, we first briefly present cross-country estimations which make use of institutional indexes from the World Bank's Governance Matters database and UNESCO's data on graduation of university students in different disciplines from about 100 countries of the world. We establish a strong positive association between the quality of institutions and graduation in sciences, and a negative one – between institutional quality and graduation in law. In contrast with these clear-cut linkages, no other field of study in UNESCO's classification exhibits statistically significant correlation with institutional quality. We show that the impact of institutions on the allocation of talent appears to be particularly stark for the economies in transition. These results should be treated with greater caution due to the small number of observations. On the other hand, the advantage of looking at this subset of countries is that prior to transition, institutions and educational systems there exhibited significant uniformity thus alleviating the endogeneity concerns. We show that a profound institutional divergence that occurred within the group after transition was closely followed by talent allocation patterns that match institutional variations.

A major drawback of cross-country analysis is that it is subject to omitted variables biases and other potential endogeneities.[5] Moreover, the available cross-country data do not allow for testing a major prediction of our theory, i.e., that within certain range of abilities, sensitivity of the allocation of talent to institutional quality rises in talent. Of course, university graduates are expected to be more talented than others in the same age groups, but in many countries, including Russia, post-secondary education has become almost a social norm, and this distinction is thus blurred. Furthermore, we have no variable for aptitude as UNESCO data do not provide such information.

To address these issues, we turn to the Russian data, using regions (instead of countries) as jurisdictional units of analysis. In doing so we take advantage of significant variations of institutional quality in the Russian regions, both cross-sectionally and over time rarely observed within a single nation (Baranov et al., 2015). At the same time, the Russian regions are parts of the same economy and polity, and we can use fixed effects estimation to account for time invariant regional factors, and hence omitted variable biases are less likely, which is in general a major strength of subnational comparative studies (Snyder, 2001).

To gauge the allocation of talent we make use of a unique data set of enrollment of nearly all of Russian students pursuing post-secondary degrees over 2011-2014 period. The dataset is assembled by the National Research University Higher School of Economics under the "Monitoring of quality of higher education enrollment" project. Every entry of the dataset specifies the field of study chosen by a matriculating student, the region (in fact, the institution) where he/she is enrolled, and his/her score on the Unified State Examination (USE), which serves as a basis for admission decision and is used as a talent proxy in our regressions.

First, similarly to our cross-country estimates we use aggregated individual enrollment data, but we enhance the analysis by running regressions for the subsample of more talented students with USE scores in the top quantiles of regional distributions. Interestingly, the results for the entire

[5] One important omission in country-level empirical work on the allocation of talent is due to the fact that educational systems differ greatly across countries. For example, in order to become a lawyer in the US a person has to first obtain general education (a Bachelor's degree) and then graduate from a law school. In some other countries, including Russia, legal education is obtained right after high school and takes about the same time as other undergraduate degrees.

sample typically are not statistically significant while the results for the top quantiles are. This implies that enrollments in STEM, on the one hand, and in law, on the other, are indeed affected by regional institutional quality in a way that agrees with our theory. Therefore, institutions do affect the allocation of stronger talents in today's Russia. These results also suggest that in a country such as Russia with high proportions of enrollment in post-secondary education, it is important to account for the level of ability beyond the simple fact of college attendance.

Next, we use individual data from the whole pool of university enrollees over the period of observation, and find direct evidence that the impact of institutions on the allocation of talent indeed rises in talent. Stronger Russian talents are particularly sensitive to institutional quality, which means that poor institutions commonly observed in Russia divert the best and brightest from activities where they would have contributed to the country's economic development and modernization.

Finally, we address the issue of migration of university graduates which could weaken the link between institutional quality in a region where a student is pursuing his/her degree, and the allocation of talent. We show that controlling for such migration does not undermine the validity of our findings although the possibility to migrate naturally lowers the sensitivity of talent allocation to the region's institutional quality.[6]

The rest of the paper proceeds as follows. In Section II we present the theoretical model. Our cross-country data and regression estimates are presented in Section III. In section IV we describe the Russian data and present empirical findings based on these data. Section V concludes.

II. The Model

We use an equilibrium model in which individuals choose between directly productive and unproductive activities based on anticipated payoffs, which in their turn are affected by the quality of institutions such as property rights protection (see also, e.g., Murphy, Shleifer, and Vishny 1993; Grossman 1994; Acemoglu 1995; Mehlum, Moene, and Torvik 2006; Mariani, 2007).

II.1 Preferences, activities, and technologies

Consider an economy with a unit continuum of individuals who are characterized by talent $\theta \geq 0$ and idiosyncratic preference for redistribution over directly productive activities $w \in \mathbb{R}$. The above parameters are distributed independently from each other; cumulative distributions and (everywhere

[6] Note that migration could also affect country-level results, particularly for smaller countries with few educational opportunities as the secondary and tertiary level. However, earlier country-level allocation of talent studies typically do not control for migration.

positive) densities of θ and w are, respectively, $G(\theta)$ and $g(\theta)$, and $H(w)$ and $h(w)$. For simplicity talent measure is normalized to unity: $\int_0^\infty \theta g(\theta) d\theta = 1$.

Individuals have utility functions $u(y, i; w)$, where $y \geq 0$ is income, and $i \in \{1,2\}$ – occupational choice; $i = 1$ corresponds to productive activities, and $i = 2$ – to rent-seeking. Denote $u_i(y; w) \equiv u(y, i; w)$, $i = 1,2$; both functions are assumed monotonically increasing in income y. We further assume the following single-crossing conditions: for any $y_1, y_2 \geq 0$ the difference $u_1(y_1; w) - u_2(y_2; w)$ is monotonically decreasing in w, and $\lim_{w\to\infty}[u_1(y_1; w) - u_2(y_2; w)] < 0$, $\lim_{w\to-\infty}[u_1(y_1; w) - u_2(y_2; w)] > 0$.

Individuals specialize in either production or redistribution, and each individual inelastically supplies a unit of effort towards the chosen activity.[7] A unit of effort translates into θ units of effective labor (Solow 1956) no matter to what particular activity it applies; the total stock of effective labor to be divided between production and redistribution thus equals 1. The technology of production exhibits constant returns to scale and output measure is normalized so that aggregate effective labor Θ supplied towards productive purposes produces gross output $Y = \Theta$.

Property rights of producers can be protected publicly and/or privately. The quality of public property rights protection is measured by the share σ of the output that a producer securely owns irrespective of his or her private protection efforts. The rest of the output is contested by re-distributors; however, as in Grossman and Kim (1995), we assume that a producer can partially offset attempts on the publicly unprotected portion of her output by means of private protection. To this end, a producer has to retain protective services of re-distributors. If x units of effective labor of re-distributors is hired for protection per unit of output, then the share of output that the producer keeps goes up from σ to $\sigma + (1-\sigma)f(x)$, where $f(x)$ is smooth, monotonically increasing, concave and such that $f(0) = 0, f'(0) = \infty$, $\lim_{x\to\infty} f(x) = 1$. Services of re-distributors are available at the market rate c per unit of their effective labor, and producers' demand for such services per unit of output is determined from the following profit-maximization problem:

$$\max_{x\geq 0}[(1-\sigma)f(x) - cx] \tag{1}$$

which gives $x = x^*(c, \sigma) = (f')^{-1}\left(\frac{c}{1-\sigma}\right)$.

The portion of the gross output that lacks public protection and that the producers have failed to protect privately is $\Theta(1-\sigma)(1-f(x^*(c,\sigma)))$, and is available for grab by re-distributors who are not engaged in private protection and instead become rent-seeking predators. We assume, as in Tullock (1980), that the above share of the output is divided among the rent-seekers in proportion to

[7] A more general model with elastic effort supply derived from utility maximization leads to nearly identical conclusions.

their effective labor supplied towards predation.[8] This labor is the balance of the total effective labor supply which is equal 1 net of the producers' labor Θ and the labor of re-distributors hired for private protection $\Theta x^*(c,\sigma)$.

II.2 Equilibrium

In equilibrium, redistributors earn the same rate of returns per unit of their effective labor in private protection and predation, and hence

$$c = \frac{\Theta(1-\sigma)(1-f(x^*(c,\sigma)))}{1-\Theta-\Theta x^*(c,\sigma)}. \tag{2}$$

The net return per unit of effective labor in production equals

$$d(c,\sigma) \equiv \sigma + (1-\sigma)f(x^*(c,\sigma)) - cx^*(c,\sigma) \tag{3}$$

and hence an individual with talent θ would earn $\theta d(c)$ if she is engaged in productive activities, or θc, if she deals in redistribution. If this individual's idiosyncratic preference for redistribution is w, her activity choice will be based on the comparison of respective utilities $u_1(\theta d(c);w)$ and $u_2(\theta c;w)$. Denote $w(y_1,y_2)$ the activity selection threshold which solves the equation $u_1(y_1;w) = u_2(y_2;w)$; due to the single-crossing conditions such threshold always exists, is unique, and monotonically increases (decreases) in y_1 (y_2). An individual (θ,w) will select productive activities iff $w \leq w(\theta d(c,\sigma),\theta c)$ – assume that a tie is decided in favor of production [9], and therefore

$$\Theta = \int_0^\infty H(w(\theta d(c,\sigma),\theta c))\theta g(\theta)d\theta. \tag{4}$$

In equilibrium c, and Θ are jointly determined from equations (2), (4). Once c is known, the number (share) Π of agents participating in productive activities obtains as

$$\Pi = \int_0^\infty H(w(\theta d(c,\sigma),\theta c))g(\theta)d\theta. \tag{5}$$

[8] For micro-foundations of this assumption see Polishchuk and Tonis (2011).

[9] The assumption that an individual's choice is driven by a combination of expected material reward and idiosyncratic preferences is similar to probabilistic voting models where voters choose between political parties based on economic considerations and ideological leanings (Persson and Tabellini 2000).

<u>Proposition 1.</u> For any level $\sigma \in (0,1)$ of institutional quality there exists unique equilibrium $c = c(\sigma), \Theta = \Theta(\sigma)$, satisfying equations (2), (4).

<u>Proof.</u> Equation (2) implicitly defines Θ as an increasing function of c. Indeed,

$$\Theta = c/[c + cx^*(c,\sigma) + (1-\sigma)\big(1 - f\big(x^*(c,\sigma)\big)\big], \qquad (6)$$

and by differentiating the above expression by c and making use of the envelope theorem for the maximization problem (1), one can show that $\Theta_c > 0$. Vice versa, equation (4) defines Θ as a *de*creasing function of c; to see this, observe that $d(c,\sigma)$ is a decreasing function of c (again using the envelope theorem). Furthermore, along the curve defined by equation (2) one has $\lim_{c\to 0}\Theta = 0$, and $\lim_{c\to\infty}\Theta = 1$. On the other hand, along the curve (4), $\lim_{c\to 0}\Theta > 0$, which proves the existence and uniqueness of equilibrium. ■

II.3 Comparative statics: impact of institutions

In this sub-section we study the impact on equilibrium of the quality of property rights protection σ.

<u>Proposition 2.</u> The equilibrium aggregate effective labor supply $\Theta(\sigma)$, and the payoff to effective labor in production $d(c(\sigma),\sigma)$ both increase in σ.

<u>Proof.</u> Notice that an increase in σ due to the envelope theorem shifts the curves (2) and (3) upwards in (c,Θ) axes, and therefore pushes up the equilibrium value of Θ. To establish the same for effective labor, assume first that the payoff to effective labor in redistribution $c(\sigma)$ decreases in σ. In such case $d(c(\sigma),\sigma)$, being an increasing function in σ and decreasing in c, also goes up. If $c(\sigma)$ does *not* decrease in σ, then $d(c(\sigma),\sigma)$ should still go up – otherwise for all talent levels θ threshold values $w(\theta d(c,\sigma),\theta c)$ will be decreasing in σ, and so, according to (4), will be $\Theta(\sigma)$, which would contradict the already proven first part of the Proposition. ■

One would expect that better property rights protection improves the attractiveness of productive activities over redistribution, and hence reallocates labor supply away from redistribution to production in every talent cohort θ. This would be the case if the payoffs in production and redistribution go in the opposite directions – the former, according to Proposition 2, always increases in σ, and if in addition the latter decreases in σ, then, as argued in the proof of the above proposition, the threshold $w(\theta d(c,\sigma),\theta c)$ would be increasing in σ for all θ, drawing more individuals into productive activities. Although it sounds highly plausible that better protection of property rights makes redistribution less rewarding, this might not always be the case, as increased output (due to better property rights protection) and/or lower supply of effective labor $(1-\ \Theta(\sigma))$ towards residstribution could increase the payoff to the latter (Murphy, Shleifer, and Vishny 1991; Polishchuk and Savvateev 2004). In such case participation thresholds $w(\theta d(c(\sigma),\sigma),\theta c(\sigma))$ could decrease, depending on preferences configuration, for some levels of talent.[10] To rule out such eventuality, unlikely as it may be, we impose a further assumption on preferences. Specifically, we will assume through the end of this section the following linear utility functions:

$$u_1(y;w)=y;\ u_2(y;w)=y+w. \tag{7}$$

Proposition 3. For utility functions (7), an increase in property rights protection σ expands participation in productive activities for every talent cohort $\theta>0$, and hence increases the aggregate labor supply towards productive activities $\Pi(\sigma)$.

Proof. For preferences (7), one has $w(y_1,y_2)=y_1-y_2$. Equation (4) takes the following form:

$$\Theta=\int_0^\infty H(\theta\Delta)\theta g(\theta)d\theta. \tag{4'}$$

where $\Delta\equiv d(c,\sigma)-c$ denotes the difference between the payoffs per unit of effective labor in production and redistribution. According to Proposition 2, in equilibrium left-hand side $\Theta(\sigma)$ of the above equation increases in σ, and hence the equilibrium value $\Delta(\sigma)$ is also an increasing function of σ. This means that the production participation threshold $\theta\Delta(\sigma)$ increases in σ for any $\theta>0$,[11] and so does the aggregate share of agents participating in production $\Pi(\sigma)=\int_0^\infty H\big(\theta\Delta(\sigma)\big)g(\theta)d\theta$. ■

II.4 Comparative statics: impact of institutions and talent

According to Proposition 3, improvement of property rights increases participation in productive activities for every (positive) level of talent. However the strength of this effect varies and

[10] Notice however that since the aggregate supply of effective labor goes up according to Proposition 2, this is "less likely" (in the sense of integral (4)) than the opposite reaction, when the production participation threshold for a cohort actually goes up.

[11] Slightly extending this finding, we will be assuming thereafter that $\Delta'(\sigma)>0$.

depends on the level of talent and institutional quality. Indeed, participation $\Pi(\theta,\sigma)$ in productive activities in the talent cohort θ, measured by the share of those participating in production in the total size of the cohort, equals $H\big(\theta\Delta(\sigma)\big)$. The marginal returns to improved institutions in the participation in productive activities is as follows:

$$\frac{\partial\Pi(\theta,\sigma)}{\partial\sigma} = \theta h\big(\theta\Delta(\sigma)\big)\Delta'(\sigma). \tag{8}$$

It was shown in the proof of Proposition 3, that $\Delta(\sigma)$ is a monotonically increasing function; assume that in fact $\Delta'(\sigma) > 0$ and that the density function $h\big(\theta\Delta(\sigma)\big)$ is positive. It now follows from (8) that in the zero talent cohort institutions have no impact on the choice between productive activities and rent-seeking, and such choice is driven entirely by idiosyncratic preferences. For positive levels of talent such impact exists and its strength increases in talent at least for smaller θ, i.e., in the "low to medium" talent range. Indeed, one has

$$\frac{\partial^2\Pi(\theta,\sigma)}{\partial\theta\partial\sigma} = [h\big(\theta\Delta(\sigma)\big) + \theta\Delta(\sigma)h'(\theta\Delta(\sigma))]\Delta'(\sigma), \tag{9}$$

and for sufficiently small θ the above expression is always positive.

The payoff to improved property rights in the allocation of *top* talent depends on the level of institutional quality σ. Begin with the break-even institutional quality $\sigma_0 \in (0,1)$, for which the payoffs to productive activities and redistribution are equal to each other, and therefore $\Delta(\sigma_0) = 0$. In such case

$$\frac{\partial^2\Pi(\theta,\sigma_0)}{\partial\theta\partial\sigma} = h\big(\theta\Delta(\sigma_0)\big)\,\Delta'(\sigma_0) > 0$$

and hence the payoff to better institutions is a linear increasing function of talent (Figure 1a). It means that around the break-even level of institutional quality talents are highly sensitive to the protection of property rights.

On the other hand, assuming $\lim\limits_{|w|\to\infty} wh(w) = 0$, one obtains for $\Delta(\sigma) \neq 0$ that

$$\lim_{\theta\to\infty}\frac{\partial\Pi(\theta,\sigma)}{\partial\sigma} = 0.$$

Furthermore one can easily check that $\frac{\partial^2\Pi(\theta,\sigma)}{\partial\theta\partial\sigma} < 0$ for sufficiently high θ. It means that for institutions on either side of the break-even level top talents are increasingly indifferent to small changes in institutional quality (Figure 1b). Combining these findings, we conclude that the allocation of talent in cohort θ between production and redistribution as a function of institutional quality approximates a step function for top talents, i.e., when $\theta \to \infty$.

The above analysis summarizes in the following

Proposition 4. One has $\frac{\partial \Pi(\theta,\sigma)}{\partial \sigma} = 0$ for $\theta = 0$, and $\frac{\partial \Pi(\theta,\sigma)}{\partial \sigma} > 0, \frac{\partial^2 \Pi(\theta,\sigma)}{\partial \theta \partial \sigma} > 0$ for sufficiently small $\theta > 0$. Furthermore, if $\lim_{|w| \to \infty} wh(w) = 0$, then $\lim_{\theta \to \infty} \frac{\partial \Pi(\theta,\sigma)}{\partial \sigma} = \infty$ if $\Delta(\sigma) = 0$, and $\lim_{\theta \to \infty} \frac{\partial \Pi(\theta,\sigma)}{\partial \sigma} = 0$ otherwise. ■

II.5. Impact of mobility

Suppose that the above-described economy is a part (jurisdiction) of a bigger economic entity, e.g., a national economy in the global economy, or a subnational unit in a federation, and that labor is partially mobile between the jurisdiction and the rest of the encompassing entity. Assume that a mobile individual can move freely and costlessly to any other jurisdiction of the entity, that the share of such individuals in the economy is $p \in [0,1]$ (which is a mobility measure) and that mobility is statistically independent from talent and the propensity for redistribution. Finally, assume that the jurisdiction is “non-pivotal”, i.e. the payoffs to productive activities and redistribution are not the highest across the encompassing entity.

Denote c the *domestic* payoff to redistribution, and $\Delta \equiv d(c,\sigma) - c$ the difference between *domestic* payoffs to productive activities and redistribution. Furthermore, denote d_0 and c_0 the highest payoffs to respectively productive activities and redistribution available in the encompassing economy, and let $\Delta_0 \equiv d_0 - c_0$. Since the jurisdiction is non-pivotal, mobile individuals will move outside of the jurisdiction and be choosing between the payoffs θd_0 and θc_0, whereas those who are immobile will choose between θd and θc. Therefore, the share of agents in the economy who will be engaged in productive activities is as follows:

$$\tilde{\Pi} \equiv p \int_0^\infty H(\theta \Delta_0) g(\theta) d\theta + (1-p) \int_0^\infty H(\theta \Delta) g(\theta) d\theta. \tag{10}$$

Domestic equilibrium $c = c(\sigma), \Theta = \Theta(\sigma, p)$, and $\Delta = \Delta(\sigma)$ satisfies the following equations:

$$c = \frac{\Theta(1-\sigma)(1 - f(x^*(c,\sigma)))}{1 - p - \Theta - \Theta x^*(c,\sigma)}, \tag{2'}$$

$$\Theta = (1-p)\int_0^\infty H(\theta\Delta)\theta g(\theta)d\theta. \qquad (4'')$$

Notice that c, $d(c,\sigma)$, and Δ do not depend on p and hence can be taken from the original model with $p = 0$. This is due to the scale invariance of the model, where the payoffs to productive activities and redistribution do not depend on the size of participating agents' continuum. Indeed, substitution $\widetilde{\Theta} \equiv \Theta/(1-p)$ reduces equations $(2')$ and $(4'')$ to their original versions (2) and (4). This observation leads to the conclusion that the allocation of effort between productive activities and redistribution is less sensitive to institutional quality in jurisdictions with higher inter-jurisdictional mobility.

Proposition 5. One has

$$\frac{\partial^2\widetilde{\Pi}(p,\sigma)}{\partial p\partial\sigma} < 0, \qquad (11)$$

where $\widetilde{\Pi}(p,\sigma)$ is the equilibrium enrollment (10) in productive activities calculated at $\Delta = \Delta(\sigma)$.

Proof. This follows directly from $\frac{\partial^2\widetilde{\Pi}(p,\sigma)}{\partial p\partial\sigma} = -\Delta'(\sigma)\int_0^\infty h(\theta\Delta(\sigma))\theta g(\theta)d\theta.$ ■

The above theory generates the following testable hypotheses about the selection of fields of study by university students. First, improvement of property rights protection and other similar institutions should increase the enrollment in disciplines that equip students for productive activities and *de*crease enrollment in disciplines that could be useful in redistribution. Second, such effect is more pronounced for more (but not necessarily exceptionally) gifted students, than for those with low level of talent. Third, mobility of students after graduation should weaken the above effect. In the remainder of the paper we take these hypotheses to data.

III. Cross-country analysis

Our theory implies that in countries with a firmly established rule of law and adequate protection of property rights, we should observe stronger interest in education that prepares students for productive activities, whereas poor institutions raise the attractiveness among younger people of subject areas that could equip for redistribution. Furthermore, such institution-related discrepancy should be more pronounced for an upper part of the talent distribution where one should expect to find those pursuing post-secondary education. Hence we gauge the allocation of talent in response to the quality of institutions by the enrollment and/or graduation of college and university students in different fields of study. As in Murphy, Shleifer, and Vishny (1991), we use, with appropriate caveats, the share of law school graduates as a proxy for the allocation of talent to redistribution. The share of those majoring in sciences (STEM, broadly defined to include life and physical sciences, mathematics, engineering, and computing) is our measure of talent allocation towards directly productive activities.

To develop a country-level benchmark preceding our analysis for Russian regions and to test robustness by using different jurisdictional units, we begin with a cross-country empirical analysis of the impact of institutions on the allocation of talent. Our source of cross-country data on student graduation is the UNESCO Institute of Statistics,[12] which stores information on the number of graduates in tertiary education for 23 educational programs in 102 countries over the period from 1999 to 2009. Unfortunately, the database has quite a few gaps; for example, data on law school graduates are available for 26 countries in 2009, 47 countries in 2008, but for only 9 countries in 2007. In order to maximize the number of observations, we treat available data as a cross section and take the latest available graduation data for a given field in a country. This should not significantly bias our results for two reasons. Most of the data are available only for the years close to 2009: for instance, 80% of our data on law and STEM graduates are from the 2005-2009 period, so that the coverage of this period is fairly accurate and complete.

To measure the quality of institutions, we use the World Bank's Governance Matters database (Kaufmann, Kraay, and Mastruzzi 2010) and select the following measures of institutional quality: rule of law (including the quality of contract enforcement, property rights, and courts); government effectiveness (quality of public service, policies, and independence from political pressure); and control of corruption. In addition, given the centrality of property rights protection for our analysis, we add the Heritage Foundation's property rights index to the list (Miller and Holmes 2010). We average these indexes for the 2000-2005 period and use the results as explanatory variables. Such choice of timing helps alleviate, although certainly not eliminate, reverse causality concerns;[13] furthermore, this timing reflects a lag between the choice of subject area and student's graduation.

Our analysis incorporates various controls which can be expected to affect the allocation of talent, such as GDP per capita, structure of the economy (share of services, manufacturing and agriculture, exports of manufacturing goods), measures of the prevalence of post-secondary

[12] We are grateful to UNESCO's Chiao-Ling Chien and Albert Motivans who kindly provided detailed data not available from UNESCO's open-access sources.

[13] We also ran 2SLS regressions using either settler mortality or the fraction of English speaking population (or both) as instruments for institutions. The results are broadly similar to the OLS regressions although statistical significance of the instrumented institutional quality variables is somewhat lower. Settler mortality instrument is a rather weak instrument for most of our institutional quality measures and it has been criticized in the literature (Glaeser et al. 2004, and Albouy 2012) on substantive grounds. Moreover, it limits our sample to only 35 observations. The fraction of English-speaking population also might not satisfy the exclusion restriction even though the regressions easily pass overidentification tests when both instruments are used.

education, public sector size, and emigration of post-secondary degree holders (all from the World Development Indicators database), oil reserves (CIA World Factbook), economic inequality measured by the Gini index (United Nations Statistical Database), and ethno-linguistic heterogeneity measured by Alesina et al.'s (2003) ethnic fractionalization index.[14]

Table 1 contains descriptive statistics for the main variables for cross-country regressions. The table shows such statistics for all countries in the sample and also for the sub-samples with stronger and weaker institutions above and below the median Rule of Law Index. In each case, we report means and standard deviations (in parentheses), and the total number of countries for which all the data are available.

A comparison of enrollment levels for sub-samples reveals stark differences between countries with strong and weak institutions. Thus, the average share of law school graduates in the countries with a weaker rule of law is almost twice as high as in countries where the rule of law is stronger. Conversely, the average share of science graduates for countries with above the median Rule of Law Index is more than 40% higher than the same share for countries below the median. These differences are statistically significant at the 1% level.

The discrepancy in enrollment between the two groups of countries is even more striking if we use differences between the shares of law and science graduates, which measure relative attractiveness of different fields of study. For countries with weaker institutions, the average of such differences is positive and equals 1.43 percentage points, whereas for countries with stronger institutions it is negative and equals 5.52 percentage points. We treat this difference as yet another dependent variable whose distribution is closer to the normal than the distributions of separate enrollment data for law and science.

We start with estimating the following cross-country regressions relating the allocation of talent to indexes of institutional quality:

$$(Un)productive\ Activities_{\ i} = \beta_0 + \beta_1\, Institutional\ Quality_i + \beta_2\, X_i + \varepsilon_i, \qquad (12)$$

where $(Un)productive\ Activities$ measures reflect the allocation of talent between subject areas of post-secondary education, $Institutional\ Quality$ is one of the indexes listed in the previous section, X_i is the vector of additional covariates serving as control variables, and ε_i is the error term. The coefficient of interest is β_1 capturing the impact of institutions on the allocation of talent.

We employ an extensive set of control variables to reduce the likelihood of an omitted variable bias. The set of controls reflects factors other than institutions that could possibly influence the allocation of talent and which are commonly used in similar cross-country analyses.

[14] The tables presented below do not show all of the controls listed in the text in order to limit the table size.

Notice that emigration of tertiary educated could disconnect educational choices from the quality of national institutions. Education in sciences is more “portable” than in law (Mariani, 2007), and much of brain drain occurs in the STEM fields (Gibson, McKenzie, 2011). Therefore the prospect to emigrate could increase the relative attractiveness of sciences vs. law irrespective of domestic factors. To address this possibility, we control for the emigration rate of post-secondary degree holders.

We estimate model (12) with the share of law graduates as a dependent variable and report results in Table 2. In the first column with no control variables, the coefficient of the Rule of Law Index is, as expected, negative and highly statistically significant. When we add one after another our control variables (columns (2) to (8)), the negative association between institutional quality and law school graduation remains highly significant and grows in magnitude. These estimations show that, ironically, an increase in lawlessness is associated with higher graduation in law. Figure 2 shows a scatterplot for the regression with a full set of controls.

In the next regression (Table 3) the dependent variable is the share of science graduates, while the procedure otherwise remains the same. This time the coefficient of interest is positive, as expected, and in most specifications significant at the 1% or 5% levels. It is noteworthy that no field of study from the UNESCO dataset other than law and sciences exhibits a statistically significant association between the share of graduates and the rule of law or any other commonly used measure of institutional quality.

On average across specifications, an improvement of one standard deviation in the rule of law, holding other factors constant, is associated with an increase by 0.25 standard deviations of the share of science graduates. A scatterplot illustrating this link is presented on Figure 3.

Since the quality of institutions is negatively associated with the share of law students and positively – with the share of those majoring in sciences, the difference between these two shares should be particularly sensitive to the institutional quality. We test this for all four measures of institutional quality listed in the previous section and the results in Table 4 with the main control variables included.

All four indexes of institutional performance are strongly negatively associated with the dependent variable, which is consistent with our hypothesis. The strength of this connection can be seen from the fact that a one standard deviation increase in the Rule of Law Index is associated with a 0.55 standard deviations decrease in the difference between the shares of law and science graduates.

Finally, in Table 5 we report the results of OLS estimations of (12) for the sub-sample of transition economies for all three measures of the allocation of talent – graduation in law; in sciences; and the difference thereof as dependent variable, and the Rule of Law Index as a measure of institutional quality. For all three measures their coefficients are substantially – 25 % and up – higher than for the full sample of nations. The scatter plot presented in Figure 4 illustrates the strong association between the quality of institutions and allocation of talent in the former Soviet Union and Central and Eastern Europe, although these regressions and the scatter plot suffer from a particularly small number of observations.

Further illustrations of the "natural experiment" within the group are provided by comparisons of different countries that are neighbors and otherwise comparable and similar to each other. A case in point is the divergence between Ukraine and Poland described at the outset at the paper. Both countries experienced an explosive growth of interest in the legal profession in the early 1990s to fill the voids left by their pre-transition educational systems, and at that time education in science and engineering suffered a precipitous decline. However, over time the enrollment in law schools in Poland subsided and enrolment in science and engineering recovered, whereas no such adjustment has occurred in Ukraine (Figure 5). A stark difference between the two countries can be seen in the numbers of law schools: law degrees are conferred by 16 universities in Poland, whereas in Ukraine the number of such institutions runs into the hundreds.

IV. Evidence from Russia

Although the results from cross-country analysis strongly support our theory, they are also subject to several challenges. First, cross-country regressions are susceptible to endogeneity, both because of omitted variables and because of the possibility of reverse causality. Second, the data on the relative talent of people going into various occupations in each country are rather crude and potentially subject to a significant measurement error. Third, countries differ in the structure of their education systems and the meaning and content of science and legal education. We alleviate if not fully eliminate these problems by using regional level data on individuals in Russia who enroll in various disciplines. These data are available for several years and, most important, come with a measure of individual ability.

Russian institutions are notoriously weak (see, e.g., Polishchuk 2013) and in accordance with our theory one should expect crowding out of science and engineering by law among more talented Russian youth. This is clearly illustrated by the distributions of the scores from the 2010 Unified State Examinations (USE; the Russian version of a national SAT-like test) of applicants seeking education in various fields, which is presented in Figure 6. This Figure shows USE scores for the applicants to "Aviation and Space Technologies" departments and Departments of Law. Keeping in mind that the number of applicants to law is considerably greater than that for Aviation and Space, this Figure reflects a strong preference of Russian university applicants with high USE scores to law over even the most cutting-edge engineering disciplines. Apparently the proverbial perception of "rocket science" as a highly talent-intensive area is at odds with the actual allocation of top talents in modern Russia.

This illustration, however, does not provide direct evidence that changes in institutional quality cause certain re-allocation of talent. To present such evidence, we need multiple jurisdictions with variations of institutional quality from one jurisdiction to another and data on allocation of (variable) talent within each of the jurisdictions. As indicated in the Introduction, Russian regions serve this purpose.

IV.1. Data

Our main regional-level data consist of the proportions of individuals who choose to matriculate in various disciplines at almost all universities in Russia's regions for 2011-2014, the shares of enrollees in different percentiles of USE scores, and the measures of institutional quality of each region. Our individual-level data include individual's discipline choices and individual USE scores.[15] We use the individual's average USE scores for the two mandatory subjects – Russian language and mathematics. We also have the data on whether the individual's study is funded by the state ("budget") or the individual pays for his/her education out of pocket ("paid"), but the analysis of these data is beyond the scope of this study. More detail on the Russian procedures for application, admissions, and studying in colleges and universities are presented in the Appendix.

As a measure of institutional quality of a region, we use primarily the investment risk index from the rating agency Expert RA. The higher value of this index corresponds to lower institutional quality, and so to make the results comparable to some other institutional quality indices and to make them easier to understand we invert this index by subtracting its value for each region from unity.[16] To check robustness, we use alternative institutional quality measures specified below. Other regional characteristics used as controls in most regressions include logarithm of per capita gross regional product (GRP) in the region in constant year 2000 prices, the shares of manufacturing, mining, and of state administration in the value added in the region, and the average temperature in January.

Per capita GRP reflects the general level of development of the region, the shares of manufacturing and of mining reflect the structure of the region's economy. Both of these industries require engineers and scientists and thus are expected to increase the propensity of individuals to choose science and engineering professions, but mining industry also reflects rent availability in the region and may provide incentives to acquire professions such as law and public administration that are typically more involved in redistribution. The share of state administration might be associated with greater demand for lawyers and public administration graduates. The region's temperature in January is a general characteristic of the region that may affect various aspects of the economy.

[15] The regional-level data enrollment shares are more complete than the data on individual choices, because the former include branch campuses of regional universities and some private schools that are excluded from the individual-level dataset.

[16] Expert RA apparently changed the methodology of calculating the index in

We drop Moscow, Moscow oblast', and St. Petersburg from our regressions, because the cities of Moscow and St. Petersburg attract a large number of students from outside who later go back to their regions and because Moscow oblast' data are combined with the city of Moscow in our database. Therefore, the choices of disciplines by matriculants in Moscow and St. Petersburg universities may not adequately reflect institutional environment in these cities.

All variables and sources for them are described in Table 6. Table 7 shows descriptive statistics for our variables.

IV.2. Results for aggregate data

Although our main focus is on estimation using the data on individual matriculants, we first estimate region-level regressions that are comparable to country-level ones in that they are based on aggregate data by region on enrollments in different disciplines. We run separate regressions for the entire population of matriculants and for those with USE scores above a certain threshold. This allows us to see whether the enrollment decisions of high ability individuals are different from those of lower ability ones.

We estimate the following regression model:

$$AoT_j = \beta_o + \beta_1 IQ_j + \beta_2 X_j + \varepsilon_j \tag{13}$$

As in country-level regressions, we use both shares of enrollments in particular groups of disciplines as well as differences in these shares as allocation of talent (*AoT*) measures. Specifically, two of our dependent variables represent shares in total enrollments of, respectively, STEM and law and public administration. Two other dependent variables are calculated as differences and relative differences between STEM and the law and public administration shares. Unlike in the cross-country regressions, we also use as dependent variables these measures for the matriculants in the top quartile and top decile of USE scores. As mentioned earlier, the use of top percentiles is particularly important in the Russian case where enrollment in colleges is quite high, implying that college enrollment itself is not necessarily a sign of an individual being in the top portion of ability distribution.

We use the investment risk index described in the Data section above as our main independent variable. This measure is rescaled by subtracting its original value from unity in order to make higher values of this measure correspond to higher institutional quality. The advantage of this measure is that it is available for a large number of regions and for all years, for which we have matriculation data. However, investment risk might not be the most appropriate measure of institutional quality for our purposes because, for example, it incorporates economic trends within a region and financial situation of regional governments. Our control variables, particularly per capita GRP data, alleviate these concerns but do not eliminate them completely. More generally, no measure of institutional quality is perfect and thus we also estimate our regressions using some other measures. Unfortunately, no other measure of institutional quality of Russia's regions comes close to investment risk index in terms of coverage across space and over time.

Our data cover a rather short period of time and our independent variables change only slowly from one year to another. Therefore, fixed effects regressions might not yield statistically significant results. More important, fixed effects (FE) do not estimate the impact of cross-regional differences in institutional quality and other regional characteristics. For these reasons, we focus on the so-called within-between (WB) specification based on Mundlak (1978) and Bell and Jones (2015). This is a random-effects estimator that includes both the time-invariant means and deviations from their means for all time-varying variables. It also can include time-invariant variables. This method allows for simultaneous estimation of between-effects and within-effects while taking advantage of higher efficiency of random-effects estimates. In these regressions, the coefficients of the means of time-varying variables, including our measures of institutional quality, are essentially estimates of between-effects while the coefficients of deviations from the means of these variables are essentially estimates of within-effects.[17]

The results of WB regressions based on regional-level aggregate data are shown in Tables 8 and 9. (To save space, we show only the coefficients of institutional quality variables.) With only a couple of exceptions, the estimates of the effects of change in institutional quality in a region over time (within effects) are statistically insignificant. The between-effects estimates (see coefficients of the means of regional institutional quality) are mostly insignificant for the regressions based on the entire enrollments, but are typically statistically significant at conventional levels for the top percentiles of the matriculants and agree with our hypotheses. This result underlines the need for using ability measures rather than relying on the data for overall enrollments in various disciplines. Note, however, that running separate regressions for top percentiles of the USE scores is a rather crude way of accounting for the impact of ability on the link between institutional quality and the choice of occupation. A better approach requires examination of individual USE scores and choices, which is the subject of the next section.

IV.3. Individual data

[17] The coefficients of the deviations of the time varying variables in our WB regressions are indeed virtually identical to the corresponding FE estimates and the regressions easily pass Hausman tests. The results of fixed effects regressions for regional-level aggregate data are available upon request.

We now turn to the main focus of our empirical analysis – regressions based on individual data on the matriculants in different disciplines. These data let us utilize information on the USE score of each individual in a region.

Our benchmark empirical specification is a linear probability model (LPM) because its estimates are easy to interpret. In addition, LPM allows for the inclusion of fixed effects that account for unobserved heterogeneities among regions, although as we mentioned earlier, we do not emphasize fixed effects estimation because regional fixed effects may hide part of the effect of institutional quality on the allocation of talent. We also use Probit models as robustness checks. Specifically, we estimate the following regression:

$$DISC\_CHOICE_i = \beta_0 + \beta_1 USE_i + \beta_2 IQ_j + \beta_3 USE_i \times IQ_j + \gamma X_j + \varepsilon_i \qquad (14)$$

where $DISC\_CHOICE_i$ is a dummy variable that reflects individual i's choice of discipline. We use three different measures of this choice. Variable $STEM_i$ (LAW_i) takes on a value of 1 (0) if individual i matriculates in sciences or engineering (law or public administration) and the value of 0 (1) otherwise. Variable $STEM\_LAW_i$ is set to unity if $STEM_i = 1$ and equals zero if $LAW_i = 1$. Otherwise, it is set to missing. As before, IQ_j denotes a measure of institutional quality of the region. $USE_i \times IQ_j$ is an interaction term between the individual's USE score and institutional quality of the region, and X_j represents regional level control variables that include variables reflecting the structure of the region's economy, log of per capita GRP, log of population, average temperature in January, and time fixed effects.

One difficulty of estimating (14) is that the errors within each region could be correlated. The standard although rather conservative approach to dealing with this problem is to cluster errors by region.[18]

We first estimate fixed effects and WB random effects LPM regressions. In these regressions we control for the same variables as we did in the case of aggregate data, although in regressions with fixed effects we, of course, do not include the average temperature and the means of time varying variables. In all regressions, we are mainly interested in marginal effects of the institutional quality measure as reflected in the coefficients β_2 and β_3, values of USE scores, correlations between USE scores and institutional quality, and statistical significance of these marginal effects. Furthermore, we focus on the marginal effects of institutions at relatively high ranges of USE scores. This is important for confirming the implications of our model and also because individuals with low USE scores

[18] We present only the results of regressions with clustered errors whenever we are able to estimate them. If we do not cluster errors by region, the standard errors typically become dramatically smaller and, correspondingly, t-statistics become much higher.

typically would be significantly constrained in their choices of discipline, being able to matriculate only in those departments that would accept them. Note that because institutional quality of the regions changes over time, it is informative to present marginal effects of institutional quality even in fixed effects regressions. Although it remains the case that regional fixed effects might subsume part of the marginal effect of institutional quality measure, this does not appear to be the case. The estimates obtained with regional fixed and random effects are remarkably close and easily satisfy Hausman test.

The results presented in Table 10 strongly support our theory. Both the interaction terms and marginal effects have the "right" signs (i.e., they are positive for $STEM$ and $STEM\_LAW$ regressions and negative for regressions with LAW as a dependent variable), and are mostly statistically significant. The only exception is the marginal effect of institutional quality on enrollment in law and public administration at USE score of 70 that has the 'right" sign but is not statistically significant at the conventional levels. Since USE score of 70 does not represent a particularly talented group of individuals, the lack of statistical significance here does not contradict our theory. Moreover, the absolute values of marginal effects show a clear tendency to increase with USE scores, which is also a prediction of our model.

The estimates of the coefficients of control variables obtained in the fixed effects specification are mostly statistically insignificant, presumably because these variables do not change much over a relatively short period of time. The only exception is the coefficient of the logarithm of per capita GRP that is positively associated with the enrollment in law and public administration. Not surprisingly, in the WB specification the regional means of manufacturing and mining shares are positively associated with the enrollment in STEM disciplines while the regional mean of per capita GRP is positively correlated with enrollment in law and public administration. Somewhat unexpectedly, the regional mean of the share of state administration is not correlated with enrollment in law and public administration. The marginal effects of institutional quality in the pooled OLS estimates are somewhat higher in absolute value than those in the FE and WB regressions, but the difference is not large (see Table 11).

Although LPM with clustered errors is our preferred specification, we also recognize its potential limitations such as the possibility of producing predicted probabilities outside of [0,1] interval and the fact that marginal effects are linear in the relevant variables.[19] We address these issues by estimating a Probit model, noting, however, that this model also imposes rather strict assumption of normality of the error distribution. Also, estimating fixed effects Probit is problematic (see Lancaster 2000). Moreover, we have had difficulties obtaining clustered standard errors in random effects Probit

[19] The first consideration is not particularly important. Out of more than 1.2 million observations, only three predicted probabilities are negative for $STEM$ regressions and only four are negative for LAW regressions. The problem is a bit worse for $STEM\_LAW$ regressions where about 0.3% of predicted probabilities are slightly greater than unity.

regressions presumably due to the large size of the dataset. Table 12 presents marginal effects of institutional quality estimated by Probit (columns 1-3) and random effects Probit (columns 4-6). The estimates of the Probit coefficients by themselves are not particularly informative. We present only the estimates of the marginal effects that are directly relevant for our story. The other coefficient estimates are available upon request. Overall, Probit estimates of the coefficients and of marginal effects are consistent with LPM ones. Again, all the interaction terms have coefficients of the expected sign and are statistically significant. In fact, statistical significance of Probit results (both for pooled data and for random effects) is greater than for LPM. We note, however, that standard errors in random effects Probit are not clustered by region and thus the statistical significance of the marginal effects is likely to be significantly overestimated. In terms of the size of marginal effects, Probit results for pooled data are similar to those for LPM but random effects Probit estimates appear to be considerably larger than for other estimation methods.

The effects of institutional quality on the allocation of talent are not only statistically significant but also substantial numerically. For example, according to the LPM marginal effect estimates of the regression with $STEM_i$ as the dependent variable (column 4 of Table 10), one standard deviation improvement of institutional quality increases the probability that the individuals with USE score of 80 would choose STEM discipline rather than any other subject by about 0.032. Given that about 28% of the people with USE scores between 75 and 85 in our data choose to enroll in STEM disciplines, this represents a more than 10% increase in the probability of enrollment in STEM. At the USE score of 90 the effect is considerably stronger. One standard deviation increase in institutional quality increases the probability of matriculating in a STEM discipline by about 0.042 while the proportion of those with USE scores between 85 and 95 who enroll in STEM is only 0.204. One standard deviation worsening of institutional quality raises the probability that a person with USE score around 80 would enroll in law or public administration by almost 0.01, which is a considerable change given that the propensity of a person with such USE scores to take up law or public administration is only 0.077.

The above empirical analysis using both aggregate and individual data provides strong empirical support for our theory. In particular, Russian high school graduates of higher ability are sensitive to the quality of regional institutions while selecting their fields of study and the direction of the observed impact of institutional quality on the allocation of talent agrees with what the theory predicts. Furthermore, by using individual data we could estimate full marginal effect of institutional quality on the allocation of talent, conditional on the talent level. Such marginal effects are statistically significant, and, in agreement with the theory, steadily grow in magnitude as the talent level rises.

IV.4. Robustness checks: using alternative institutional quality measures and accounting for migration

The strong results for Russia's regions obtained above are based on comparing either STEM or law and public administration disciplines to all others or to each other. Are there any other broadly defined disciplines that might exhibit relationships to institutional quality that would be similarly strong but not supported by the theory? As such a placebo test, we ran regressions (14) for all other disciplines with more than 100,000 matriculants. These disciplines were Agricultural Studies, Economics and Management, Education, Health, Humanities and Social Sciences. None of these five disciplines exhibited statistically significant marginal effects for USE scores of 60 and above (recall that USE average is slightly above 60). This suggests that the institutional quality does not strongly impact the allocation for the disciplines the payoffs to which do not significantly depend on institutions.

So far in the regressions in this section have been based on one measure of institutional quality – regional investment risk index. We chose this measure to a large extent because it is available for most regions and for all years in our sample. In addition, this indicator is broad, taking into account sociological, ecological, government effectiveness, and criminological aspects of regional environment. However, this measure might be too broad, because it also incorporates economic trends and financial situation of regional government and private enterprises. Even though we control for regional per capita output, this might not entirely separate the effects of economic development from institutional quality per se within the index. As a robustness check of our results, we use other measures of institutional quality, namely those based on BEEPS and a corruption index from FOM.[20] The results based on these other measures are generally weaker in terms of statistical significance, but none of them contradicts the results based on the investment risk index. The weaker statistical significance of these indicators is not surprising given that BEEPS survey data are available only for 2011 and 2012 while FOM index exists only for 2011. Also, we cluster errors by regions and BEEPS data are available only for 34 of our regions. There are also questions about the regional representativeness of the BEEPS samples.

The small number of regions and years of coverage are particularly problematic for estimates based on aggregate data. The only institutional quality indicator from BEEPS that yields statistically significant results for aggregate data is based on the answers of firm managers to a question about the degree to which obtaining business licenses presents obstacles to doing business. The answers are given on an ordinal scale from 1 to 4, with 1 being no obstacle and 4 denoting a severe obstacle. That is, institutional quality of the region is inversely related to the value of the indicator. As Table 13 shows, the results based on the entire sample of matriculants are statistically insignificant, but the

[20] See Baranov et al. (2015) for a description of other institutional quality measures.

estimates for upper percentiles of the distribution of USE scores are mostly statistically significant and have the signs supporting the predictions of our model.[21]

The results for alternative institutional quality indicators strengthen somewhat when we use individual-level data. Here, at least some of the marginal effects of institutional become statistically significant not only for business licensing, but also for courts as an obstacle to doing business (see Table 14).[22] In addition, as shown in Table 15, most of marginal effects estimates based on the corruption measure from FOM are also statistically significant and confirm our model's predictions.[23]

As noted earlier, one could argue that a university graduate could be pursuing his/her trade in a region other than where the university is located, and, therefore, the possibility of migration of university graduates after graduation to another Russian region (or perhaps abroad) is a source of noise in our data. Moreover, if the relationship between migration rates and regional institutions is systematic, this could introduce biases in our estimates. To address such concerns, we use the data collected by the Russian Ministry of Education and Science on migration of university graduates out of the region of graduation in 2014 (http://graduate.edu.ru/).[24] According to the available data, for most of the regions such migration is mostly in the 10%-35% range.

One way to account for migration of graduates is to estimate the marginal effects of institutional quality on the choice of discipline depending on the scale of outmigration using the following regression models for, respectively, aggregate and individual data:

$$AoT_j = \beta_o + \beta_1 IQ_j + \beta_3 STAY_j + \beta_4 IQ_J \times STAY_j + \beta_5 X_j + \varepsilon_j, \qquad (15)$$

$$DISC\_CHOICE_i = \beta_0 + \beta_1 USE_i + \beta_2 IQ_j + \beta_3 STAY_j + \beta_4 USE_i \times IQ_j + \beta_5 USE_i \times STAY_j + \beta_6 IQ_j \times STAY_j + \beta_7 USE_i \times IQ_j \times STAY_j + \gamma X_j + \varepsilon_i \qquad (16)$$

where $STAY_j$ is the share of graduates staying in the region. Estimation results for aggregate regional data are presented in Tables 16-17 and for individual data in Table 18. The results show that such marginal effects are significant at high USE scores and proportions of graduates staying in the region, and tend to rise in magnitude in the percentage of graduates staying in the region, which agrees with our conjectures about the impact of institutions on the allocation of talent. That is, accounting for

[21] The Table contains pooled OLS estimates. Random effects are similar but with somewhat lower statistical significance presumably due to the small number of observations.

[22] This indicator is also based on the answers of firm managers on a 1 to 4 scale with 1 being no obstacle and 4 meaning severe obstacle.

[23] This measure is based on a survey of 54,400 respondents conducted in 74 regions in February 2011. The index reflects the percentage of respondents who gave a positive answer to the question "Have you personally in the last year or two encountered a state official who asked or expected from you an unofficial side payment for his/her service?"

[24] Ideally, we would need the interregional migration data broken down by discipline. Unfortunately, we do not have such data.

migration leaves intact our findings of the impact of talent on the full marginal effect of institutions, and hence Russian regional data continue to support our theory once migration of university graduates is factored in.

V. Concluding comments

Institutions affect economic behavior, and long-term investment decisions are particularly sensitive to the institutional quality. Insecure property rights, a weak rule of law, and excessive red-tape elevate investment risks and suppress physical capital accumulation. We show that institutions also strongly affect investments in human capital and hence the allocation of talent. Market-supporting institutions attract talents to productive activities, and this is reflected in the choices of fields of study by university students, many of whom select STEM disciplines. Poor institutions, on the other hand, make rent-seeking and other kinds of redistribution more attractive than socially productive activities, and this causes higher enrollment in law, public administration, and similar educational programs.

Pritchett (2001) invoked the famous metaphor of North (1990) that piracy and chemical manufacturing alike could benefit from education, to illustrate the hypothesis that social returns to education could be negligible or even negative, if the acquired knowledge and skills are applied for socially unproductive purposes. More specifically, human capital accumulation is driven by private returns and as such is much less sensitive to institutional quality than its allocation between productive and unproductive activities, which affects public returns to human capital. Education is usually expected to generate positive externalities ranging from increased productivity and adoption of new technologies to improved democratic participation. However, inadequate institutions may cause *negative* educational externalities with rent-seeking as the medium.

This paper contributes to the debates in the literature over relative significance of human capital and institutions by providing direct evidence of the complementarity between institutions and education, based on the allocation of talent. Our results confirm the general dictum that higher quality institutions and policies are essential for making proper use of factors of production, including investments in human capital. Furthermore, we find that poor institutions cause deeper distortions of talent allocation among higher ability individuals. As Murphy et al. (1991) demonstrated, this exacerbates damage to economic growth and welfare, since the best and the brightest are deflected from productive activities, including key entrepreneurial and managerial positions, and drawn instead into redistribution.

Our main results are based on the data from Russia’s regions. High level of education is usually considered as one of Russia’s comparative advantages and a possible driver of economic growth at a time when natural resources are devalued by low commodity prices and access to capital, both domestic and foreign, is limited. Our analysis implies that human capital can substantially contribute to economic growth only if institutional reforms are implemented, securing property rights and otherwise rewarding productive activities – otherwise human capital in Russia will continue to be misallocated in the activities where its contribution to growth and welfare is insignificant at best. Without improving its institutions Russia is not likely to be able to make full use of post-secondary education and other investments in human capital as drivers of economic growth.

REFERENCES

Acemoglu, Daron, "Reward Structures and the Allocation of Talent," *European Economic Review,* **39** (1995), 17–33.

Acemoglu, Daron, Simon Johnson and James Robinson, "The Colonial Origins of Comparative Development: An Empirical Investigation," *The American Economic Review,* **91** (2001), 1369–1401.

Alesina, Alberto, Arnaud Devleeschauwer, William Easterly, Sergio Kurlat, and RomainWacziarg "Fractionalization," *Journal of Economic Growth,* **8** (2003), 155–194.

Arruñada, Benito, "Pitfalls to Avoid when Measuring Institutions: Is 'Doing Business' Damaging Business?", *Journal of Comparative Economics,* **35** (2007), 729-747.

Albouy, David. "The Colonial Origins of Comparative Development: An Empirical Investigation: Comment." American Economic Review, **102** (2012), 3059-76.

Baranov Alexey, Malkov Egor, Polischuk Leonid, Rochlitz Michael, Syunyaev Georgiy. "How (not) to measure Russian regional institutions," *Russian Journal of Economics*. **1**, 2015, 154-181.

Barro, Robert, and Jong-Wha Lee, "Schooling Quality in a Cross-Section of Countries," *Economica,* **38** (2001), 465–488.

Baumol, William, "Entrepreneurship: Productive, Unproductive, and Destructive," *Journal of Political Economy*, **98** (1990), 893-921.

Bell, Andrew, and Kelvyn Jones, "Explaining Fixed Effects: Random Effects Modeling of Time-Series Cross-Sectional and Panel Data," *Political Science Research and Methods*, **3** (2015), 133–153.

Besley, Timothy, and Torsten Persson, *Pillars of Prosperity: The Political Economics of Development Clusters*, (Princeton: Princeton University Press, 2011).

Brumm, Harold, "Rent Seeking and Economic Growth: Evidence from the States," *Cato Journal,* **19** (1999), 7-16.

De Soto, Hernando, *The Other Path.* New York, Harper and Row, 1989.

Dezalay, Yves and Brian Garth. "Law. Lawyers, and Social Capital: "Rule of Law Versus Relational Capitalism" *Social & Legal Studies,* **6** (1997), 109-141.

Glaeser, E. L., R. La Porta, F. Lopez-de-Silanes, and A. Shleifer. "Do Institutions Cause Growth?" *Journal of Economic Growth* **9** (2004),271-303.Grossman, Herschel, "Production, Appropriation, and Land Reform," *The American Economic Review*, **84** (1994), 705–712.

Grossman, Herschel and Minseong Kim, "Swords or Plowshares? A Theory of the Security of Claims to Property", *Journal of Political Economy*, **103** (1995), 1275-1288.

Hadfield, Gillian. "Don't Forget the Lawyers: The Role of Lawyers in Promoting the Rule of Law in Emerging Market Democracies," *DePaul Law Review,* **56** (2007), 401-421.

Kaufmann, Daniel, Aart Kraay and Massimo Mastruzzi, “The Worldwide Governance Indicators: A Summary of Methodology, Data and Analytical Issues,” *World Bank Policy Research No.4978* (2010).

Laband, David, and John Sophocleus. “The Social Cost of rent-seeking: First Estimates.” *Public Choice,* **58** (1988), 269-275.

Lancaster, Tony. “The incidental parameters problem since 1948,” *Journal of Econometrics*, **95** (2000), 391-413.

La Porta, Rafael, Florencio Lopez-de-Silanes and Andrei Shelifer, “The Economic Consequences of Legal Origins,” *Journal of Economic Literature,* **46** (2008), 285–332

Levchenko, Andrei, “Institutional Quality and International Trade,” *Review of Economic Studies,* **74** (2007), 791–819.

Mariani, Fabio, “Migration as an antidote to rent-seeking?” *Journal of Development Economics*, **84** (2007), 609-630.

Mehlum, Halvor, Karl Moene, and Ragnar Torvik, “Predator or Prey? Parasitic Enterprises in Economic Development,” *European Economic Review,* **47** (2003), 275–294

Mehlum, Halvor, Karl Moene, and Ragnar Torvik, “Institutions and the Resource Curse,” *Economic Journal,* **116** (2006), 1–20.

Miller, Terry and Kim Holmes, *Index of Economic Freedom,* (Washington DC: The Heritage Foundation and Dow Jones & Co., Inc., 2010).

Mundlak, Yair, “Pooling of Time-series and Cross-section Data,” *Econometrica* **46** (1978), 69–85.

Murphy, Kevin, Andrei Shleifer and Robert Vishny, “The Allocation of Talent: Implication for Growth,” *Quarterly Journal of Economics*, **113** (1991), 503–531

Murphy, Kevin, Andrei Shleifer and Robert Vishny, “Why Is Rent Seeking So Costly to Growth?” *American Economic Review Papers and Proceedings,* **83** (1993), 409–414.

Nunn, Nathan, “Relationship-Specificity, Incomplete Contracts, and the Pattern of Trade,” *Quarterly Journal of Economics*, **122** (2007), 569–600.

North, Douglass, *Institutions, Institutional Change, and Economic Performance*, (Cambridge: Cambridge University Press, 1990).

Persson, Torsten and Guido Tabellini, *Political Economics*, (Cambridge, MA: MIT Press, 2000).

Polishchuk, Leonid, “Institutional Performance,” In: M. Alexeev, Sh. Weber (eds.) *Handbook of Russian Economy*, (Oxford: Oxford University Press, 2013), 189-220.

Polishchuk, Leonid, and Alexei Savvateev, “Spontaneous (Non)emergence of Property Rights,” *Economics of Transition,* **12** (2004), 103–127

Polishchuk, Leonid, and Alexander Tonis, “Endogenous Contest Success Functions: a Mechanism Design Approach,” *Economic Theory,* **4** (2011).

Pritchett, Lant, "Where Has All the Education Gone?" *The World Bank Economic Review,* **15** (2001), 367–391.

Regiony Rossii, various years. *Regiony Rossii: sotsial'no-ekonomicheskie pokazateli*, available at http://www.gks.ru/wps/wcm/connect/rosstat/rosstatsite/main/publishing/catalog/statisticCollections/doc_1138623506156 .

Rodrik, Dani, Arvind Subramanian and Francesco Trebbi, "Institutions Rule: the Primacy of Institutions over Geography and Integration in Economic Development," *Journal of Economic Growth*, **9** (2004), 131–165.

Snyder, Richard. "Scaling down: The subnational comparative method," *Studies in Comparative International Development*, **36** (2001), 93–110.

Solow, Robert "A Contribution to the Theory of Economic Growth," *Quarterly Journal of Economics*, **70** (1956), 65–94.

Tollison, Robert, "Rent Seeking: A Survey," *Kyklos,* **35** (1982), 575-602.

Tullock, Gordon, "Efficient Rent-Seeking," in *Toward a Theory of the Rent-Seeking Society,* J. Buchanan, J. Tollison, and G. Tullock eds. (College Station: Texas A&M University Press, 1980).

TABLES

Table 1. Descriptive Cross-Country Statistics

	All countries	Strong institution countries	Weak institution countries	Data Source
	(1)	(2)	(3)	(4)
A. Allocation of talent measures				
Share of Law graduates, %	6.22	4.21	8.2 7	UNESCO Educational Statistics http://www.uis.unesco.org
	(4.90)	(2.90)	(5.66)	
Share of Science graduates, %	8.30	9.72	6.84	
	(4.63)	(4.92)	(3.85)	
Difference between shares of law and science graduates, %	-2.08	-5.52	1.43	
	(7.15)	(5.90)	(6.64)	
B. Institutional quality indexes				
Rule of Law, average index for 2000-2005	0.13	1.00	-0.74	
	(1.01)	(0.63)	(0.36)	Governance Matters Database, info.worldbank.org
Government Effectiveness, average index for 2000-2005	0.25	1.09	-0.59	
	(1.02)	(0.71)	(0.39)	
Control of Corruption, average index for 2000-2005	0.19	1.03	-0.68	
	(1.05)	(0.79)	(0.37)	
Private Property Protection, average index for 2000-2005	3.5	4.25	2.7	
	(1.13)	(0.81)	(0.82)	
C. Controls and instruments				
GDP per capita, PPP, in 2005 dollars	15064	24 597	5 329	World Development Indicators (WDI), data.worldbank.org
	(13 873)	(13 378)	(4 337)	
Average GDP growth rate per capita, 1990-2010, %	2.03	2.07	2.08	
	(1.57)	(1.00)	(1.98)	
Tertiary education, gross enrollment ratio, %	40.8	55.3	26.0	
	(27.9)	(23.3)	(24.2)	
Services, value added, % GDP	59.0	66.4	51.6	WDI
	(14.0)	(11.3)	(12.5)	
Government expenditure, % GDP	16.6	18.5	14.5	WDI
	(5.7)	(4.2)	(6.5)	

Oil reserves, proved reserves of crude oil in million barrels	10 346	9 983	10 716	CIA World Factbook
	(38 457)	(45 281)	(30 445)	
Ethnolinguistic fractionalization index	0.39	0.30	0.47	Alesina et. al (2003)
	(0.25)	(0.21)	(0.25)	
Gini index	0.39	0.33	0.45	WDI
	(0.10)	(0.07)	(0.08)	
Trade (exports plus imports), % GDP	0.90	1.03	0.76	WDI
	(0.54)	(0.64)	(0.37)	
Emigration rate of tertiary educated, %	14.1	12.7	15.6	WDI
	(13.8)	(11.4)	(15.9)	
Log Population	16.2	15.9	16.5	WDI
	(1.5)	(1.5)	(1.4)	
French Legal Origin	0.43	0.31	0.57	La Porta et al, (2008)
	(0.49)	(0.47)	(0.49)	
Observations	95	48	47	

Notes: Mean values of main variables with standard deviations in parentheses. Values of GDP per capita, Tertiary Schooling, Services, Oil reserves, Gini, Government Expenditures, Trade and Population are for 2009. Emigration data are for 2000. Average GDP Growth data are from the last update of Penn World Tables 7.1. Tertiary education and change in tertiary education data are from the Barro-Lee dataset.

Table 2. OLS Regressions for Share of Law School Graduates

	Dependent variable: *Share of Law graduates*								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Rule of Law	-0.380***	-0.530***	-0.589***	-0.578***	-0.581***	-0.563***	-0.486***	-0.580***	-0.466***
	(0.100)	(0.161)	(0.172)	(0.168)	(0.171)	(0.170)	(0.168)	(0.207)	(0.119)
Log GDP per capita		0.218	0.218	0.207	0.232	0.0571	0.157	0.152	-0.0461
		(0.170)	(0.167)	(0.174)	(0.181)	(0.194)	(0.220)	(0.321)	(0.128)
School Tertiary		-0.335	-0.422	-0.433	-0.366	-0.0516	-0.581	-0.0209	0.609*
		(0.516)	(0.471)	(0.471)	(0.481)	(0.461)	(0.514)	(0.566)	(0.359)
Services, % of GDP			0.777	0.837	0.776	1.500	1.466	0.197	1.770**
			(1.014)	(1.040)	(1.053)	(1.060)	(1.046)	(1.392)	(0.832)
Log (1+Oil reserves)				0.00545	-2.57e-05	0.0626**	0.0542	0.0388	0.0575**
				(0.0259)	(0.0255)	(0.0307)	(0.0375)	(0.0450)	(0.0238)
Ethnic Fractionalization					0.285	0.327	0.286	0.352	-0.116
					(0.542)	(0.509)	(0.503)	(0.515)	(0.342)
Log Populaion						-0.219***	-0.357***	-0.335***	-0.178***
						(0.0779)	(0.0886)	(0.106)	(0.0596)
Gini coefficient							0.925	0.648	
							(0.0134)	(1.314)	
Trade to GDP ratio							-0.526**	-0.351	
							(0.00228)	(0.240)	
Emigration rate of tertiary educated, %								-0.00199	
								(0.0132)	
Government expenditure, % GDP								0.0285	
								(0.0254)	
French Legal Origin =1								0.522*	
								(0.295)	
R&D spending, % GDP								0.136	
								(0.142)	
Export of manufactured products, % total export								-0.152	
								(0.537)	
Constant	0.109	-1.707	-2.123	-2.072	-2.379	1.947	3.726	3.210	1.749
	(0.105)	(1.362)	(1.319)	(1.337)	(1.470)	(2.125)	(2.658)	(3.882)	(1.571)
Observations	95	95	95	95	95	95	81	72	87
R-squared	0.145	0.165	0.171	0.171	0.175	0.230	0.322	0.400	0.278

Notes: Robust standard errors are in parentheses; *** p<0.01, ** p<0.05, * p<0. Columns (1) through (8) report estimations of model (6) with different sets of control variables, and column (9) – with excluded outliers. The regression coefficients reported for Rule of Law index are standardized beta coefficients.

Table 3. OLS Regressions for Share of Science Graduates

	Dependent variable: *Share of Science graduates*								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Rule of Law	0.234***	0.257***	0.205*	0.258**	0.258**	0.252**	0.262**	0.353**	0.326***
	(0.0740)	(0.0970)	(0.106)	(0.120)	(0.120)	(0.118)	(0.117)	(0.143)	(0.0919)
Log GDP percapita		0.194	0.194	0.134	0.137	0.191	0.250	0.120	-0.000884
		(0.137)	(0.132)	(0.142)	(0.148)	(0.148)	(0.179)	(0.206)	(0.110)
School Tertiary		-1.261**	-1.339**	-1.395**	-1.386**	-1.482***	-1.179**	-0.966	-0.470
		(0.565)	(0.574)	(0.574)	(0.563)	(0.558)	(0.495)	(0.607)	(0.293)
Services, % GDP			0.700	1.020	1.012	0.789	0.235	0.577	-0.0459
			(0.744)	(0.714)	(0.707)	(0.746)	(0.736)	(1.148)	(0.599)
Log Oil reserves				0.0289	0.0281	0.00887	-0.0119	-0.00170	0.00421
				(0.0211)	(0.0226)	(0.0272)	(0.0286)	(0.0369)	(0.0214)
Ethnic Fractionalization					0.0378	0.0249	0.493	0.213	0.125
					(0.356)	(0.360)	(0.380)	(0.402)	(0.291)
Log Populaion						0.0674	0.114**	0.0915	0.0773*
						(0.0530)	(0.0509)	(0.0956)	(0.0425)
Gini coefficient							-0.0210	-0.0812	
							(0.845)	(0.985)	
Trade to GDP ratio							0.289	0.413	
							(0.248)	(0.337)	
Emigration rate of tertiary educated, %								0.00423	
								(0.00873)	
Government expenditure, % GDP								-0.0265	
								(0.0205)	
French Legal Origin =1								0.0979	
								(0.198)	
R&D spending, % GDP								0.0207	
								(0.138)	
Export of manufactured products, % total export								0.112	
								(0.492)	
Constant	-0.240***	-1.487	-1.861	-1.594	-1.635	-2.964*	-4.487**	-2.963	-1.453
	(0.0718)	(1.044)	(1.141)	(1.211)	(1.307)	(1.544)	(1.935)	(2.738)	(1.349)
Observations	95	95	95	95	95	95	81	72	90
R-squared	0.102	0.199	0.208	0.223	0.223	0.233	0.339	0.410	0.211

Notes: Robust standard errors are in parentheses; *** p<0.01, ** p<0.05, * p<0. Columns (1) through (8) report estimations of model (6) with different sets of control variables, and column (9) – with excluded outliers.

Table 4. OLS Regressions for Difference between Shares of Law School and Science Graduates

	Dependent variable: *Difference between Shares of Law and Science graduates*			
	(1)	(2)	(3)	(4)
Rule of Law	-0.552***			
	(0.146)			
Government Effectiveness		-0.387**		
		(0.152)		
Control for Corruption			-0.383***	
			(0.117)	
Private Property Protection				-0.294**
				(0.133)
Log GDP percapita	-0.116	-0.188	-0.228	-0.339*
	(0.170)	(0.188)	(0.164)	(0.187)
School Tertiary	1.152**	1.153**	1.140**	1.013
	(0.561)	(0.575)	(0.569)	(0.696)
Services, % GDP	0.298	0.0628	0.218	0.101
	(0.873)	(0.941)	(0.890)	(0.971)
Log Oil reserves	0.0318	0.0440	0.0520*	0.0589**
	(0.0307)	(0.0306)	(0.0302)	(0.0295)
Ethnic Fractionalization	0.182	0.236	0.144	0.0169
	(0.421)	(0.432)	(0.435)	(0.518)
Log Populaion	-0.190***	-0.179**	-0.208***	-0.219***
	(0.0671)	(0.0682)	(0.0658)	(0.0739)
Constant	3.487*	4.060*	4.777**	7.135***
	(1.994)	(2.127)	(1.848)	(1.995)
Observations	95	95	95	83
R-squared	0.310	0.246	0.266	0.301

Notes: Robust standard errors are in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Columns (1) through (4) report estimations of model (6) with different institutional quality indexes. The regression coefficients reported for institutional quality indices are standardized beta coefficients.

Table 5. OLS Regressions for the Economies in Transition

	Share of Law Graduates	*Share of Science Graduates*	*Difference between Shares of Law and Science graduates*
	(1)	(2)	(3)
Rule of Law	-0.735**	0.571***	-0.912***
	(0.307)	(0.129)	(0.148)
Log of GDP per capita	-0.286	0.320**	-0.432**
	(0.313)	(0.146)	(0.158)
School Tertiary	0.399	-1.477***	1.421***
	(0.892)	(0.427)	(0.398)
Services, % of GDP	3.992*	-1.845**	3.946***
	(2.099)	(0.819)	(0.973)
Log of Oil reserves	0.0303	0.0490	-0.0205
	(0.0895)	(0.0504)	(0.0486)
Ethnic fractionalization	-0.554	2.224***	-2.127***
	(1.160)	(0.549)	(0.607)
Log of Populaion	-0.246	0.148	-0.271*
	(0.227)	(0.130)	(0.130)
Constant	4.181	-4.827*	6.363**
	(5.001)	(2.596)	(2.404)
Observations	20	20	20
R-squared	0.601	0.735	0.833

Notes: Robust standard errors are in parentheses; *** $p<0.01$, ** $p<0.05$, * $p<0.1$. The regression coefficients reported for Rule of Law index are standardized beta coefficients.

Table 6. Description of Russian Regional Variables and Sources

Variable	Description
Unified State Examination (USE) score	Individual USE scores for students matriculating in various disciplines at almost all Russian universities. These data are combined with the discipline of the matriculant and the location of the university. Source: National Research University Higher School of Economics under the “Monitoring of quality of higher education enrollment” project
Per capita GRP	Per capita GRP in thousands of year 2000 rubles (deflated by GDP deflator). Source: Regiony Rossii, various years and authors calculations
Share of manufacturing	Share (in percent) of manufacturing in value added in the region. Source: Regiony Rossii for 2014.
Share of mining	Share (in percent) of mining in value added in the region. Source: Regiony Rossii for 2014.
Share of state administration	Share (in percent) of state administration in value added in the region. Source: Regiony Rossii for 2014.
Investment risk index	Composite investment risk ratings of Russia’s regions. Higher value of the index indicates higher investment risk. In the regressions we invert this index by subtracting its value from unity. Source: http://www.raexpert.ru/ratings/regions/
Average January temperature	Average temperature (C^0) in January. Source: RSE (2012).

Table 7. Descriptive Statistics for Russian Regions

	Mean	Standard deviation	Minimum	Maximum	No. of obs.
Per capita GRP (thousand 2000 RR)	56.63	45.61	13.69	350.42	307
Population	1,545,700	1,097,787	148,105	5,453,908	307
Investment risk index	0.297	0.088	0.147	.616	307
Average January temperature (C^0)	-13.39	7.35	-36.5	-0.1	307
Share of graduates staying the region after graduation	.701	.104	.323	.918	307
Share of manufacturing in value added (%)	17.80	10.07	1.2	41.3	307
Share of mining in value added (%)	8.46	13.59	0	67.9	307
Share of state administration in value added (%)	8.45	4.49	1.7	28.5	307
EGE scores for engineering and sciences matriculants	60.48	11.65	26.3	100	421,831
EGE scores for law and public administration matriculants	65.35	12.58	28.2	100	108,594
Share of matriculants in engineering and sciences	0.328	0.093	0.049	0.601	307
Share of matriculants in law and public administration	0.071	0.040	0.0	0.322	307
Relative difference in the above shares	0.623	0.234	-0.545	1	307

Table 8. Relationship between shares of STEM and LAW matriculants and institutional quality ("within-between" random effects model; aggregate data)

	$STEM$	LAW	$STEM$	LAW	$STEM$	LAW
	Entire sample	Entire sample	Top 25%	Top 25%	Top 10%	Top 10%
	(1)	(2)	(3)	(4)	(5)	(6)
Inverse investment risk index (mean)	.297 (.220)	-.138# (.090)	.313 (.231)	-.293** (.129)	.441** (.218)	-.226# (.140)
Inverse investment risk index (deviation)	.246* (.137)	.082 (.075)	-.027 (.178)	.062 (.097)	-.152 (.212)	.161 (.145)
Number of observations^	309	309	309	308	308	308
Number of regions	78	78	78	78	78	78
R-squared (within)	.058	.158	.093	.040	.113	.043
R-squared (between)	.207	.283	.220	.283	.226	.211

Notes: All regressions include year fixed effects and a number of control variables;
Robust standard errors clustered by region are in parentheses;
*** -- significant at 1% level; ** -- significant at 5% level; * - significant at 10% level; # - significant at 15% level
^ -- we do not have USE data on one of the regions (Altai Republic) for 2014 and thus have only 263 observations for the regressions that contain USE percentile data

Table 9. Relationship between differences in shares of STEM and LAW matriculants and institutional quality ("within-between" random effects model; aggregate data)

	$STEM - LAW$	$\frac{STEM - LAW}{STEM + LAW}$	$STEM - LAW$	$\frac{STEM - LAW}{STEM + LAW}$	$STEM - LAW$	$\frac{STEM - LAW}{STEM + LAW}$
	Entire sample	Entire sample	Top 25%	Top 25%	Top 10%	Top 10%
	(1)	(2)	(3)	(4)	(5)	(6)
Inverse investment risk index (mean)	.439# (.299)	1.14# (.764)	.614* (.319)	1.90** (.894)	.659** (.275)	2.59*** (.963)
Inverse investment risk index (deviation)	.197 (.184)	.042 (.424)	-.009 (.228)	.273 (.662)	-.222 (.264)	.282 (.895)
Number of observations^	309	309	308	308	308	308
Number of regions	78	78	78	78	78	78
R-squared (within)	.114	.140	.089	.094	.114	.067
R-squared (between)	.240	.302	.251	.406	.253	.283

Notes: All regressions include year fixed effects and a number of control variables;
Robust standard errors clustered by region are in parentheses;
*** -- significant at 1% level; ** -- significant at 5% level; * - significant at 10% level; # - significant at 15% level
^ -- we do not have USE data on one of the regions (Altai Republic) for 2014 and thus have only 263 observations for the regressions that contain USE percentile data

Table 10. LPM regressions for individual data (fixed effects and WB estimator)

	Fixed effects			"within-between" RE estimator		
Dependent variable:	$STEM$	LAW	$STEM\_LAW$	$STEM$	LAW	$STEM\_LAW$
	(1)	(2)	(3)	(4)	(5)	(6)
USE_i score	-.014*** (.003)	.004** (.002)	-.020*** (.005)	-.014*** (.003)	.004** (.002)	-.020*** (.006)
IQ_j	-.735** (.306)	.229# (.154)	-1.25*** (.450)	-.736** (.305)	.230# (.153)	-1.25*** (.449)
$USE_i \times IQ_j$	.015*** (.004)	-.005* (.002)	.023*** (.007)	.015*** (.004)	-.005** (.002)	.023*** (.007)
Marginal effect of IQ_j at $USE_i = 70$	.305* (.176)	-.091 (.068)	.387** (.193)	.304* (.175)	-.089 (.067)	.384** (.190)
Marginal effect of IQ_j at $USE_i = 80$	.453** (.192)	-.137* (.079)	.620*** (.237)	.453** (.191)	-.135* (.078)	.618*** (.234)
Marginal effect of IQ_j at $USE_i = 90$	.602*** (.216)	-.182* (.095)	.854*** (.292)	.601*** (.214)	-.180* (.093)	.851*** (.290)
Manufacturing share (means in RE columns)	.0018 (.0016)	.0001 (.0013)	.0003 (.0028)	.004*** (.001)	-.0017*** (.0005)	.006*** (.001)
Mining share (means in RE columns)	.0006 (.0027)	-.0006 (.0013)	.0012 (.0031)	.003** (.001)	-.002** (.001)	.005** (.002)
State administration share (means in RE columns)	.004 (.006)	.0003 (.0027)	-.0017 (.0070)	.008* (.004)	-.0006 (.0019)	.006 (.005)
Log of per capita GRP (means in RE columns)	-.064 (.070)	.060** (.029)	-.161** (.078)	-.035 (.042)	.040** (.019)	-.098* (.055)
Log of population (means in RE columns)	.081 (.252)	-.085 (.134)	.228 (.354)	.049*** (.015)	.001 (.008)	.025 (.023)
Mean January temperature	-	-	-	-.001 (.001)	.0010* (.0006)	-.003# (.002)
R-squared (within)	.007	.002	.013	.007	.002	.013
Number of observations	1,294,019	1,294,019	554,018	1,294,019	1,294,019	554,018
Number of regions	77	77	77	77	77	77

Notes: Standard errors in parentheses are clustered by region;
All regressions include time dummies; WB regressions include deviations from the means of time-varying variables (their coefficients are almost identical to those of fixed effects;
*** -- significant at 1% level; ** -- significant at 5% level; * - significant at 10% level; # - significant at 15% level

Table 11. Pooled OLS regressions (pooled OLS; individual-level data)

Dependent variable:	$STEM$	LAW	$STEM\_LAW$
	(1)	(2)	(3)
USE_i score	-.014*** (.003)	.004** (.002)	-.019*** (.005)
IQ_j	-.634* (.340)	.226# (.153)	-1.07** (.508)
$USE_i \times IQ_j$	.015*** (.004)	-.005** (.002)	.022*** (.008)
Marginal effect of IQ_j at $USE_i = 70$	.404*** (.141)	-.100*** (.037)	.485*** (.129)
Marginal effect of IQ_j at $USE_i = 80$	.552*** (.142)	-.146*** (.043)	.707*** (.166)
Marginal effect of IQ_j at $USE_i = 90$	.700*** (.162)	-.193*** (.057)	.929*** (.233)
Manufacturing share	.0027*** (.0010)	-.0009** (.0004)	.0028** (.0011)
Mining share	.0026** (.0012)	-.0009** (.004)	.0026** (.0011)
State administration share	.001 (.005)	-.0029** (.0014)	-.006 (.004)
Log of per capita GRP	-.056 (.045)	.026* (.014)	-.071* (.040)
Log of population	.033* (.019)	.013** (.006)	-.016 (.017)
Mean January temperature	-.003* (.002)	.0008* (.0005)	-.003* (.002)
R-squared	.013	.005	.022
Number of observations	1,294,019	1,294,019	554,018
Number of regions	77	77	77

Notes: Clustered standard errors are in parentheses;
All regressions include time dummies;
*** -- significant at 1% level; ** -- significant at 5% level; * - significant at 10% level; significant at 15% level

Table 12. Probit regressions for individual data (pooled and random effects)

	Pooled			Random effects		
Dependent variable:	$STEM$	LAW	$STEM\_LAW$	$STEM$	LAW	$STEM\_LAW$
	(1)	(2)	(3)	(4)	(5)	(6)
USE_i score	-.044*** (.010)	.025*** (.009)	-.064*** (.018)	-.045*** (.001)	.025*** (.0015)	-.068*** (.002)
IQ_j	-2.16** (1.00)	1.48# (1.01)	-3.67** (1.82)	-2.46*** (.117)	1.46*** (.162)	-4.20*** (.214)
$USE_i \times IQ_j$	.049*** (.014)	-.029** (.013)	.074*** (.025)	.049*** (.002)	-.028*** (.002)	.077*** (.003)
Marginal effect of IQ_j at $USE_i = 70$	.453*** (.138)	-.077** (.037)	.398*** (.121)	.975*** (.078)	-.469*** (.111)	1.18*** (.139)
Marginal effect of IQ_j at $USE_i = 80$	.603*** (.147)	-.124*** (.041)	.639*** (.152)	1.47*** (.083)	-.745*** (.116)	1.94*** (.147)
Marginal effect of IQ_j at $USE_i = 90$	.737*** (.162)	-.176*** (.054)	.904*** (.207)	1.96*** (.090)	-1.02*** (.124)	2.71*** (.159)
Pseudo R-squared	.010	.010	.024	-	-	-
Number of observations	1,294,019	1,294,019	554,018	1,294,019	1,294,019	554,018
Number of regions	77	77	77	77	77	77

Notes: Standard errors are in parentheses; they are clustered by region in columns (1)-(4);
All regressions have time dummies and our standard set of controls;
*** -- significant at 1% level; ** -- significant at 5% level; * - significant at 10% level; # - significant at 15% level

Table 13. Relationship between the difficulty of obtaining business licenses and the choice of discipline (pooled OLS; aggregate data)

	$STEM$	LAW	$STEM$	LAW	$STEM$	LAW
	Entire sample	Entire sample	Top 25%	Top 25%	Top 10%	Top 10%
	(1)	(2)	(3)	(4)	(5)	(6)
Obtaining business licenses as an obstacle to doing business	-.041 (.041)	.014 (.017)	-.053 (.039)	.041* (.021)	-.056* (.031)	.043** (.021)
R-squared	.377	.370	.314	.405	.346	.356
	$STEM - LAW$	$\frac{STEM - LAW}{STEM + LAW}$	$STEM - LAW$	$\frac{STEM - LAW}{STEM + LAW}$	$STEM - LAW$	$\frac{STEM - LAW}{STEM + LAW}$
	Entire sample	Entire sample	Top 25%	Top 25%	Top 10%	Top 10%
	(7)	(8)	(9)	(10)	(11)	(12)
Obtaining business licenses as an obstacle to doing business	-.055 (.054)	-.096 (.114)	-.094* (.051)	-.224# (.139)	-.099** (.042)	-.303** (.127)
R-squared	.404	.366	.346	.373	.362	.355
Number of observations	61	61	61	61	61	61
Number of regions	34	34	34	34	34	34

Notes: All regressions include year fixed effects and our standard set of control variables;
Robust standard errors clustered by region are in parentheses;
*** -- significant at 1% level; ** -- significant at 5% level; * - significant at 10% level; # - significant at 15% level

Table 14. LPM regressions for BEEPS measures (pooled OLS; 2011-2012; individual-level data)

Institutional quality measure:	Courts as obstacle			Permits as obstacle		
Dependent variable:	$STEM$	LAW	$STEM\_LAW$	$STEM$	LAW	$STEM\_LAW$
	(1)	(2)	(3)	(4)	(5)	(6)
USE_i score	-.001 (.001)	.0003 (.0003)	-.0015* (.0008)	-.0016 (.0014)	-.0002 (.0004)	-.0006 (.0011)
IQ_j	.214** (.086)	-.054 (.040)	.155* (.089)	.099 (.098)	-.064* (.036)	.140# (.094)
$USE_i \times IQ_j$	-.003** (.001)	.001 (.001)	-.0026* (.0015)	-.0017 (.0015)	.0013** (.0006)	-.004* (.002)
Marginal effect of IQ_j at $USE_i = 70$	-.017 (.015)	.007 (.012)	-.028 (.025)	-.018 (.018)	.025** (.010)	-.061** (.026)
Marginal effect of IQ_j at $USE_i = 80$	-.049** (.024)	.016 (.019)	-.055 (.039)	-.035 (.026)	.037** (.015)	-.090** (.038)
Marginal effect of IQ_j at $USE_i = 90$	-.082** (.036)	.025 (.026)	-.081# (.053)	-.052 (.039)	.050** (.020)	-.119** (.052)
R-squared (overall)	.011	.005	.016	.011	.005	.017
Number of observations	364,993	364,993	161,654	364,993	364,993	161,654
Number of regions	34	34	34	34	34	34

Notes: Standard errors clustered by region are in parentheses;
All regressions have several control variables and time dummies;
*** -- significant at 1% level; ** -- significant at 5% level; * - significant at 10% level.

Table 15. LPM and Probit regressions for FOM measure (2011; individual-level data)

	LPM (OLS)			Probit		
Dependent variable:	$STEM$	LAW	$STEM\_LAW$	$STEM$	LAW	$STEM\_LAW$
	(1)	(2)	(3)	(4)	(5)	(6)
USE_i score	-.0000 (.0018)	-.0001 (.0005)	.0015 (.0015)	.0006 (.0049)	.002 (.004)	.001 (.007)
IQ_j	.006 (.006)	-.003# (.002)	.014*** (.005)	.020 (.015)	-.014 (.015)	.041* (.023)
$USE_i \times IQ_j$	-.0002* (.0001)	.0001 (.0000)	-.0003*** (.0001)	-.0005** (.0003)	.0003 (.0002)	-.0009** (.0004)
Marginal effect of IQ_j at $USE_i = 70$	-.005** (.002)	.0014# (.0009)	-.006** (.003)	-.006** (.002)	.001 (.001)	-.005* (.003)
Marginal effect of IQ_j at $USE_i = 80$	-.007** (.003)	.0020* (.0011)	-.009*** (.003)	-.007** (.003)	.0018 (.0013)	-.008** (.004)
Marginal effect of IQ_j at $USE_i = 90$	-.009** (.004)	.0026* (.0014)	-.012*** (.004)	-.009** (.003)	.0025# (.0017)	-.011** (.005)
R-squared/Pseudo R-squared	.017	.007	.030	.013	.014	.035
Number of observations	274,585	274,585	118,075	274,585	274,585	118,075
Number of regions	70	70	70	70	70	70

Notes: Clustered standard errors are in parentheses;

All regressions have several control variables and time dummies;

*** -- significant at 1% level; ** -- significant at 5% level; * - significant at 10% level; # - significant at 15% level

Table 16. Relationship between shares of STEM and LAW matriculants and institutional quality accounting for migration in 2014 (OLS; aggregate data)

Dependent variable	$STEM$	LAW	$STEM$	LAW	$STEM$	LAW
	Entire sample	Entire sample	Top 25%	Top 25%	Top 10%	Top 10%
	(1)	(2)	(3)	(4)	(5)	(6)
Inverse investment risk index (IQ)	-1.23 (1.08)	.357 (.402)	-1.29 (1.02)	.989* (.571)	-.942 (1.04)	.565 (.554)
Share of graduates staying in the region ($STAY$)	-1.41 (1.11)	.293 (.401)	-1.48# (1.02)	1.13** (.544)	-1.19 (1.07)	.675 (.537)
$IQ \times STAY$	1.98 (1.49)	-.456 (.555)	2.04# (1.37)	-1.52* (.801)	1.82 (1.37)	-.890 (.776)
Marginal effect of IQ at $STAY = 0.70$	.156 (.202)	.038 (.080)	.138 (.229)	-.075 (.097)	.332# (.225)	-.058 (.106)
Marginal effect of IQ at $STAY = 0.80$	.355# (.240)	-.007 (.094)	.341 (.247)	-.228* (.130)	.513** (.233)	-.147 (.131)
Marginal effect of IQ at $STAY = 0.90$	.553# (.345)	-.053 (.132)	.545* (.328)	-.379** (.193)	.695** (.309)	-.236 (.187)
Number of observations	77	77	76	76	76	76
R-squared	.170	.178	.179	.213	.155	.127

Notes: All regressions include our standard set of control variables;
Robust standard errors are in parentheses;
*** -- significant at 1% level; ** -- significant at 5% level; * - significant at 10% level; # - significant at 15% level

Table 17. Relationship between shares of STEM and LAW matriculants and institutional quality accounting for migration in 2014 (OLS; aggregate data)

Dependent variable	$STEM - LAW$	$\frac{STEM - LAW}{STEM + LAW}$	$STEM - LAW$	$\frac{STEM - LAW}{STEM + LAW}$	$STEM - LAW$	$\frac{STEM - LAW}{STEM + LAW}$
	Entire sample	Entire sample	Top 25%	Top 25%	Top 10%	Top 10%
	(1)	(2)	(3)	(4)	(5)	(6)
Inverse investment risk index (IQ)	-.671 (.737)	-1.26 (1.55)	-1.30 (.788)	-4.05** (1.88)	-.641 (.905)	-2.34 (2.60)
Share of graduates staying in the region ($STAY$)	-.514 (.768)	-.448 (1.61)	-1.39* (.791)	-4.29** (1.88)	-.792 (.940)	-2.95 (2.65)
$IQ \times STAY$	1.07 (.994)	1.73 (2.16)	2.06** (1.03)	6.31** (2.49)	1.32 (1.17)	4.58 (3.43)
Marginal effect of IQ at $STAY = 0.70$	.081 (.173)	-.050 (.351)	.137 (.197)	.373 (.465)	.285 (.203)	.864# (.559)
Marginal effect of IQ at $STAY = 0.80$	.188 (.189)	.123 (.416)	.343* (.202)	1.00** (.491)	.417** (.200)	1.32** (.572)
Marginal effect of IQ at $STAY = 0.90$	.296 (.247)	.296 (.562)	.549** (.253)	1.64*** (.624)	.549** (.258)	1.78** (.760)
Number of observations	77	77	76	76	76	76
R-squared	.226	.270	.251	.274	.179	.185

Notes: All regressions include year fixed effects and our standard control variables;
Robust standard errors clustered by region are in parentheses;
*** -- significant at 1% level; ** -- significant at 5% level; * - significant at 10% level; # - significant at 15% level

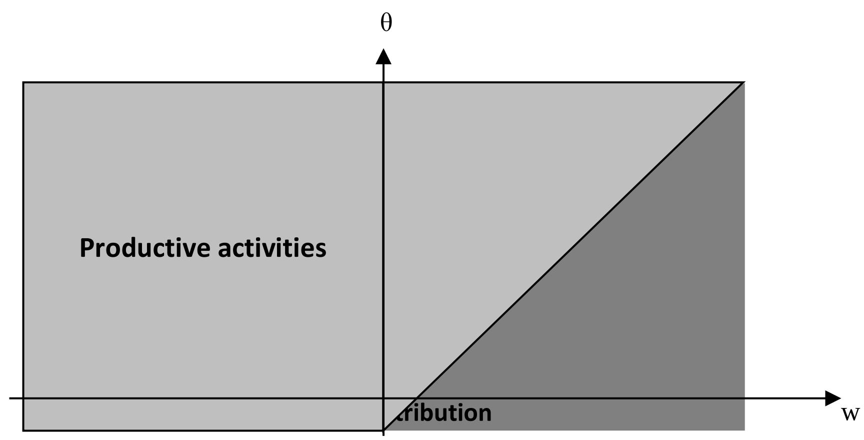
Table 18. Linear probability and Probit models with migration measure (2014 data; individual-level data)

	LPM (OLS)			Probit		
Dependent variable:	$STEM$	LAW	$STEM\_LAW$	$STEM$	LAW	$STEM\_LAW$
	(1)	(2)	(3)	(4)	(5)	(6)
USE_i score	-.002 (.049)	-.017 (.015)	.050 (.056)	.016 (.153)	-.093 (.098)	.144 (.203)
IQ_j	.764 (3.52)	-1.04 (1.19)	3.31 (3.75)	3.42 (10.37)	-5.28 (8.07)	9.76 (14.45)
$STAY_j$	1.55 (3.67)	-1.40 (1.18)	4.72 (3.90)	6.12 (11.00)	-7.88 (7.78)	14.89 (14.86)
$USE_i \times STAY_j$	-.019 (.067)	.026 (.020)	-.088 (.078)	-.094 (.213)	.142 (.127)	-.264 (.279)
$USE_i \times IQ_j$	.002 (.064)	.019 (.020)	-.058 (.074)	-.023 (.200)	.093 (.130)	-.157 (.267)
$IQ_j \times STAY_j$	-1.90 (4.80)	1.56 (1.61)	-5.50 (5.22)	-7.64 (14.37)	8.03 (10.69)	-16.66 (19.88)
$USE_i \times IQ_j \times STAY_j$	.022 (.088)	-.029 (.027)	.103 (.102)	.114 (.279)	-.148 (.169)	.296 (.368)
Marginal effect of IQ_j at $USE_i = 80$ & $STAY_j = .7$	.859*** (.263)	-.063 (.114)	.575* (.317)	.901*** (.265)	-.065 (.106)	.549* (.290)
Marginal effect of IQ_j at $USE_i = 80$ & $STAY_j = .8$	.847*** (.320)	-.139 (.123)	.852** (.413)	.936*** (.353)	-.127 (.110)	.785** (.372)
Marginal effect of IQ_j at $USE_i = 80$& $STAY_j = .9$	.835 (.581)	-.214 (.192)	1.13# (.740)	.969# (.633)	-.200 (.181)	1.04# (.705)
Marginal effect of IQ_j at $USE_i = 90$ & $STAY_j = .7$	1.04*** (.317)	-.077 (.138)	.716* (.381)	1.06*** (.310)	-.078 (.126)	.693** (.350)
Marginal effect of IQ_j at $USE_i = 90$& $STAY_j = .8$	1.05*** (.400)	-.182 (.149)	1.10** (.515)	1.12*** (.429)	-.168 (.135)	1.05** (.473)
Marginal effect of IQ_j at $USE_i = 90$& $STAY_j = .9$	1.06# (.726)	-.286 (.232)	1.48# (.923)	1.17# (.756)	-.281 (.230)	1.44# (.904)
Number of observations	304,619	304,619	131,741	304,619	304,619	131,741
Number of regions	76	76	76	76	76	76
R2/Pseudo R2	.013	.004	.014	.010	.008	.016

Notes: All regressions include our standard control variables;
Robust standard errors clustered by region are in parentheses;
*** -- significant at 1% level; ** -- significant at 5% level; * - significant at 10% level; # - significant at 15% level

FIGURES

a) Strong institutions



b) Weak institutions

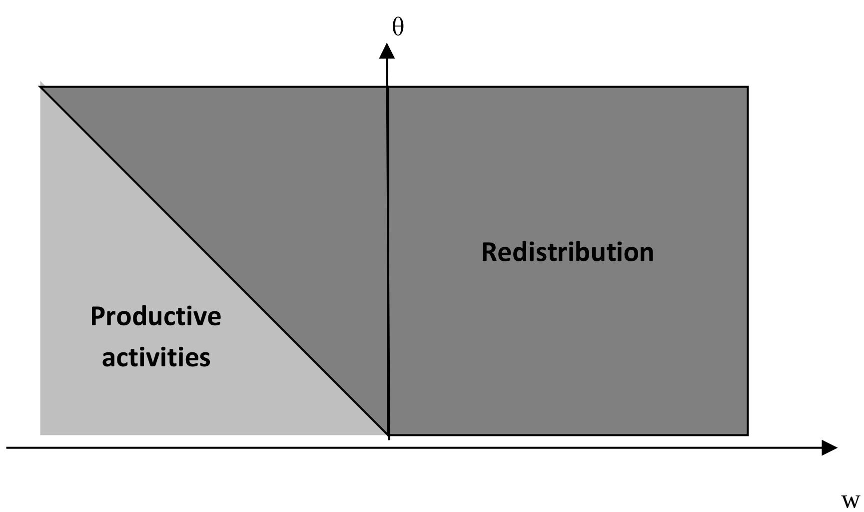


Figure 1.—Allocation of Talent Under Strong (a) and Weak (b) Institutions

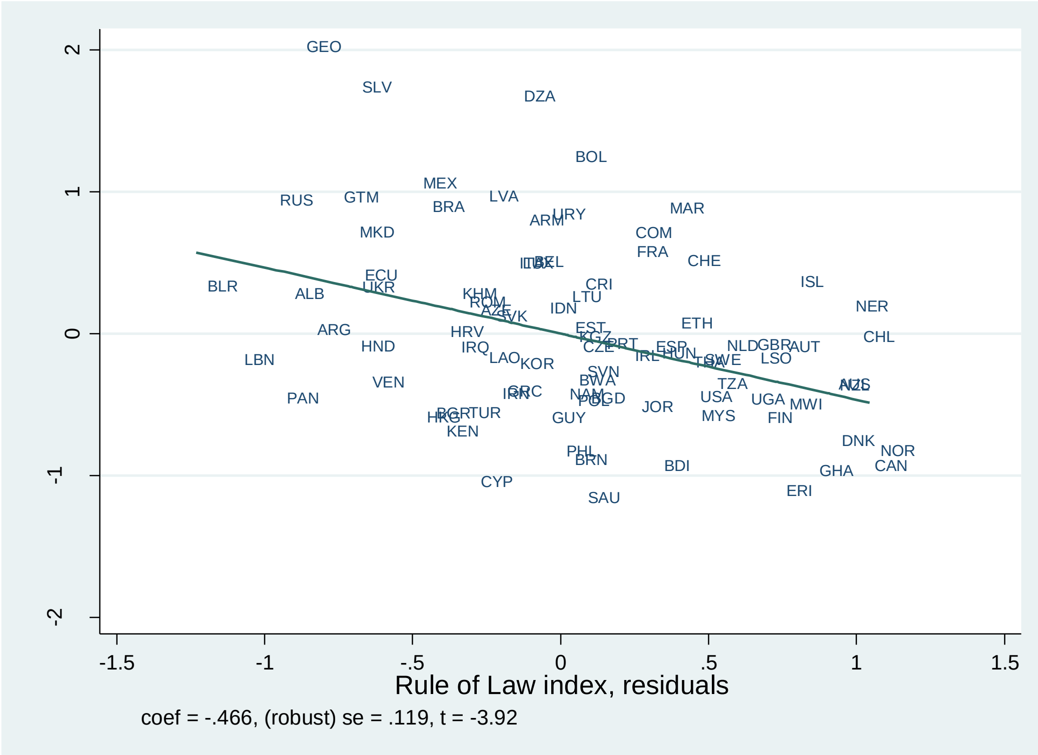


Figure 2. —Quality of Institutions and Graduation in Law

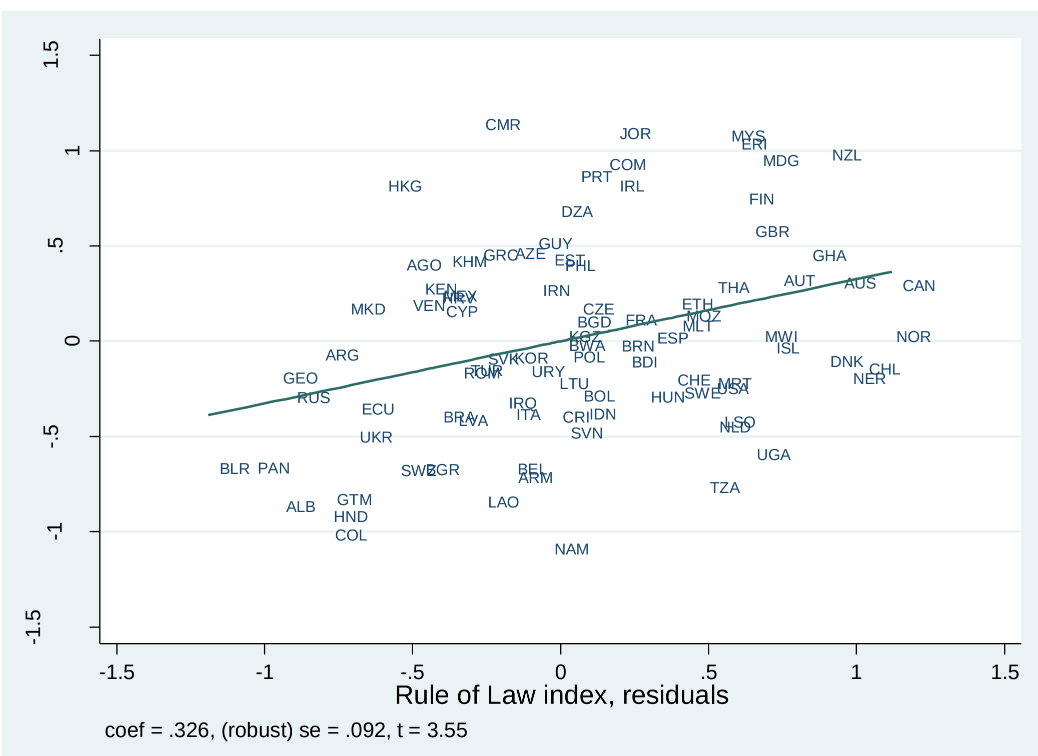


Figure 3. —Quality of Institutions and Graduation in Science

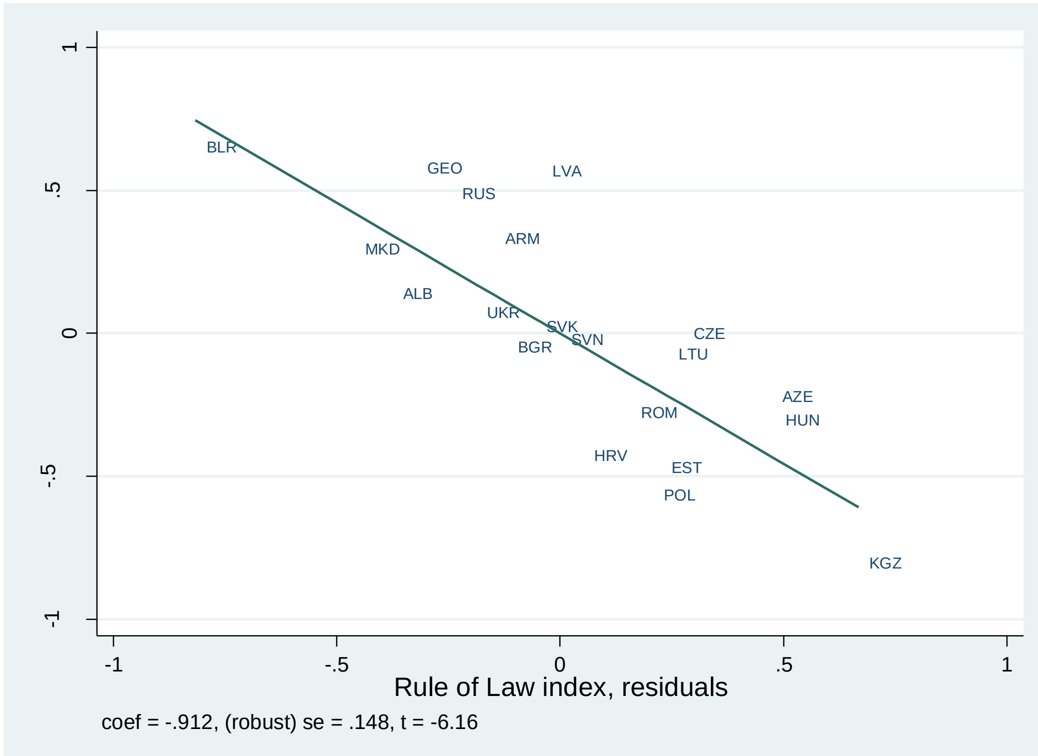
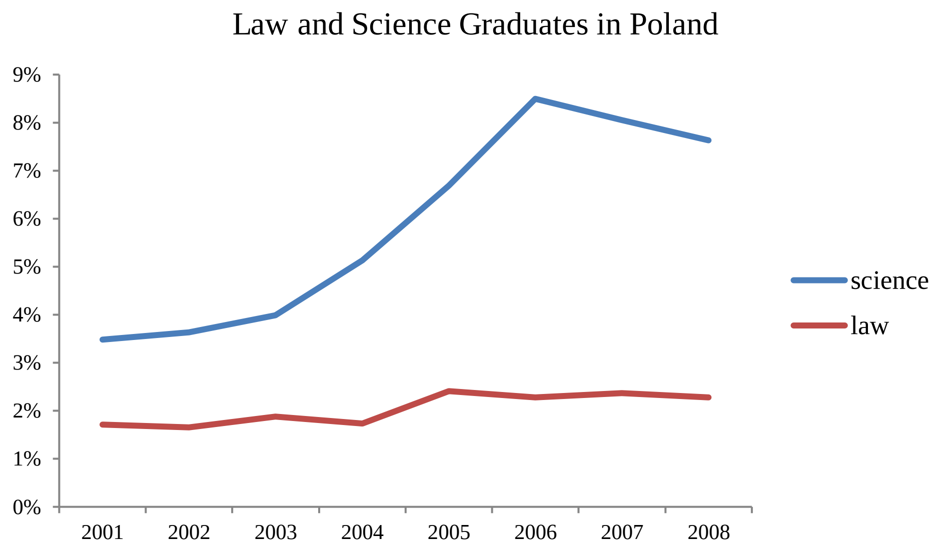


Figure 4. —Quality of Institutions and Difference between Law and Science Graduation rates in Post-Communist Countries



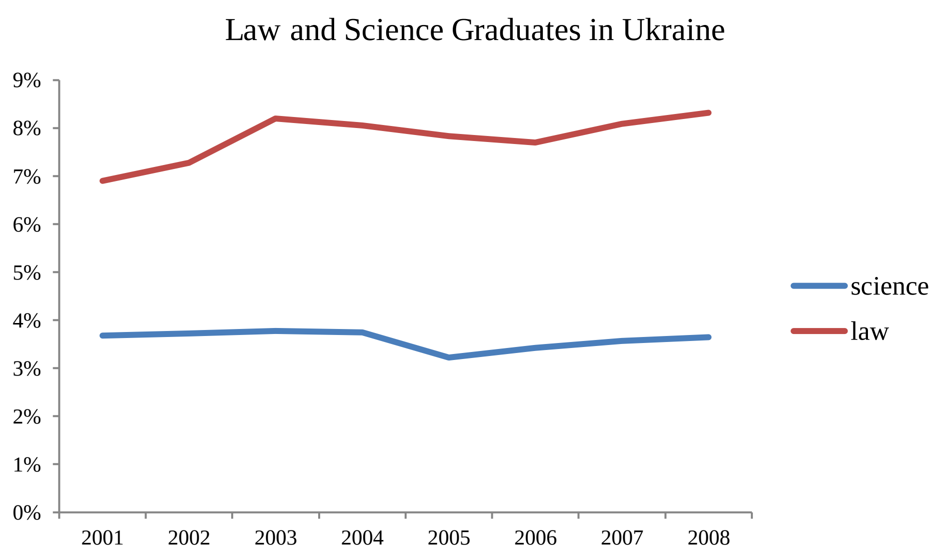


Figure 5. —Law and Science Graduation trends in Poland and Ukraine (Source: UNESCO Educational Statistics)

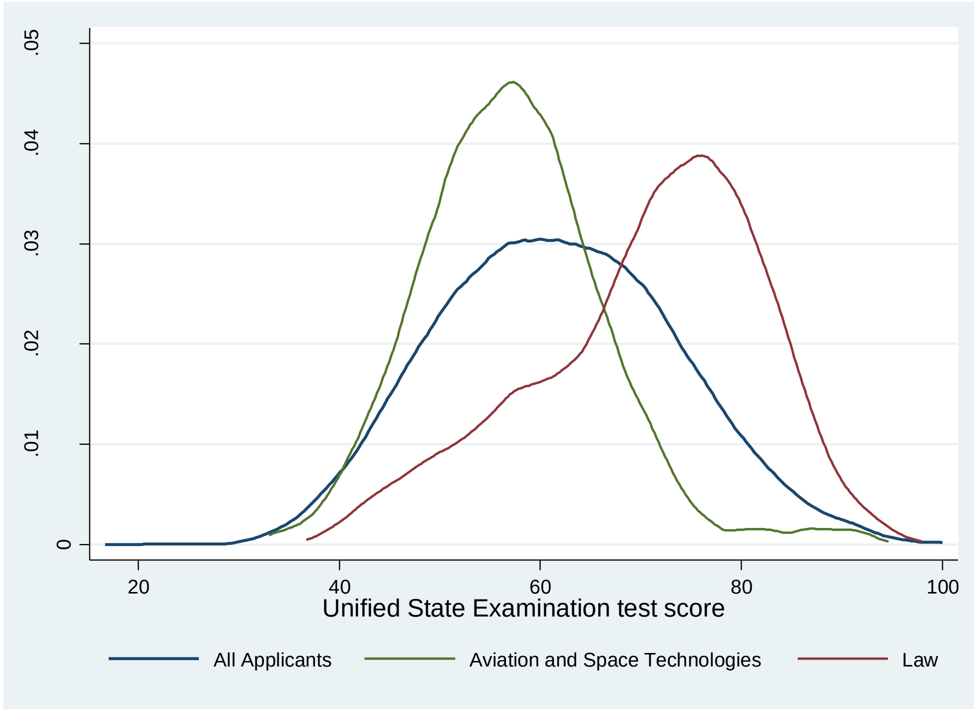


Figure 6. —Distribution of 2010 Unified State Examination Test Scores for all university applicants in Russia (Source: Russian Federal Education Web-portal (www.edu.ru))[25]

[25] We are grateful to Gregory Androushchak and Alexander Novikov (Center for Institutional Studies at the Higher School of Economics) who kindly provided detailed individual level data not available from open access sources.

Appendix

A brief description of the Unified State Examination

In order to graduate from high school and to apply to an institution of higher education, a person needs to take the Unified State Exam (USE or, *ediniy gosudarstvenniy ekzamen, EGE*, in Russian) and submit the scores with the application. USE is a series of national-level exams in different subjects. First introduced in some regions in 2001 on an experimental basis, USE become mandatory in the entire country. It is the main entrance test for higher education although some tertiary educational institutions require additional entrance examinations. All graduating high school students must take USE in Russian and mathematics and exceed a certain threshold score in order to graduate, but there are also a number of optional subjects such as physics, chemistry, history etc. Some of these optional USE subjects might be required by particular disciplines in particular universities.

It is important to understand that in Russia the prospective college students must make their choice of the main discipline to be studied before they matriculate. That is, a person may apply to a Mathematics Department (a Faculty of Mathematics) or to a History Department rather than to a university in general. This would be somewhat similar to the requirement to declare one's major before matriculating at a US university. Another important characteristic of the Russian higher education system that is relevant to our analysis is that legal education in Russia is obtained at an undergraduate level. That is, Russia's law schools (Faculties of Jurisprudence) accept students right after high school.