

INSTITUTIONS AND THE ALLOCATION OF TALENT: CROSS-NATIONAL AND SUBNATIONAL EVIDENCE*

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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. Also, 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 negative. These findings reflect the gap between private and public returns to post-secondary education in Russia, and demonstrate that without improving institutions in the country, investments in human capital might not promote 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 et al. [2001]; Easterly and Levine [2003]; Rodrik et al. [2004]; Besley and Persson [2011]). There is also a general consensus that the institutions affect economic outcomes through 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 (Murphy et al. [1993]; Mehlum et al. [2003]), and especially talent, whose area of application is highly sensitive to institutional quality (Baumol [1990]; Murphy et al. [1991]). However, rigorous empirical support of this conjecture so far has been lacking, and the present paper partially fills this gap.

We provide evidence that institutional quality strongly influences the allocation of talent measured by the selection of fields of study by university students. The use of the fields of study as a proxy for talent allocation was initially proposed in the seminal paper by Murphy et al. (1991). This proxy has several motivations. First, the choice of a field of post-secondary education is one of the lifetime's most important investment decisions, which is presumably driven in large part by the expected rewards in different occupations. Second, such rewards are affected by institutions which serve as "sorting factors" among professions depending on the latter's location between production and redistribution. Third, there are various sources of data on educational choices by university students which allow for cross-checking of findings drawn from independent data sets.

We also follow Murphy et al. (1991) in using enrollment in sciences, or in sciences, technology, engineering, and mathematics combined (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 stronger appeal of redistribution. The choice of enrollment or graduation in law and STEM as measures of attractiveness of unproductive and productive activities, while intuitively plausible, warrants some explanation.

Education in STEM 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. Nunn (2007) and Levchenko (2013) show that good institutions favor contract-intensive industries, nearly all of which are in hi-tech and hence science and engineering areas.

The tradition to associate legal profession with redistribution and, particularly, rent-seeking, has a long pedigree (reviewed, for example, in Tollison [1982]) and finds some empirical support (Laband and Sophocleus [1988]; Brumm [1999]). At the same time law plays a key 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. Instead of engaging in the debates about the contribution of the legal profession to economic outcomes (see, e.g., Epp [1992]; Olson [1992]), we are interested in *variation* between jurisdictions and across time 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 describe what happens “at the margin”, one can infer that such marginal outcomes in the case of poor institutions are likely to lead to a lopsided allocation of talent well in excess of the “optimal number of lawyers” (Magee [1992]) and thus reflect institutional pathologies and failures.⁵

We draw our hypotheses from a general 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 private protection from such attempts making up for the

⁵ Thus, de Soto (1989) argues that red tape inflates the demand for legal services, in which case lawyers are not just rent-seekers but also 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]).

insufficiency of public protection of property rights). 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 considerations (Baumol [1990]; Acemoglu [1995]). Novel features of the model are the inclusion of “offensive” and “defensive” activities as parts of redistribution, the analysis of complementarity between talent and institutional quality, and the inclusion of cross-jurisdictional migration.

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. Intuitively, more talented individuals possess valuable assets which could earn high payoff, and allocate these assets judiciously paying attention to the institution-driven payoff differentials. Meanwhile, for less able individuals such differentials are of lower magnitude and hence of smaller significance relative to idiosyncratic preferences, which renders occupational choices of such individuals less institutionally sensitive.

To test these predictions empirically, we use two sources of data: (i) cross-country variations of university students’ graduation in different disciplines, and (ii) choices of the fields of study by Russian university applicants. In the first case we perform cross-country estimations that make use of institutional indexes from the Worldwide Governance Indicators database and UNESCO’s data on graduation of university students from about 100 countries of the world. We establish a robust and strong, both statistically and numerically, 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.

These findings, stark and illuminating as they may be, suffer from two potentially serious drawbacks. First, there is an endogeneity concern, endemic for cross-country empirical analyses. To alleviate such concern, we include an array of control variables which do not affect the results, and check the OLS results by instrumenting institutional quality. We also consider the sub-sample of post-communist nations where both institutions and educational systems exhibited significant uniformity prior to the transition, but profoundly diverged afterwards, and show that the institutional divergence that occurred within the group was closely followed by talent allocation patterns that match institutional variations.⁶

Second, 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 ability of university graduates, 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 among Russian regions, both cross-sectionally and over time (Baranov et al. [2015]). At the same time, the Russian regions are parts of the same economy and polity, and hence omitted variable biases are less likely, which is in general a major strength of subnational comparative studies (Snyder [2001]). In addition, the pseudo-panel nature of our data allows for the use of fixed effects estimation, further reducing potential endogeneities.

To gauge the allocation of talent we make use of a unique data set of enrollment over 2011-2014 period of nearly all of Russian students pursuing post-secondary degrees (a total of about 1,300,000

⁶ Another complication of country-level empirical work is due to the fact that educational systems differ substantially across countries. For example, to obtain a law degree in the US one has first to obtain general education (a Bachelor's degree) and then graduate from a law school. In some other countries, including Russia, legal education is available immediately after high school and takes about the same time as other undergraduate degrees.

individuals. 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 Unified State Examination (USE) score, which serves as a basis for admission decision and is used as a talent proxy in our regressions.

We use a two-pronged identification strategy to isolate the impact of regional institutions on the allocation of talent, and show that such impact is more pronounced for higher-ability individuals. First, similarly to the cross-country estimates, we use aggregated individual enrollment data, but enhance the analysis by running regressions (within-between estimators for panel data) both for all matriculants and for the subsample of more talented enrollees with USE scores in the top quantiles of regional distributions. While the results for the entire sample have the predicted signs, typically they are not statistically significant, whereas 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 associated with regional institutional quality in a way that agrees with our theory.

Next, we use individual data from the whole pool of university enrollees over the period of observation, and find strong direct evidence that the impact of institutions on the allocation of talent indeed rises in talent. More talented among younger Russians are particularly sensitive to institutional quality, which means that poor institutions commonly observed in Russia's regions tend to 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, consistent with our model, the possibility to migrate naturally lowers the sensitivity of talent allocation to the region's institutional quality.

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 Murphy et al. [1993]; Grossman [1994]; Acemoglu [1995]; Mehlum et al. [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 $\alpha \in \mathbb{R}$. The above parameters are distributed independently from each other; cumulative distributions and (everywhere positive) densities of θ and α are, respectively, $G(\theta)$ and $g(\theta)$, and $H(\alpha)$ and $h(\alpha)$. For simplicity talent measure is normalized to unity: $\int_0^\infty \theta g(\theta) d\theta = 1$.

Individuals have utility functions $u(y, i; \alpha)$, where $y \geq 0$ is income, and $i \in \{1, 2\}$ – occupational choice; $i = 1$ corresponds to productive activities, and $i = 2$ – to redistribution. Denote $u_i(y; \alpha) \equiv u(y, i; \alpha)$, $i = 1, 2$; 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 $u_1(y_1; \alpha) - u_2(y_2; \alpha)$ is monotonically decreasing in α , and $\lim_{\alpha \rightarrow \infty} [u_1(y_1; \alpha) - u_2(y_2; \alpha)] < 0$, $\lim_{\alpha \rightarrow -\infty} [u_1(y_1; \alpha) - u_2(y_2; \alpha)] > 0$.

Individuals specialize in either production or redistribution, and each individual inelastically supplies a unit of effort towards the chosen activity.⁷ As in, for example, Dewatripont et al. (1999), talent is an effort multiplier: 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

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

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 $f(0) = 0, f'(0) = \infty, \lim_{x \rightarrow \infty} f(x) = 1$. Services of re-distributors are available at the market rate w per unit of their effective labor, and producers' demand for such services per unit of output is determined from the following profit-maximization problem:

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

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

The portion of the gross output that lacks public protection and that the producers have failed to protect privately is $\Theta(1 - \sigma)(1 - f(x^*(w, \sigma)))$, 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 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 $\Theta x^*(w, \sigma)$.

II.2 Equilibrium

⁸ For micro-foundations of this assumption see Polishchuk and Tonis (2013).

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

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

The net return per unit of effective labor in production equals

$$d(w, \sigma) \equiv \sigma + (1 - \sigma)f(x^*(w, \sigma)) - wx^*(w, \sigma) \quad (3)$$

and hence an individual with talent θ would earn $\theta d(w)$ if she is engaged in productive activities, or θw , if she deals in redistribution. If this individual's idiosyncratic preference for redistribution is α , her activity choice will be based on the comparison of respective utilities $u_1(\theta d(w); \alpha)$ and $u_2(\theta w; \alpha)$. Denote $\tilde{\alpha}(y_1, y_2)$ the activity selection threshold which solves the equation $u_1(y_1; \alpha) = u_2(y_2; \alpha)$; due to the single-crossing conditions such threshold always exists, is unique, and monotonically increases (decreases) in y_1 (y_2). An individual (θ, α) will select productive activities iff $\alpha \leq \tilde{\alpha}(\theta d(w, \sigma), \theta w)$ – assume that a tie is decided in favor of production⁹, and therefore

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

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

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

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

Proof. Equation (2) implicitly defines Θ as an increasing function of w . Indeed,

$$\Theta = w / [w + wx^*(w, \sigma) + (1 - \sigma)(1 - f(x^*(w, \sigma)))] \quad (6)$$

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).

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

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

Proof. Notice that an increase in σ due to the envelope theorem shifts the curves (2) and (3) upwards in (w, 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 $w(\sigma)$ decreases in σ . In such case $d(w(\sigma), \sigma)$, being an increasing function in σ and decreasing in w , also goes up. If $w(\sigma)$ does *not* decrease in σ , then $d(w(\sigma), \sigma)$ should still go up – otherwise for all talent levels θ threshold values $\tilde{\alpha}(\theta d(w, \sigma), \theta w)$ 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 $\tilde{\alpha}(\theta d(w, \sigma), \theta w)$ 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 redistribution could increase the payoff to the latter (Murphy et al. [1991]; Polishchuk and Savvateev [2004]). In such case participation thresholds $\tilde{\alpha}(\theta d(w(\sigma), \sigma), \theta w(\sigma))$ 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:

$$u_1(y; \alpha) = y; u_2(y; \alpha) = y + \alpha. \quad (7)$$

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 $w\tilde{\alpha}(y_1, y_2) = y_1 - y_2$. Equation (4) takes the following form:

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

where $\Delta \equiv d(w, \sigma) - w$ 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 $\Pi(\sigma) = \int_0^\infty H(\theta\Delta(\sigma))g(\theta)d\theta$. ■

II.4 Comparative statics: impact of institutions and talent

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 $\Delta'(\sigma) > 0$.

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 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 cohort total, equals $H(\theta\Delta(\sigma))$. The marginal returns to improved institutions in the participation in productive activities is as follows:

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

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 $h(\theta\Delta(\sigma))$ 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

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

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 this case

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

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 top talents are highly sensitive to the protection of property rights.

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

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

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 $\theta \rightarrow \infty$.

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 $\lim_{|w| \rightarrow \infty} wh(w) = 0$, then $\lim_{\theta \rightarrow \infty} \frac{\partial \Pi(\theta, \sigma)}{\partial \sigma} = \infty$ if $\Delta(\sigma) = 0$, and $\lim_{\theta \rightarrow \infty} \frac{\partial \Pi(\theta, \sigma)}{\partial \sigma} = 0$ otherwise. ■

[Figure 1 here]

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, θ , and the propensity for redistribution, α . 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 w the *domestic* payoff to redistribution, and $\Delta \equiv d(w, \sigma) - w$ the difference between *domestic* payoffs to productive activities and redistribution. Furthermore, denote d_0 and w_0 the highest payoffs to respectively productive activities and redistribution available in the encompassing economy,

and let $\Delta_0 \equiv d_0 - w_0$. Since the jurisdiction is non-pivotal, mobile individuals will move outside of the jurisdiction and be choosing between the payoffs θd_0 and θw_0 , whereas those who are immobile will choose between θd and θw . Therefore, the share of agents in the economy who will be engaged in productive activities is as follows:

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

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

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

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

Notice that w , $d(w, \sigma)$, 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 $\tilde{\Theta} \equiv \Theta/(1-p)$ 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.

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

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

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

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 decrease

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

III.1 Data

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 would normally 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 explained in the Introduction, we follow Murphy et al. (1991) in using, 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 (broadly defined to include life and physical sciences, mathematics, and computing) is our measure of talent allocation towards directly productive activities.

To develop a country-level benchmark preceding our analysis for Russian regions presented in the next section of the paper, 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

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.

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, since 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 Worldwide Governance Indicators database (Kaufmann et al. [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, preceding the period of the allocation of talent measurement, and use the results as explanatory variables.¹³ Such choice of timing helps alleviate, although not eliminate, the reverse causality concerns; 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 education, public sector size, country population, trade-to-GDP ratio, and emigration of post-secondary degree holders (all from the World Development Indicators database), oil reserves (CIA World Factbook),

¹³ Our set of dependent and independent variables is similar to that of Ebeke et al. (2015), who study the impact of oil resources on the allocation of talent in developing countries, conditional on the institutional quality, testing the theory of Mehlum et al. (2006), according to which resource wealth boosts rent-seeking ("grabbing") against the backdrop of poor institutions. In our analysis, unlike Ebeke et al. (2015), institutions are not just moderating the impact of resource wealth (in the sense of Baron and Kenny [1986]), but serve as a direct driver of the allocation of talent.

economic inequality measured by the Gini index (United Nations Statistical Database), and ethnolinguistic 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

¹⁴ We control for GDP per capita since it is plausible that wealthier and poorer countries have different reward structures which are not directly related to the quality of institutions. In addition, more economically advanced countries are able to afford more “capital-intensive” education in sciences, and this supply-side effect could have an impact on the allocation of talent. In the same vein we control for country-level R&D expenditures, as this affects the demand for those trained in sciences, and poor countries invest in R&D far less than rich ones not only in absolute, but also in relative terms (Goñi and Maloney [2014]). GDP structure measured by the share of services and manufacturing in GDP and manufacturing in exports, could be correlated with the demand for lawyers and scientists. There could also be a link between the size and structure of the student body, which explains controlling for the aggregate enrollment in tertiary education. As mentioned earlier, allocation of talent could be affected by natural resources in what is known as the “resource-curse” (see especially Ebeke et al. [2015]); to account for such link, we use oil reserves as a control variable. In addition, our controls include population (as a proxy for market size) and general government expenditure (% of GDP) as a proxy for government size, which according to Pritchett (2001) might have an impact on the allocation of talent. The trade-to-GDP ratio reflects the openness of national economies which can also be relevant for the allocation of talent (Hanushek and Woessmann [2008]). Finally, emigration of tertiary educated could disconnect educational choices from the quality of national institutions, since education in sciences is more “portable” than education in law (Mariani [2007]), and much of brain drain occurs in the STEM fields (Gibson and 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. The tables presented below do not show some of the above controls in order to limit the table size.

negative and equals 5.52 percentage points. We use this difference as yet another dependent variable in cross-country regressions, as its distribution is closer to the normal than the distributions of separate enrollment data for law and science.

III.2 Benchmark regressions

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

$$(Un)productive\ Activities_i = \beta_0 + \beta_1 Institutional\ Quality_i + \beta_2 X_i + \varepsilon_i, \quad (11)$$

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 estimate model (11) 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.

[Insert Figure 2 here]

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.

[Insert Figure 3 here]

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 present 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.

III.3 Further robustness checks

The nature of the relationship between institutions and the allocation of talent in the above regressions has been consistent across various indexes of students' choice between science and law, alternative measures of institutional quality, and sets of control variables. Here we report results of further tests, most of the time without presenting detailed estimations which are available from the authors upon request.

To address the concern that our control variables still do not fully eliminate an omitted variable bias that could be expected for an extremely diverse group of countries, we reduce the full sample to various more homogeneous sub-groups and estimate model (11) for such sub-groups. First, we restrict our estimation to poorer countries by excluding OECD and high-income non-OECD countries (according to the World Bank's classifications). Next, we perform the opposite exercise by retaining only the wealthier part of the sample. The two other estimations are confined to former colonies of

European powers and to post-communist transition countries in Central and Eastern Europe and the former Soviet Union. In all of such estimations the coefficient of the Rule of Law Index is negative and significant at the 1% level. The value of this coefficient is higher for poorer countries, former colonies, and transition nations, than for the sample at large.

The sub-sample of transition countries is of particular interest due to its quasi “natural experiment” features. Soviet domination ensured relatively high uniformity of institutions and post-secondary educational systems across the region (see, e.g., Wrenn [1963]). Command economies gave strong priorities to higher education in engineering and sciences (Pop-Eleches [2014]), whereas law schools were rare and far less prestigious and appealing to younger talents.¹⁵ Similarity of former command economies at the outset of their transition to free market and the availability of strong educational potential in sciences and engineering alleviates the concern that the allocation of students across fields of studies was at least in part a “supply-side” phenomenon reflecting the pre-existing capacities of national university systems. The divergence in allocation of talent that ensued could be with greater confidence ascribed to “demand-side” forces, which in their turn reflected the uneven quality of post-communist institutions.

In Table 5 we report the results of OLS estimations of model (11) 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 (notice however that the number of observations in this reduced sample is rather small). 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.

[Insert Figure 4 here]

¹⁵ This appears to be at odds with our theory, since the institutions of the command economy were obviously quite poor from the market economy’s perspective. In fact, our logic assumes a *market* economy, no matter how distorted, with a degree of economic freedoms and educational system responding to prospective students’ demand. Rigid command economies did not meet such assumptions and are thus exceptions from our rule. However, after the collapse of central planning they confirm the rule with exceptional clarity.

We also ran 2SLS regressions using instrumental variables for institutions proposed in earlier literature. Specifically, we use either European settler mortality (for the sub-sample of former colonies), or the fraction of English speaking population, or both, as instruments. 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 rather weak for most of our institutional quality measures, and it has been criticized in the literature on substantive grounds (Glaeser et al. [2004], and Albouy [2012]). Moreover, it limits our sample to only 35 observations. The fraction of English-speaking population also might not satisfy the exclusion restriction, although the regressions easily pass overidentification tests when both instruments are used.

Finally, there are confounding variables which are linked both with institutions and the allocation of talent. We consider several such variables and show that in the absence of institutions they are significant for the graduation in law, but lose significance once institutions have been factored in – in other words, institutions fully mediate (Baron and Kenny [1986]) the impact of these variables on the allocation of talent. The first example is given by the share of the informal sector in GDP. Since informal economy by definition is outside of the realm of law, one would expect a negative correlation between its size and the graduation in law. In fact, when graduation in law is regressed on the size of informal economy (with standard controls, but excluding institutional quality), the informal sector's coefficient is *positive* and statistically significant. This counterintuitive result reflects the influence of institutions – informal economy is inversely related to institutional quality (De Soto [1989]; Djankov et al. [2002]), and the latter in its turn is negatively correlated with the graduation in law. The pivotal role of institutions becomes evident once the rule of law index is brought back into the regression – it has the expected negative sign and renders the size of informal sector statistically insignificant.

In the second example the confounding variable is legal origin. French legal origin reduces the need for trial lawyers, but is more “lawyer-intensive” in dealing with regulatory matters. The coefficient of French legal origin in a regression explaining the graduation in law is positive and significant, but here too the observed effect is due to omitted institutions, which are adversely affected

by civil law in comparison to common law systems (La Porta et al. [2008]). The inclusion of institutions into regression reduces the coefficient of legal origin in magnitude and makes it statistically insignificant. Finally, more lawyers are required to represent their clients vis-à-vis the state when government agencies and civil servants are mistrusted by the public. This is confirmed by a regression of the graduation in law on distrust in civil servants, where the latter obtains a positive and highly significant coefficient. On the other hand, mistrust in civil servants could be correlated with poor institutions (e.g., when both are caused by a lack of social capital – see Aghion et al. [2010]), and the inclusion of institutions in the regression leaves distrust in civil servants insignificant while reducing its coefficient by two thirds (Table 8, Column 8).

The above examples demonstrate a consistent pattern: various factors affect the allocation of talent as long as institutions are taken out of the equation. Once institutions are reinstated, they trump such factors and stand out among other variables as a key determinant of the allocation of talent variations across nations.

IV. Evidence from Russia

Although the results from cross-country analysis strongly support our theory, they are also subject to several caveats. First, cross-country regressions are susceptible to endogeneity because of omitted variables, possible reverse causality, and measurement errors. Second, countries differ in the structure of their education systems and the meaning and content of science and legal education. Third, we do not have reliable and comparable cross-country data on the abilities of university graduates, which precludes testing the hypothesis that the allocation of greater talents is more responsive to the institutional quality.

We alleviate if not fully eliminate these problems by using finer-grained individual-level data on the enrollment in post-secondary education in different regions of the Russian Federation. These data are available for several years and, most important, come with a chosen field of study and 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 5. 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 obtain such evidence, we need multiple jurisdictions with substantial variations of institutional quality from one jurisdiction to another, and data on the allocation of (variable) talent within each of the jurisdictions. As indicated in the Introduction, Russian regions (over 80 subnational units of the Russian Federation) serve this purpose.

Russian institutional disparities among regions far exceed what can be expected from a country, even as vast and diverse as Russia, with a single polity, legal system, and economic space. Russian regions exhibit profound variations in their investment climate and business environment (Zubarevich [2010]) due to highly uneven red tape, entry barriers, share of the informal economy, and costs and risks of doing business (World Bank [2014]; Baranov et al. [2015]). These disparities go back to the early years of the Russian transition when a weak central government offered the regions to “take as much power as they could handle” (Polishchuk [2001]). The subsequent consolidation of the central government did not bring about greater institutional uniformity due to a still weak oversight and enforcement capacity (Yakovlev and Zhuravskaya [2013]), regime’s willingness to tolerate local irregularities as long as some political targets are met (Reuter and Robinson [2012]), and a lack of the essential features of “market-preserving federalism” that would provide incentives to establish

investor-friendly institutions (Montinola et al. [1996]). As a result, regional institutional regimes are determined by variations of historical, geographic, political, etc., factors (Baranov et al. [2015]).

IV.1. Data

Our main source of data on the allocation of talent is the “Monitoring of quality of higher education enrollment” project administered since 2011 by the National Research University Higher School of Economics. Project database’s entries are newly enrolled university students; every entry includes the chosen university, discipline to be studied, and the student’s results of the Unified State Examination (USE) scores. USE is a mandatory examination, which similarly to US’s SAT serves as a basis for admission decisions. We use as a proxy for talent the average of USE scores for the two mandatory subjects – Russian language and mathematics. In addition we use Russian Ministry of Education and Science’s data, aggregated at the regional level, on the proportions of newly enrolled students who choose to matriculate in various disciplines, and the shares of such enrollees in different percentiles of USE scores.¹⁶ We also use data collected by the same ministry on migration of university graduates out of the region of graduation in 2014 (<http://graduate.edu.ru/>).

We combine enrollment in law and public administration¹⁷ to obtain a measure of the students’ inclination to be involved in redistribution. Russia is a textbook case of a “grabbing-hand”-type state (Shleifer and Vishny [2002]), and government bureaucracy has become a career of choice for Russian youth (Natkhov and Polishchuk [2012]).

As a measure of institutional quality of a region, we use primarily the investment risk index from the rating agency Expert RA. During the period covered by our data this index varied between 0.147 and 0.616. The higher value of the index corresponds to lower institutional quality, and so to make the

¹⁶ The regional-level data enrollment shares are somewhat 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.

¹⁷ We did not have public administration as a special field in the UNESCO database, and hence were unable to include this subject area in the cross-country analysis.

results easier to interpret, we invert this index by subtracting its value for each region from unity. 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 state administration in the value added in the region, and the average temperature in January.¹⁸ Because we are dealing with subnational units of the same country we can use a smaller set of controls than in the cross-country analysis.

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. Therefore, the choices of disciplines by matriculants in Moscow and St. Petersburg universities may not adequately reflect institutional environment in these cities. Moscow oblast' data are combined with the city of Moscow in our database.

All variables and sources thereof 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 higher ability individuals are different from those of lower ability ones.

¹⁸ 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.

We estimate the following regression model:

$$AoT_j = \beta_0 + \beta_1 IQ_j + \beta_2 X_j + \varepsilon_j \quad (12)$$

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 post-secondary education is quite common, implying that college enrollment itself is not necessarily a sign of an individual being in the top portion of ability distribution.¹⁹

We use the investment risk index described in the Data section above as our main independent variable. As mentioned earlier, 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 has drawbacks as a measure of institutional quality because 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 admittedly 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. Still, no other available measure of institutional quality of Russia's regions comes close to investment risk index in terms of coverage across space and over time.

When dealing with regional aggregate enrollment data, we have a panel dataset. However, it covers a rather short period of time and our independent variables change only slowly from one year to

¹⁹ In Russia 58% of the population in the 25-34 age group have tertiary education, well above most of the OECD countries with the exception of South Korea and Japan (Education at a Glance [2016]).

another. Therefore, fixed effects regressions might not yield statistically significant results. More important, fixed effects (FE) estimators do not capture 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, for all time-varying variables, deviations from their means. 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.²⁰

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 have the expected signs. This agrees with our hypotheses that greater talents are more sensitive to the institutional quality. These results underline the need for (and illustrate the benefits of) using ability measures rather than relying on the data for overall enrollments in various disciplines.

However, 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, conditional on institutional quality, which is the subject of the next sub-section.

²⁰ 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.

IV.3. Individual data

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 impact of institutional quality on the allocation of talent. We also use Probit models as robustness checks. Specifically, we estimate the following regression:

$$DISC_CHOICE_i = \beta_0 + \beta_1 USE_i + \beta_2 IQ_j + \beta_3 USE_i \times IQ_j + \gamma X_j + \varepsilon_i \quad (13)$$

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 (13) 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.²¹

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 , and correlations between the USE scores and institutional quality. 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 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

²¹ 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.

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.²² 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 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. Overall, Probit estimates of the coefficients and of marginal effects are consistent with LPM ones. Again, all the interaction terms have

²² 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.

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 are similar to those for LPM.

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; in other words, this is a more than 20% increase in the probability of STEM enrollment. 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 0.077.

The above 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 from average to higher.

These results are consistent across various estimation techniques, each with its own advantages and disadvantages, but all pointing out to the same patterns.

IV.4. Placebos and alternative institutional measures

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 in the Higher School of Economics' database with more than 100,000 matriculants, i.e. for 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 popularity of disciplines where the payoffs do not significantly depend on institutions.

The rather strong evidence for Russia obtained above for STEM and law and public administration is 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 such institution-related aspects as government effectiveness, and public safety and security. 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. Hence as a robustness check of our results, we use other measures of institutional quality, namely those based on the EBRD's Business Environment and Enterprise Performance Survey data for Russia (BEEPS; ebrd-beeps.com), and on a regional corruption index produced by the Public Opinion Foundation (FOM;

fom.ru)²³ The results based on these alternative 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 that can be matched with our enrollment and USE data are available only for 2011 and 2012 (at the time of writing the latest round BEEPS data were not yet available), 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 estimates for upper percentiles of the distribution of USE scores are mostly statistically significant and have the signs supporting the predictions of our model.²⁴

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 quality become statistically significant not only for business licensing, but also for courts as an obstacle to doing business (see Table 14).²⁵ In addition, as shown in Table 15, most of marginal effects estimates based

²³ See Baranov et al. (2015) for a description of these and other institutional quality measures for Russian regions.

²⁴ The Table contains pooled OLS estimates. Random effects are similar but with somewhat lower statistical significance presumably due to the small number of observations.

²⁵ 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.

on the corruption measure from FOM are also statistically significant and confirm our model's predictions.²⁶

IV.5. Impact of mobility

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 to another Russian region (or perhaps abroad) is a source of noise in our data. Moreover, if the relationship between graduates' mobility and regional institutions is systematic, this could introduce biases in our estimates. To address such concerns, we use the above referenced data collected by the Russian Ministry of Education and Science on mobility of university graduates out of the region of graduation in 2014.²⁷ According to the available data, for most of the regions such migration is in the 10%-35% range.

Recall that according to our theory, mobility between jurisdictions decreases the marginal effect of institutions for the allocation of talent. One way to test this hypothesis for Russian regions 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:

$$AoT_j = \beta_0 + \beta_1 IQ_j + \beta_3 STAY_j + \beta_4 IQ_j \times STAY_j + \beta_5 X_j + \varepsilon_j, \quad (14)$$

$$DISC_CHOICE_i = \beta_0 + \beta_1 USE_i + \beta_2 IQ_j + \beta_3 STAY_j + \beta_4 USE_i \times IQ_j + \beta_5 USE_i \times STAY_j + \beta_6 IQ_j \times STAY_j + \beta_7 USE_i \times IQ_j \times STAY_j + \gamma X_j + \varepsilon_i \quad (15)$$

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,

²⁶ 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?"

²⁷ Ideally, we would need the interregional migration data broken down by discipline, but unfortunately no such data is available.

and tend to rise in magnitude in the percentage of graduates staying in the region. This agrees with our conjectures about the impact of institutions on the allocation of talent and with the predictions of the model as to how this impact is affected by mobility. Importantly, accounting for 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 mobility 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. We show that this conclusion extends to the 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 redistribution more attractive than directly 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, gross 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 empirical 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.

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TABLES

Table 1. Descriptive Cross-Country Statistics

	All countries	Strong institution countries	Weak institution countries	Data Source
	(1)	(2)	(3)	(4)
<i>A. Allocation of talent measures</i>				
Share of Law graduates, %	6.22 (4.90)	4.21 (2.90)	8.27 (5.66)	UNESCO Educational Statistics http://www.uis.unesco.org
Share of Science graduates, %	8.30 (4.63)	9.72 (4.92)	6.84 (3.85)	
Difference between shares of law and science graduates, %	-2.08 (7.15)	-5.52 (5.90)	1.43 (6.64)	
<i>B. Institutional quality indexes</i>				
Rule of Law, average index for 2000-2005	0.13 (1.01)	1.00 (0.63)	-0.74 (0.36)	Worldwide Governance Indicators; World Bank
Government Effectiveness, average index for 2000-2005	0.25 (1.02)	1.09 (0.71)	-0.59 (0.39)	
Control of Corruption, average index for 2000-2005	0.19 (1.05)	1.03 (0.79)	-0.68 (0.37)	
Private Property Protection, average index for 2000-2005	3.5 (1.13)	4.25 (0.81)	2.7 (0.82)	
<i>C. Controls and instruments</i>				
GDP per capita, PPP, in 2005 dollars	15064 (13 873)	24 597 (13 378)	5 329 (4 337)	World Development Indicators (WDI); World bank
Average GDP growth rate per capita, 1990-2010, %	2.03 (1.57)	2.07 (1.00)	2.08 (1.98)	
Tertiary education, gross enrollment ratio, %	40.8 (27.9)	55.3 (23.3)	26.0 (24.2)	
Services, value added, % GDP	59.0 (14.0)	66.4 (11.3)	51.6 (12.5)	WDI
Government expenditure, % GDP	16.6 (5.7)	18.5 (4.2)	14.5 (6.5)	WDI

Oil reserves, proved reserves of crude oil in million barrels	10 346 (38 457)	9 983 (45 281)	10 716 (30 445)	CIA World Factbook
Ethnolinguistic fractionalization index	0.39 (0.25)	0.30 (0.21)	0.47 (0.25)	Alesina et. al., (2003)
Gini index	0.39 (0.10)	0.33 (0.07)	0.45 (0.08)	WDI
Trade (exports plus imports), % GDP	0.90 (0.54)	1.03 (0.64)	0.76 (0.37)	WDI
Emigration rate of tertiary educated, %	14.1 (13.8)	12.7 (11.4)	15.6 (15.9)	WDI
Log Population	16.2 (1.5)	15.9 (1.5)	16.5 (1.4)	WDI
French Legal Origin	0.43 (0.49)	0.31 (0.47)	0.57 (0.49)	La Porta et. al., (2008)
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: <i>Share of Law graduates</i>								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Rule of Law	-0.380*** (0.100)	-0.530*** (0.161)	-0.589*** (0.172)	-0.578*** (0.168)	-0.581*** (0.171)	-0.563*** (0.170)	-0.486*** (0.168)	-0.580*** (0.207)	-0.466*** (0.119)
Log GDP per capita		0.218 (0.170)	0.218 (0.167)	0.207 (0.174)	0.232 (0.181)	0.0571 (0.194)	0.157 (0.220)	0.152 (0.321)	-0.0461 (0.128)
School Tertiary		-0.335 (0.516)	-0.422 (0.471)	-0.433 (0.471)	-0.366 (0.481)	-0.0516 (0.461)	-0.581 (0.514)	-0.0209 (0.566)	0.609* (0.359)
Services, % of GDP			0.777 (1.014)	0.837 (1.040)	0.776 (1.053)	1.500 (1.060)	1.466 (1.046)	0.197 (1.392)	1.770** (0.832)
Log (1+Oil reserves)				0.00545 (0.0259)	-2.57e-05 (0.0255)	0.0626** (0.0307)	0.0542 (0.0375)	0.0388 (0.0450)	0.0575** (0.0238)
Ethnic Fractionalization					0.285 (0.542)	0.327 (0.509)	0.286 (0.503)	0.352 (0.515)	-0.116 (0.342)
Log Populaion						-0.219*** (0.0779)	-0.357*** (0.0886)	-0.335*** (0.106)	-0.178*** (0.0596)
Gini coefficient							0.925 (0.0134)	0.648 (1.314)	
Trade to GDP ratio							-0.526** (0.00228)	-0.351 (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 (0.105)	-1.707 (1.362)	-2.123 (1.319)	-2.072 (1.337)	-2.379 (1.470)	1.947 (2.125)	3.726 (2.658)	3.210 (3.882)	1.749 (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;

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

Columns (1) - (8) report estimations of model (6) with different sets of control variables;

Column (9) regression excludes outliers;

Regression coefficients reported for Rule of Law index are standardized beta coefficients.

Table 3. OLS Regressions for Share of Science Graduates

	Dependent variable: <i>Share of Science graduates</i>								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Rule of Law	0.234*** (0.0740)	0.257*** (0.0970)	0.205* (0.106)	0.258** (0.120)	0.258** (0.120)	0.252** (0.118)	0.262** (0.117)	0.353** (0.143)	0.326*** (0.0919)
Log GDP percapita		0.194 (0.137)	0.194 (0.132)	0.134 (0.142)	0.137 (0.148)	0.191 (0.148)	0.250 (0.179)	0.120 (0.206)	-0.0009 (0.110)
School Tertiary		-1.261** (0.565)	-1.339** (0.574)	-1.395** (0.574)	-1.386** (0.563)	-1.482*** (0.558)	-1.179** (0.495)	-0.966 (0.607)	-0.470 (0.293)
Services, % GDP			0.700 (0.744)	1.020 (0.714)	1.012 (0.707)	0.789 (0.746)	0.235 (0.736)	0.577 (1.148)	-0.0459 (0.599)
Log Oil reserves				0.0289 (0.0211)	0.0281 (0.0226)	0.00887 (0.0272)	-0.0119 (0.0286)	-0.00170 (0.0369)	0.00421 (0.0214)
Ethnic Fractionalization					0.0378 (0.356)	0.0249 (0.360)	0.493 (0.380)	0.213 (0.402)	0.125 (0.291)
Log of Populaion						0.0674 (0.0530)	0.114** (0.0509)	0.0915 (0.0956)	0.0773* (0.0425)
Gini coefficient							-0.0210 (0.845)	-0.0812 (0.985)	
Trade to GDP ratio							0.289 (0.248)	0.413 (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*** (0.0718)	-1.487 (1.044)	-1.861 (1.141)	-1.594 (1.211)	-1.635 (1.307)	-2.964* (1.544)	-4.487** (1.935)	-2.963 (2.738)	-1.453 (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;

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

Columns (1) - (8) report estimations of model (6) with different sets of control variables;

Column (9) regression excludes outliers;

Regression coefficients reported for Rule of Law index are standardized beta coefficients.

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

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

Notes: Robust standard errors are in parentheses;

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

Columns (1) - (4) report model (6) estimates for different institutional quality indexes;

Regression coefficients reported for institutional quality indices are standardized beta coefficients.

Table 5. OLS Regressions for the Economies in Transition

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

Notes: Robust standard errors are in parentheses;

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

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)

	<i>STEM</i>	<i>LAW</i>	<i>STEM</i>	<i>LAW</i>	<i>STEM</i>	<i>LAW</i>
	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)

	$\frac{STEM - LAW}{LAW}$	$\frac{STEM - LAW}{STEM + LAW}$	$\frac{STEM - LAW}{LAW}$	$\frac{STEM - LAW}{STEM + LAW}$	$\frac{STEM - LAW}{LAW}$	$\frac{STEM - LAW}{STEM + LAW}$
	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)

Dependent variable:	Fixed effects			“Within-between” RE estimator		
	<i>STEM</i>	<i>LAW</i>	<i>STEM_LAW</i>	<i>STEM</i>	<i>LAW</i>	<i>STEM_LAW</i>
	(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:	<i>STEM</i>	<i>LAW</i>	<i>STEM_LAW</i>
	(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)

Dependent variable:	Pooled			Random effects		
	<i>STEM</i>	<i>LAW</i>	<i>STEM_LAW</i>	<i>STEM</i>	<i>LAW</i>	<i>STEM_LAW</i>
	(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)	.334*** (.027)	-.067*** (.016)	.318*** (.039)
Marginal effect of IQ_j at $USE_i = 80$.603*** (.147)	-.124*** (.041)	.639*** (.152)	.478*** (.028)	-.113*** (.018)	.568*** (.046)
Marginal effect of IQ_j at $USE_i = 90$.737*** (.162)	-.176*** (.054)	.904*** (.207)	.604*** (.030)	-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)-(3);

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 (BEEPS) and the choice of discipline (pooled OLS; aggregate data)

	<i>STEM</i>	<i>LAW</i>	<i>STEM</i>	<i>LAW</i>	<i>STEM</i>	<i>LAW</i>
	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
	$\frac{STEM - LAW}{STEM + LAW}$	$\frac{STEM - LAW}{STEM + LAW}$	$\frac{STEM - LAW}{STEM + LAW}$	$\frac{STEM - LAW}{STEM + LAW}$	$\frac{STEM - LAW}{STEM + LAW}$	$\frac{STEM - LAW}{STEM + LAW}$
	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)	-.226# (.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 (WB effects; 2011-2012; individual-level data)

Institutional quality measure:	Courts as obstacle			Permits as obstacle		
Dependent variable:	<i>STEM</i>	<i>LAW</i>	<i>STEM_LAW</i>	<i>STEM</i>	<i>LAW</i>	<i>STEM_LAW</i>
	(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)	-.003* (.002)
Marginal effect of IQ_j at $USE_i = 70$	-.016 (.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 Public Opinion Foundation corruption index (2011; individual-level data)

Dependent variable:	LPM (OLS)			Probit		
	<i>STEM</i>	<i>LAW</i>	<i>STEM_LAW</i>	<i>STEM</i>	<i>LAW</i>	<i>STEM_LAW</i>
	(1)	(2)	(3)	(4)	(5)	(6)
<i>USE_i</i> score	-.0000 (.0018)	-.0001 (.0005)	.0015 (.0015)	.0006 (.0049)	.002 (.004)	.001 (.007)
<i>IQ_j</i>	.006 (.006)	-.003# (.002)	.014*** (.005)	.020 (.015)	-.014 (.015)	.041* (.023)
<i>USE_i × IQ_j</i>	-.0002* (.0001)	.0001 (.0000)	-.0003*** (.0001)	-.0005** (.0003)	.0003 (.0002)	-.0009** (.0004)
Marginal effect of <i>IQ_j</i> at <i>USE_i = 70</i>	-.005** (.002)	.0014# (.0009)	-.006** (.003)	-.006** (.002)	.001 (.001)	-.005* (.003)
Marginal effect of <i>IQ_j</i> at <i>USE_i = 80</i>	-.007** (.003)	.0020* (.0011)	-.009*** (.003)	-.007** (.003)	.0018 (.0013)	-.008** (.004)
Marginal effect of <i>IQ_j</i> at <i>USE_i = 90</i>	-.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	<i>STEM</i>	<i>LAW</i>	<i>STEM</i>	<i>LAW</i>	<i>STEM</i>	<i>LAW</i>
	Entire sample	Entire sample	Top 25%	Top 25%	Top 10%	Top 10%
	(1)	(2)	(3)	(4)	(5)	(6)
Inverse investment risk index (<i>IQ</i>)	-1.23 (1.08)	.358 (.402)	-1.29 (1.02)	.989* (.571)	-.942 (1.04)	.565 (.554)
Share of graduates staying in the region (<i>STAY</i>)	-1.41 (1.11)	.293 (.401)	-1.48# (1.02)	1.13** (.544)	-1.19 (1.07)	.675 (.537)
<i>IQ</i> × <i>STAY</i>	1.98 (1.49)	-.456 (.555)	2.04# (1.37)	-1.52* (.801)	1.82 (1.37)	-.890 (.776)
Marginal effect of <i>IQ</i> at <i>STAY</i> = 0.70	.156 (.202)	.038 (.080)	.138 (.229)	-.076 (.097)	.332# (.225)	-.058 (.106)
Marginal effect of <i>IQ</i> at <i>STAY</i> = 0.80	.355# (.240)	-.007 (.094)	.341 (.247)	-.228* (.130)	.513** (.233)	-.147 (.131)
Marginal effect of <i>IQ</i> at <i>STAY</i> = 0.90	.553# (.345)	-.053 (.132)	.545* (.328)	-.380** (.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 (<i>IQ</i>)	-.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 (<i>STAY</i>)	-.514 (.768)	-.448 (1.61)	-1.39* (.791)	-4.29** (1.88)	-.792 (.940)	-2.95 (2.65)
<i>IQ</i> × <i>STAY</i>	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 <i>IQ</i> at <i>STAY</i> = 0.70	.081 (.173)	-.050 (.351)	.137 (.197)	.373 (.465)	.285 (.203)	.864# (.559)
Marginal effect of <i>IQ</i> at <i>STAY</i> = 0.80	.188 (.189)	.123 (.416)	.343* (.202)	1.00** (.491)	.417** (.200)	1.32** (.572)
Marginal effect of <i>IQ</i> at <i>STAY</i> = 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)

Dependent variable:	LPM (OLS)			Probit		
	<i>STEM</i>	<i>LAW</i>	<i>STEM_LAW</i>	<i>STEM</i>	<i>LAW</i>	<i>STEM_LAW</i>
	(1)	(2)	(3)	(4)	(5)	(6)
<i>USE_i</i> score	-0.002 (.049)	-0.017 (.015)	.050 (.056)	.016 (.153)	-0.093 (.098)	.144 (.203)
<i>IQ_j</i>	.764 (3.52)	-1.04 (1.19)	3.31 (3.75)	3.42 (10.37)	-5.28 (8.07)	9.76 (14.45)
<i>STAY_j</i>	1.55 (3.67)	-1.40 (1.18)	4.72 (3.90)	6.12 (11.00)	-7.88 (7.78)	14.89 (14.86)
<i>USE_i × STAY_j</i>	-.019 (.067)	.026 (.020)	-.088 (.078)	-.094 (.213)	.142 (.127)	-.264 (.279)
<i>USE_i × IQ_j</i>	.002 (.064)	.019 (.020)	-.058 (.074)	-.023 (.200)	.093 (.130)	-.157 (.267)
<i>IQ_j × STAY_j</i>	-1.90 (4.80)	1.56 (1.61)	-5.50 (5.22)	-7.64 (14.37)	8.03 (10.69)	-16.66 (19.88)
<i>USE_i × IQ_j × STAY_j</i>	.022 (.088)	-.029 (.027)	.103 (.102)	.114 (.279)	-.148 (.169)	.296 (.368)
Marginal effect of <i>IQ_j</i> at <i>USE_i = 80&STAY_j = .7</i>	.859*** (.263)	-.063 (.114)	.575* (.317)	.901*** (.265)	-.065 (.106)	.549* (.290)
Marginal effect of <i>IQ_j</i> at <i>USE_i = 80&STAY_j = .8</i>	.847*** (.320)	-.139 (.123)	.852** (.413)	.936*** (.353)	-.127 (.110)	.785** (.372)
Marginal effect of <i>IQ_j</i> at <i>USE_i = 80&STAY_j = .9</i>	.835 (.581)	-.214 (.192)	1.13# (.740)	.969# (.633)	-.200 (.181)	1.04# (.705)
Marginal effect of <i>IQ_j</i> at <i>USE_i = 90&STAY_j = .7</i>	1.04*** (.317)	-.077 (.138)	.716* (.381)	1.06*** (.310)	-.078 (.126)	.693** (.350)
Marginal effect of <i>IQ_j</i> at <i>USE_i = 90&STAY_j = .8</i>	1.05*** (.400)	-.182 (.149)	1.10** (.515)	1.12*** (.429)	-.168 (.135)	1.05** (.473)
Marginal effect of <i>IQ_j</i> at <i>USE_i = 90&STAY_j = .9</i>	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

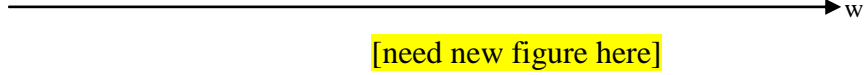


Figure 1.—Marginal Impact of Institutions on the Allocation of Talent (a – break-even institutional quality; b – other levels of institutional quality)

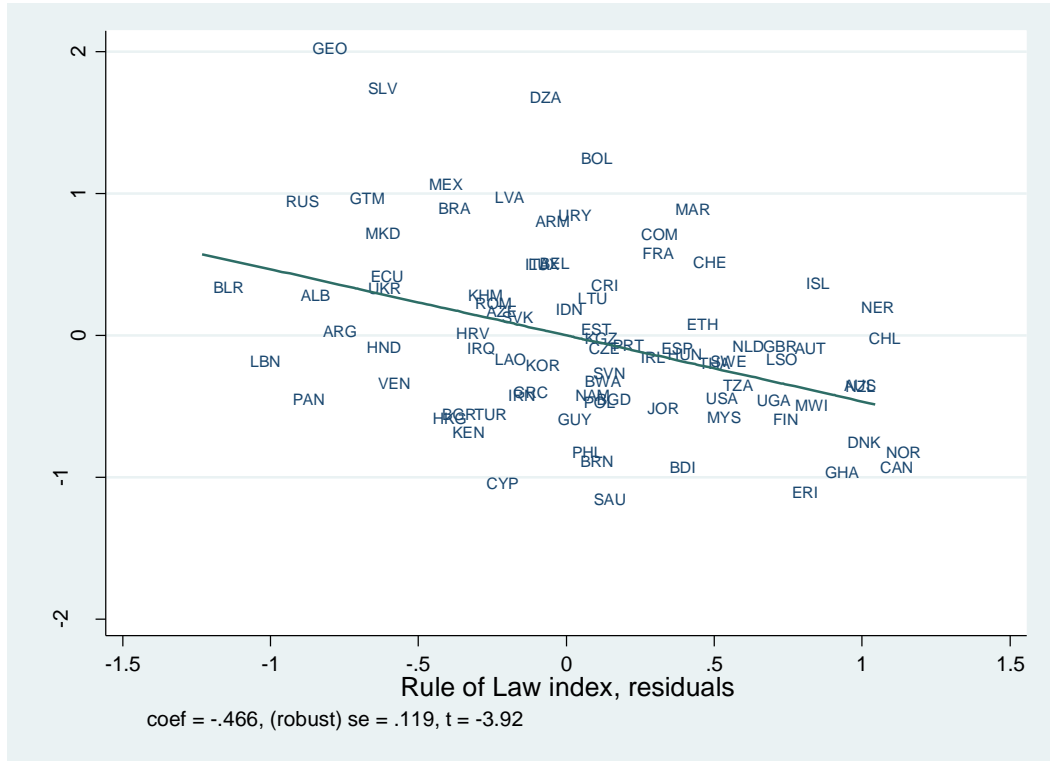


Figure 2. —Quality of Institutions and Graduation in Law

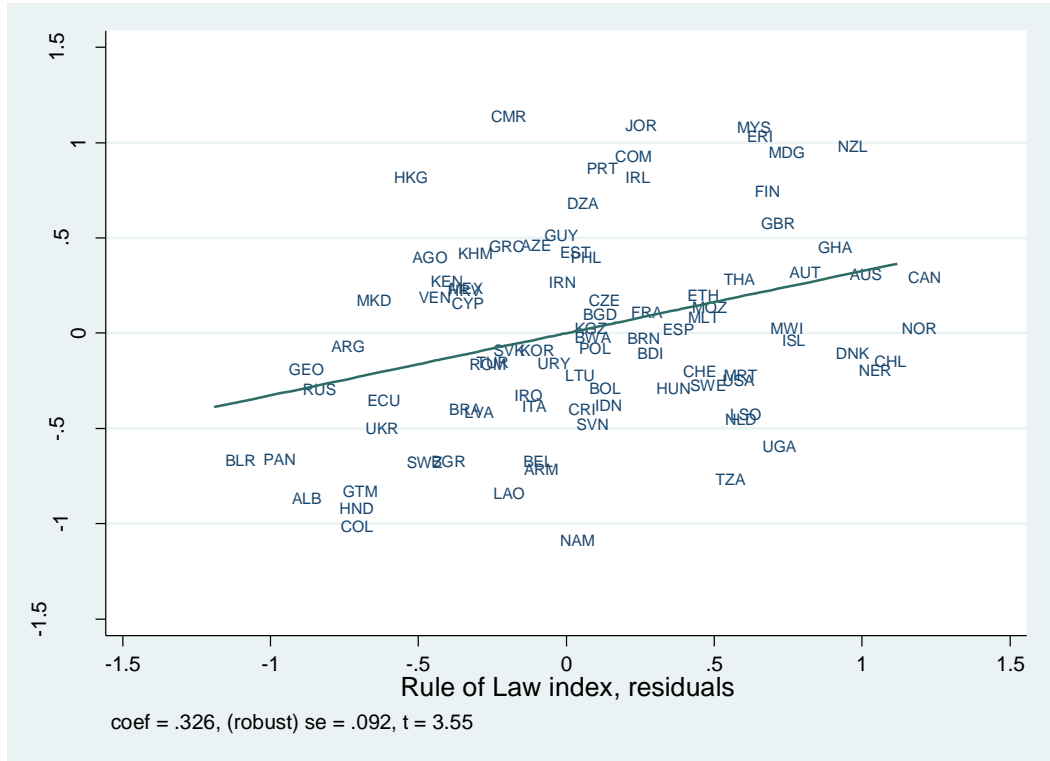


Figure 3. —Quality of Institutions and Graduation in Science

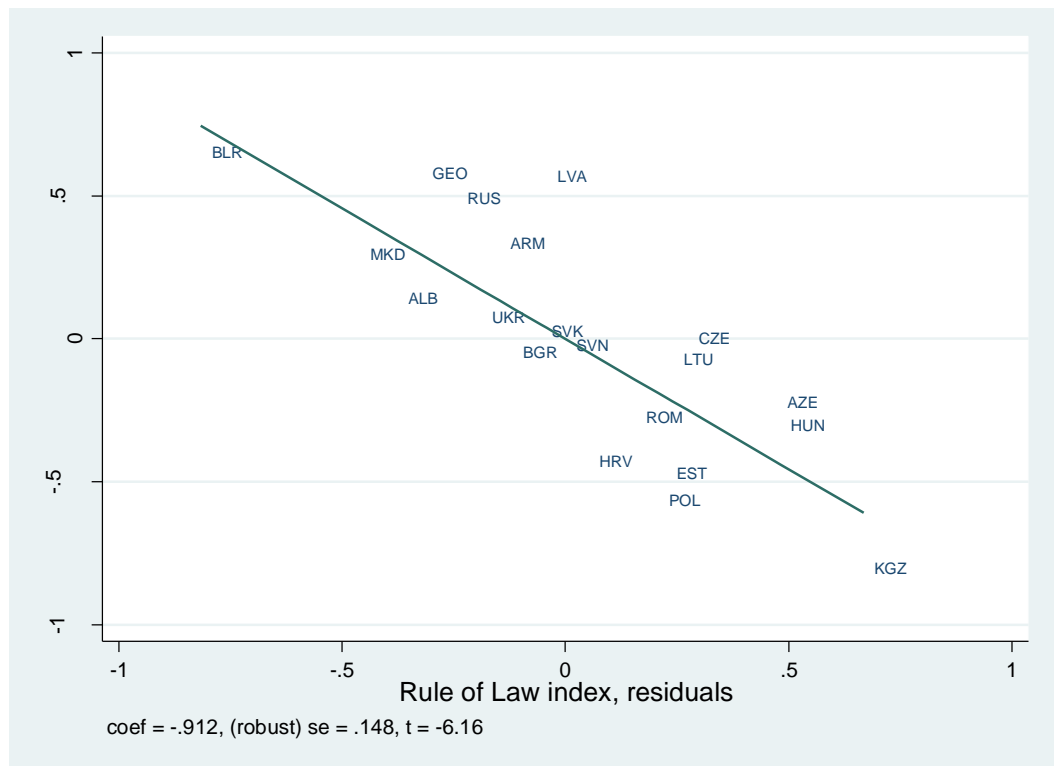


Figure 4. —Quality of Institutions and Difference between Law and Science Graduation rates in Post-Communist Countries

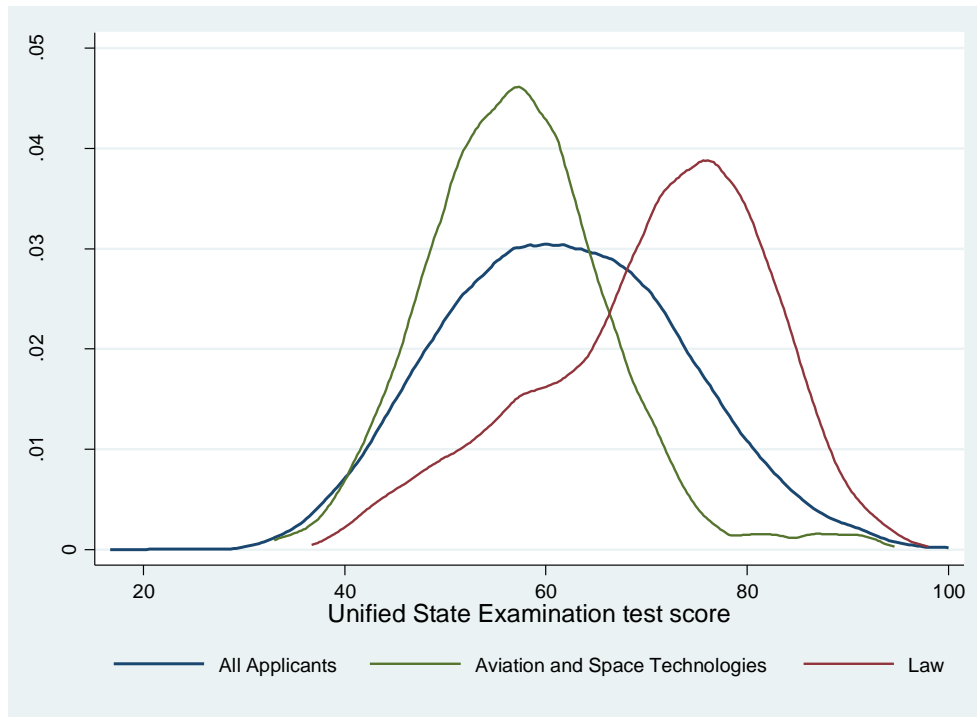


Figure 5. —Distribution of 2010 Unified State Examination Test Scores for all university applicants in Russia (Source: Russian Federal Education Web-portal (www.edu.ru))²⁸

²⁸ 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.