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ABSTRACT

The Changing Composition of Academic Majors and Wage Dynamics*

We can observe several common trends related to higher education in many countries. First, there is expansion of higher education with a shift towards majoring in the social sciences. And second, there is growing inequality among college graduates in the labor market. In Russia, these trends have been present but with an amplified magnitude in recent years. Constructing a unique data set using open-ended responses to the Russian Longitudinal Monitoring Survey, we use the Russian case to examine the effects of the changing composition of academic majors during expansion of higher education on the dynamics of wage distribution. This paper contains several contributions to the literature. First, we extend standard wage analysis across majors by exploring within-major and across-cohort variation, as well as major-specific permanent and transitory variance components and their time paths. We show that the evolving distribution of wages relates to both changes in skill prices and wage shocks induced by economic fluctuations. Next, we show that variation in skill prices relates to equilibrium effects induced by changes in the supply of graduates specialized in different fields. Uneven expansion in certain majors induces labor market saturation and leads to an increase in the wage variance of graduates from the fastest growing majors. Finally, we point out the importance of accounting for within-major heterogeneity across cohorts, which could reflect differences in student ability distribution, changes in academic content, and changes in educational quality over time.

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1 Introduction

While the classical literature considers years of education as a leading determinant of earnings heterogeneity, the recent literature argues that, given an increasingly educated workforce, workers' skills and specialization become more important than quantity of education for determining wages. For instance, Altonji et al. (2016) and Altonji et al. (2012) argue that large variation in wages among US college graduates is driven by occupation-specific human capital, which conditions workers' professional paths and careers. Altonji et al. (2014) suggest that the increasing wage inequality over the last 20 years is due to the widening inequality in returns to major-specific skills.

However, wage dynamics are not explored in the literature from the perspective of evolving skill composition of the labor force with higher education. Some descriptive estimates focus on wage differentials between groups of workers specialized in different fields (Altonji et al., 2016 and Altonji et al., 2012) or payoffs by major (Kirkeboen et al., 2016). Yet, the educated labor force does not grow homogeneously but expands under the dynamic supply of graduates specialized in different fields and supplying skills and abilities varying across cohorts. The changing skill distribution induced by the evolving major composition and expanding higher education is likely to contribute to shaping wage dynamics and re-equilibrating the labor market.

This paper studies the effects of changes in the composition of academic majors on the wage dynamics using the Russian Longitudinal Monitoring Survey (RLMS)[1] and structural analysis of wage distribution. We decompose the wage dynamics of college graduates in Russia over 2002-2016 in light of a significant expansion of higher education, which was accompanied by changes in the distribution of different fields of specialization. Boosted by the transition to a market economy, the expansion of higher education in Russia was exception-

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[1]Source: "Russia Longitudinal Monitoring survey, RLMS-HSE", conducted by National Research University "Higher School of Economics" and OOO "Demoscope" together with Carolina Population Center, University of North Carolina at Chapel Hill and the Institute of Sociology of the Federal Center of Theoretical and Applied Sociology of the Russian Academy of Sciences. (RLMS-HSE web sites: http://www.cpc.unc.edu/projects/rlms-hse, http://www.hse.ru/org/hse/rlms)

ally fast over 1995-2009. During this time there was an important shift towards majoring in the social sciences and a decline in majoring in the sciences and technical fields. While similar trends are observed in many advanced economies over past decades, the Russian context is advantageous in terms of empirical analysis of higher education and labor market dynamics because of the magnitude and speed of the changes.

The contribution of the paper is multifaceted. First, we show that growing inequality and growing variation in the price of skills in the labor market is particularly high among graduates in the fastest growing socio-economic majors. We show that changing inequality among university graduates is due to both changes in the price of skills in the labor market and wage shocks caused by economic fluctuations. The results suggest that skill price variation might relate to equilibrium effects induced by changing supply of graduates specialized in different fields.

We also contribute to the literature by providing evidence for the importance of within-major skill heterogeneity across cohorts. The heterogeneity is induced by changes in academic content and educational quality and relates to differences in student ability distribution, changes in academic content, and changes in educational quality over time.

From the methodological perspective, our study shows that wage analysis exclusively focused on mean wage returns would understate the labor market impact of the changing major composition. We contribute to the literature by exploring not only between-major wage differentials but also within-major variation. We study both of these dimensions over time and across several cohorts. Specifically, in addition to exploring the time trends of major distribution and major-specific wages, we analyze the variance of wages decomposed into permanent and transitory variations, along with their time paths, by extending the model from Baker and Solon (2003) to include major-specific parameters. This allows us to test the role of prices associated with major-specific skills in wage inequality: our structural analysis of wage variance distinguishes between wage dynamics related to the evolution of the labor market price for skill and specialization and wage dynamics related to labor market

instability and wage shocks.

The permanent and transitory components are allowed to differ by major and by cohort. The permanent variance is parameterized to capture persistent heterogeneity across workers not only in their levels of wages but also in their growth rates; it also captures evolving forces of skill supply and demand, and different prices among workers from different cohorts and educational fields. The model also accommodates permanent reordering of workers in the wage distribution. The parameters of the transitory component allow for investigating the role of labor market instability and wage shocks for determining wage inequality across majors and cohorts. The shocks are allowed to decay gradually over time to accommodate the persistence of shocks related to recession periods.

Finally, our paper is the first to make an extensive analysis of the evolving major composition and its impact on wage dynamics in the Russian context. The analysis is based on a unique data set built by coding text variables from initial open responses. Despite marked changes to higher education and the labor market, the literature is scarce regarding the particular period and setting studied in this paper. The rare exceptions include Gorodnichenko and Sabirianova-Peter (2005) reporting increasing returns to education in post-Soviet Russia, Kyui (2016, 2010) and Belskaya et al. (2020) discussing heterogeneity of returns to higher education during its expansion; Denisova and Kartseva (2006) estimating wage returns to occupational specialization; and Rudakov et al. (2019) and Gimpelson et al. (2009) showing significant wage penalties associated with mismatches between educational and occupational levels and fields of study of the university graduates.

The paper is organized as follows. Section 2 describes the Russian institutional context with a focus on the evolving supply of graduates in different fields; it also provides some international comparisons. Section 3 presents the data and documents evidence of a changing supply and demand for field-specific skills. Section 4 outlines conceptual and empirical frameworks. Section 5 presents empirical results from the wage analysis including a structural variance analysis. Section 6 provides concluding remarks.

2　Institutional Context

2.1　Russian labor market and demand for skills in the 2000s

After multiple negative macro-shocks during the transition period and a downturn in 1995-2000, the Russian economy experienced a period of strong economic growth in the first decade of the 2000s. The employment rate was remaining high throughout this time. However, unlike the transition period, when weak unemployment had been balanced by low real wages,[2] the real wages were growing along with the GDP over 2000-2008, until the global recession of 2008. In the period of 2000-2016, the Russian economy endured a reduction in manufacturing and agricultural employment and growth in the service sector, both particularly strong and fast in the first half of the period.

The persisting high employment rate is therefore not necessarily a sign of labor market stability. Gimpelson and Kapeliushnikov (2016) argue that the labor market of this period experienced significant reallocation of the labor force across market sectors and occupations. Analyzing job distributions in terms of payoffs and knowledge intensity, they show that the intensified deindustrialization of the economy induced job polarization in the manufacturing sector with relatively steady employment at the tails of the manufacturing job distribution and important reduction at the middle level.

Gimpelson and Kapeliushnikov (2016) report no evidence of labor reallocation within industries but labor reallocation toward trade and services. The service sector was expanding with increasing intensity along the job rank. Gimpelson and Kapeliushnikov (2016) find a structural shift towards higher level jobs in this sector.

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[2] While the transition economies shared multiple trends and shocks in their economies, the decline in employment was weak in Russia compared to other countries under transition (Gimpelson and Lippoldt, 2001). Instead, in the absence of labor market institutions and regulations, the Russian market adjusted by low wages, underemployment, wage arrears, as well as informal agreements and transactions.

2.2 Higher education expansion in Russia

The number of students pursuing tertiary education in Russia expanded in the 1990s and early 2000s, driven by changes in legislation and bolstered by the country's transition to the market economy and the subsequent period of economic growth.[3] Similar expansion also happened in other transition economies (Figure 1):
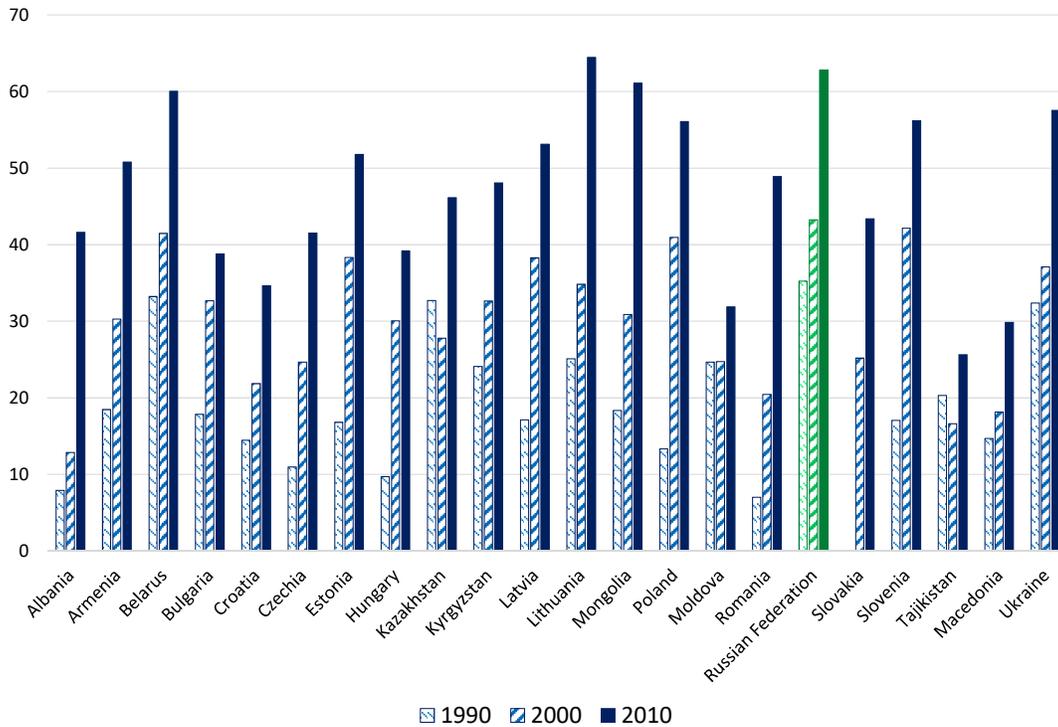
Figure 1: Enrollment in tertiary education (over 1000 population), transition economies. Sources: UNESCO Institute for Statistics, Database: Education Statistics - All Indicators.

The trend is also shared by the OECD countries (Figure 2) while at a considerably slower pace:

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[3]Starting in 1992 with the "About education" law, the previously fully state-subsidized tertiary education has been transformed into a mix form with both state-subsidized and full-tuition slots: both private tertiary institutions and public institutions admit some of the students on a full-tuition basis. This legislative change led to a massive expansion of the higher education programs, driven mainly by public institutions with smaller contribution from private institutions.
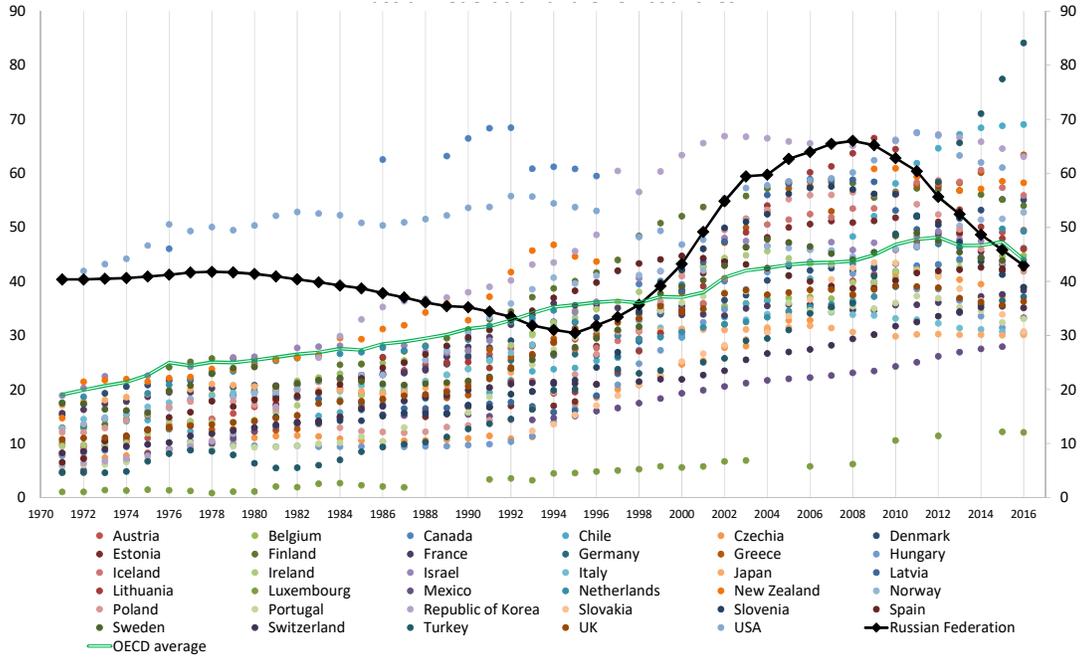
Figure 2: Enrollment in tertiary education (over 1000 population),Russia and OECD countries.
Sources: UNESCO Institute for Statistics, Database: Education Statistics - All Indicators.

Figure 3 depicts the number of students enrolled in higher education institutions in Russia over 1955-2016 and their ratio relative to the total population in the college-going age (18-22 years). The number of students increased from 2.8 million in 1990 to 7.5 million in 2008 (an increase of more than 166%) yielding the enrollment ratio increase from 30% in 1990 up to 60% in 2009. Starting in the mid-1990s, 2-5% of students (frequently in management and economics) pursued the second higher education[4]. After 2008, the number of enrolled students decreased following the demographic decline of the college-going age population (with the ratio remaining overall unchanged).[5]

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[4]Source: "Indicators of Education" statistical digests for years 2007 and 2010; Solntsev (2015).

[5]The shrinking population of young people in Russia (the demographic "hole") in the 1990s causing a decrease in the number of college students in the 2000s has multiple roots: demographic cycles engendered by World War II, various macroeconomic shocks impacting Russia, birth control technology, and emigration since the transition period.
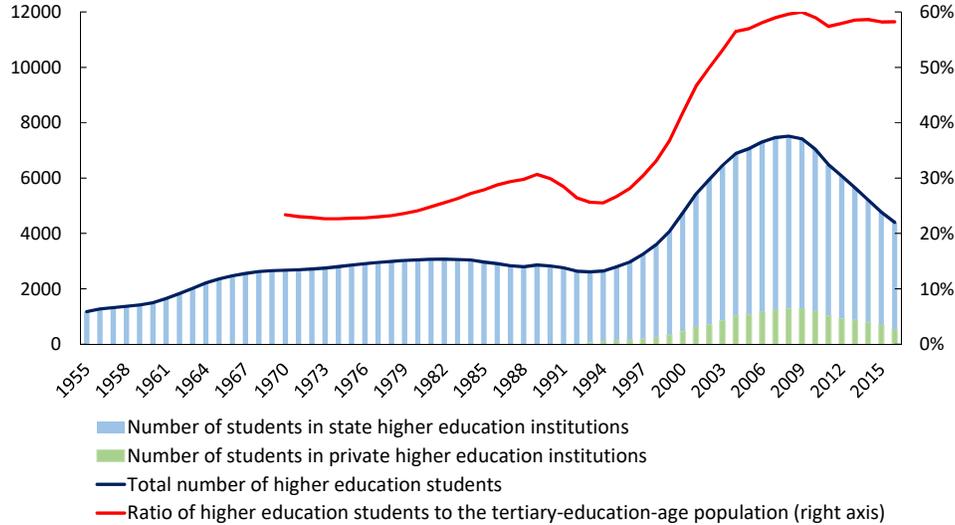
Figure 3: The number of higher education students in Russia (in thousands, left axis) and the ratio of students in higher education to the population of 18-22 years old (in percent, right axis).
Sources: "Russian Statistical Review", 1996; "Russian Statistical Annual Review", 2003, 2005; "Statistical Indicators of Russia Education" (stat.edu.ru); "Education in Russia" 2003; "Education in Russia", 2010, 2012, 2014; "Education in numbers", 2017, 2018; UNESCO, UIS data and indicators.

2.2 Expansion by Academic Majors

Importantly, the expansion of the higher education system happened disproportionately by major. It was largely driven by an increase in the proportion of students studying Economics, Management and Administration, as well as Humanities, namely Law. Figure 4 shows the number of college graduates by major of study over 1959-2016.[6]

The specialization distribution of higher education institutions was relatively stable over the Soviet period. Institutions specializing in Construction and Manufacturing were leading by the number of graduates, followed by General Education institutions. The structure of graduates by majors started sharply changing after the early 1990s.

The fraction of graduates in Economics, Management and Administration sharply in-

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[6]Note that prior to 1990 the data are only available on the specialization of educational *institutions*, which is different from the classification of majors starting from 1990. For instance, the general education institutions (depicted as "pre-1990: Education & Universities") had educational programs in Science, Humanities, etc. Thus, the data before and after 1990 are not directly comparable.

creased from less than 14% in 1990 to 40% in 2010. In terms of levels, the number of graduates in this major increased by more than 900% over this period (while the increase in the total number of higher education graduates, irrespective of major,was around 260%). The college major with the second largest increase over this time period is Humanities, which rose from 12% in 1990 up to 21% in 2010 (the number of graduates in the Humanities increased by more than 500% over this period).

In contrast, the fraction of graduates in Natural Sciences, Physics and Mathematics declined from 11% to less than 4% and the fraction of graduates in Engineering, Manufacturing and Construction declined from almost 35% down to less than 16% over the same period. However, both these groups of majors did experience an increase in the absolute value of graduates, by 24% and 68%, respectively. But the increases were much smaller than that of Economics and Humanities majors.
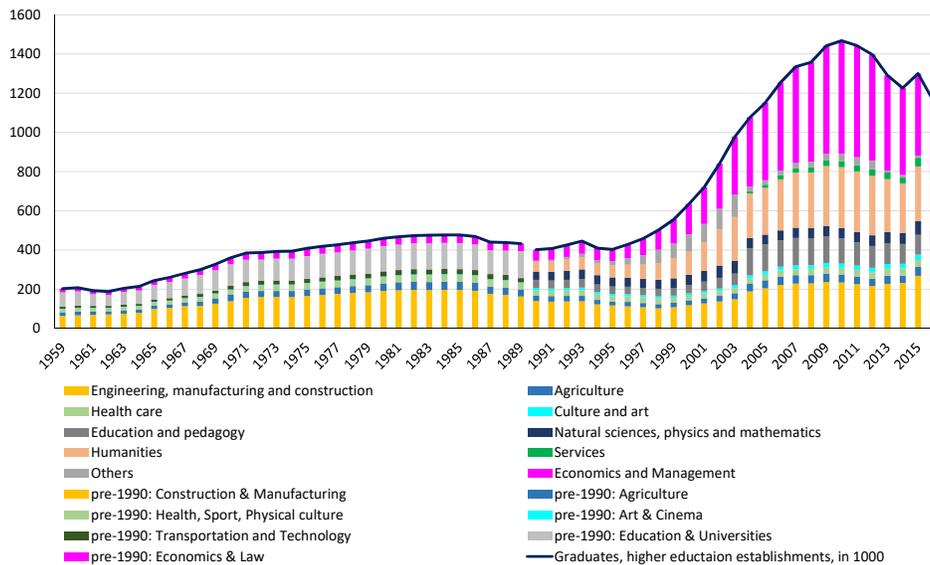
Figure 4: The number of higher education graduates in Russia, in thousands (pre-1990: by institution's specialization; post-1990: by major of studies).
Sources: "Russian Statistical Review" 1996, "Russian Statistical Yearbook" 2004, 2016, 2012, 2017.

The expansion was associated with changing educational quality and curricula. Analyzing various indicators of university resources and admission test scores, Belskaya and Sabirianova-Peter (2013) argue that the university educational quality declined over the pe-

riod of expansion. Kyui (2016) also documents increases in student-teacher ratios and total physical infrastructure for education at the beginning of the expansion. On the other hand, the curricula have been updated to align with technological advances and evolving labor market demand, in particular in the field of economics and management: The soviet curriculum in this field mainly focused on the political economy used as an ideological tool or bookkeeping and skills targeting the contribution to the planned economy (Alexeev et al., 1992; Osipian, 2004).

The demand for skills relevant to the market economy was one of the drivers of the disproportional increase in the social science university programs since the transition. Russia today is among the countries with the largest proportion of graduates in Business, Administration and Law (more than 44% of the graduates in 2013, Figure 5). Despite the deindustrialization of the economy and decline in relative supply of the graduates in sciences and engineering, Russia still keeps a relatively large proportion of graduates in Engineering, Manufacturing, and Construction (21.4%). On the other hand, it is among the countries with the lowest proportion of graduates in Arts and Humanities (4.4%), Natural Sciences, Mathematics and Statistics (1.9%), Health and Welfare (5.3%), Journalism and Information (5.5%).
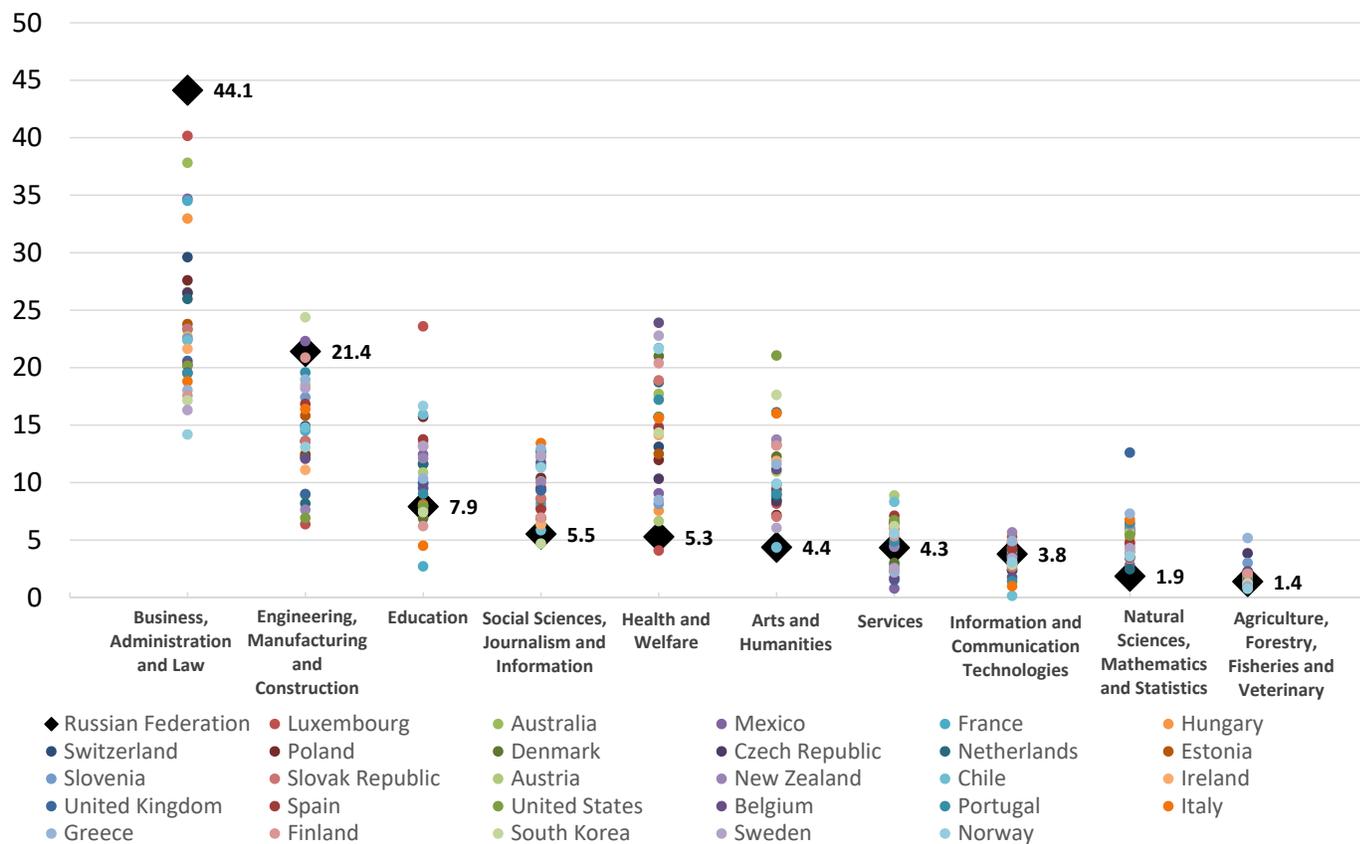
Figure 5: The distribution of graduates from tertiary education programs by major, in Russia and selected OECD countries (2013).
Sources: UNESCO Institute for Statistics, Database: Education Statistics - All Indicators.

For comparison, in the US, similar changes in college major choices have been observed, but over a much longer time horizon (Figure 6) and with a significantly smaller magnitude: the fraction of graduates majoring in Economics and Management increased from below 15% to over 20% during the 15-year period starting in the early 1970s and then remained at a level around 20%. In Russia, the percentage of graduates in these majors increased from below 15% in the early 1990s to almost 40% during the following 10 years.
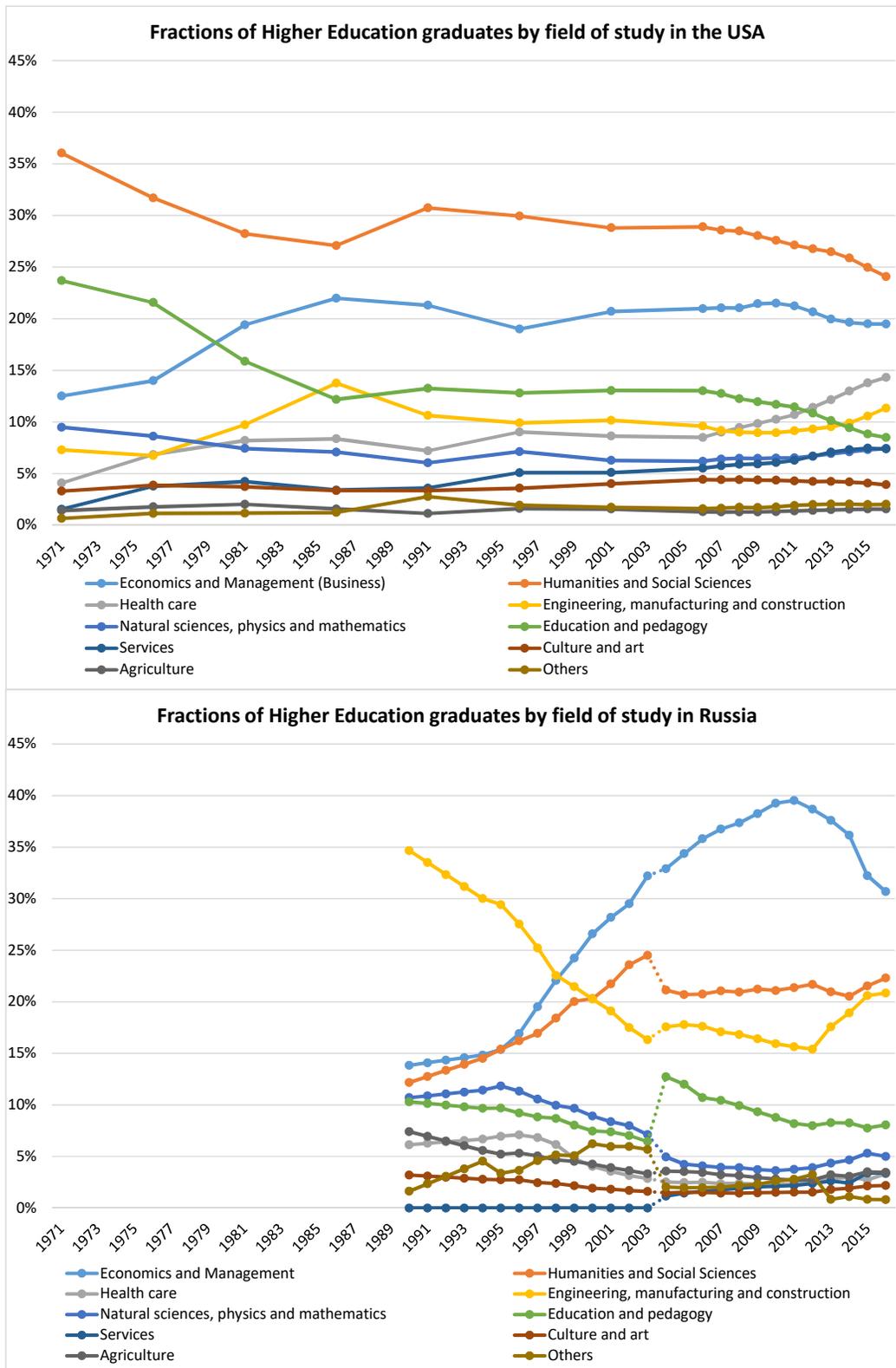
Figure 6: Major composition of higher education graduates in the USA and Russia.
Sources: For Russia - "Russian Statistical Yearbook", 2004, 2016, 2012, 2017; For the USA - U.S.
Department of Education, National Center for Education Statistics. Digest of Education Statistics,
2017; Tables: 322.10, 323.10, 324.10.

Table 1: Descriptive Statistics, Pooled data
Working-age Population with Higher Education

	Men		Women	
	Mean	SD	Mean	SD
Ln(real wage in rubles)	4.88	1.62	4.68	1.63
Labor force participation rate	0.91	0.28	0.94	0.23
Working hours in last 30 days	148.12	86.45	128.75	76.06
Number of years observed	10.64	6.11	11.42	6.35
Number of individuals	3485		4576	
Number of observations	21072		29963	

The nominal wages are adjusted by the yearly CPI index

3 Data and labor market trends

The data are drawn from the Russia Longitudinal Monitoring Survey. The RLMS is an annual panel dataset based on a nationally representative survey jointly conducted by the Carolina Population Center at the University of North Carolina at Chapel Hill (USA), Demoscope, and the Higher School of Economics (Russia). The survey has been running since 1994 with the initial sample of 4000 households, which was augmented by 2000 households in 2010. Sampled households have been followed over years, yet the resulting panel is unbalanced: individual observation windows range from 1 to 21 years with the mean span of 11 years and standard deviation of 6 years.

The individual part of the survey contains detailed information on employment and educational attainment. The employment section reports each individual's employment status, number of monthly working hours, monthly earnings, and occupation. The occupations are categorized based on ISCO 2008 classification. Table 1 reports the basic labor market statistics and numbers of workers with higher education. To deflate wages, the nominal wages (in rubles) are adjusted by the yearly CPI index.

Important for our analysis, the survey reports detailed education outcomes, including degree earned, enrollment years in educational institutions, and fields of specialization. We construct the categorical variable for college major from the open response questions

about the fields of specialization using the International Standard Classification of Educa-
tion (ISCED).[7] The individual reports are qualitative data in Russian recorded starting 2002;
they are not available in the main RLMS data set,[8] but were provided by the RLMS team
on our request for the period of 2002-2016. The resulting data set is therefore unique.

We use the first-level classification on the ISCED fields of education with the following
nine groups: Education, Humanities and arts, Social sciences, business and law, Science,
Engineering, manufacturing and construction, Agriculture, Health and welfare, Services,
and General programs. While the descriptive analysis covers all the aggregated groups, the
empirical analysis focuses on the three largest ones: Education, Social sciences, business and
law, and Engineering, manufacturing and construction. These three groups are referred to
as *Education*, *Social Sciences* and *Engineering* throughout the paper. Such an aggregation
allows for efficient empirical analysis, and is similar to the level of aggregation used in the
literature.[9]

Supply of college graduates by major

In line with the aggregate national statistics presented above, the RLMS data show a sharp
change in the distribution of college majors over time. Figure 7[10] depicts an increasing
share of university enrollments in *Social Sciences* since the 1990s and a shrinking share of
students enrolling in *Education* and *Engineering*. Figure 15 (see Appendix) shows that all
the branches of *Social Sciences* (Business and Administration, Journalism, Social Sciences,
Law) expanded. In *Science*, the main observed trend is the substitution of Mathematics
and Physics majors by Computer Sciences. In the broad *Engineering* category, not only

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[7]While the field of specialization was coded in the survey using the occupational classification ISCO 2008
for some years, we classify the academic majors differently, using the International Standard Classification
of Education (ISCED), which is conventionally adopted in the education literature about college majors.

[8]The questionnaires and data descriptions are otherwise available in both Russian and English versions.

[9]See for example Beffy et al. (2012) focusing on three broad categories when analyzing determinants of
the college major choice: a) Sciences; b) Humanities and social sciences (including art studies); c) Law,
economics, and management.

[10]The data on university enrollments by major are calculated using enrollment years reported by individ-
uals observed in the RLMS

engineering but also architecture and manufacturing majors become less popular among those enrolled at universities.
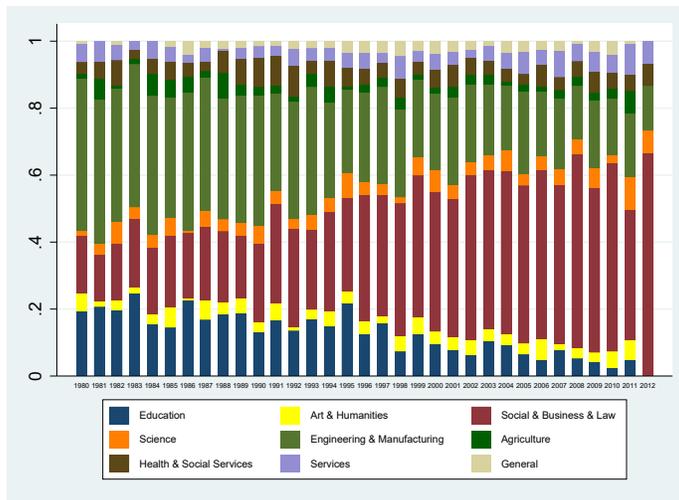
Figure 7: Distribution of majors.

We focus our analysis on the college graduates of working age in the observed years of 2002-2016 (men below 60 years old and women below 55 years old).[11] The corresponding population is born in 1945-1995. The earliest cohort, born in 1945-1955, and the latest cohort, born in 1985-1995, are weakly presented in the sample of workers in 2002-2016 and can only be observed at the very beginning or the very end of the period. The main body of the workers with higher education active in the 2002-2016 labor market consist of college graduates born in 1955-1985.

The first three 5-year cohorts, born in 1955-1970, graduated by the early 1990s. The last three 5-year cohorts, born in 1970-1985, graduated during the expansion of higher education, experiencing changing programs and curricula. Yet, the graduates born in 1980-1985 actively joined the labor market in the second part of the period only. In the empirical part of the paper devoted to wage dynamics (section 5), we focus then on the five 5-year cohorts (born in 1955-1980) which are observed in the labor market for the full period of 2002-2016.

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[11]60 and 55 were the official retirement ages, for men and women respectively, during the analyzed period. Starting from 2019 the retirement ages are being gradually increased each year with the goal to reach 65 and 60 years, respectively.

The sizes of these 5-year cohorts observed in the RLMS are about 800-1500 individuals of working age per year. In line with the nationwide statistics presented above, about 25-30% of the first three of the 5-year cohorts (those graduated by the early 1990s) hold a university degree. This fraction rises to 40% for the younger, 4th and 5th cohorts (those graduated by the early 2000s) and up to 50% for the youngest cohort (studying in the 2000s). The resulting sample 5-year cohorts of the university graduates are about 200-600 individuals per year. The gender distribution of the graduates is about 60% of women and 40% of men. The gender imbalance for each sample varies slightly across cohorts and year of observation.

Labor demand for graduates by major

This section documents major-specific trends in employment rates, levels of professional occupations, and the match between the fields of specialization and occupation of the university graduates. The trends provide a piece of evidence of the changing demand for skilled workers.

The *employment rate* of the working-age college graduates was about 90% during the period analyzed. The left graph of Figure 8 shows that the employment rates of university graduates by major follow common business cycles. The highest rate is among the graduates in *Education*. This can be explained by the educational sector remaining to a large extent public sector paying low wages and workers with *Education* majors being more likely to work in the public sector (80%). Graduates in *Social sciences* and *Engineering* are equally distributed between public and private sectors. The employment trends of *Social sciences* and *Engineering* are parallel, with the *Social sciences* rate trending at the lowest level over the 2000s.

The *distribution by occupational levels*[12] of the working university graduates exhibits substantially different trends by majors over the same period. The right graph of Figure 8

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[12]Three levels aggregate several occupational categories defined by the ISCO 2008: "high" corresponds to managers and professionals; "medium" corresponds to technicians, associate professionals, and skilled agricultural or forestry workers; and the "low" level corresponds to clerical support workers, service, sale, craft and related trade workers, plant and machine operators, and elementary occupations.

shows that the average level of occupation of *Social sciences* graduates is decreasing over the period considered. There is no change for *Engineering* majors and an increase for graduates in *Education* over the same period.
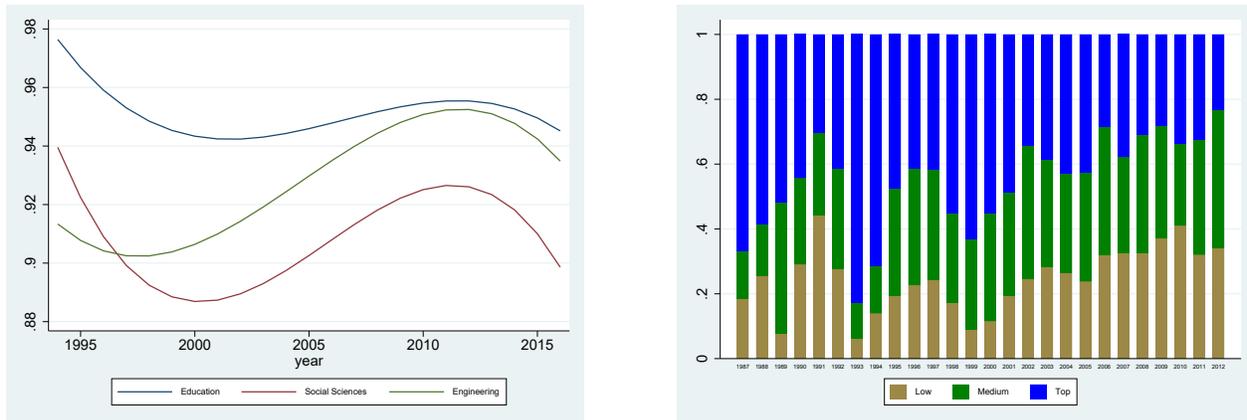
Figure 8: Employment rates by major (left); *Social sciences* graduates by occupation level (right)

The *occupation-specialization matching* of the graduates also varies significantly across major groups.[13] Figure 9 shows time trends for match of specialization net of regional and observed human capital differences (years of education and age in a quadratic form). The trends are reported separately for men and women. The patterns are obtained using a probit model with cubic time trends.[14]

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[13]The occupation-specialization match is defined as a match of fields of work and graduation (see Table 3, Appendix). Occupation categories are provided by the RLMS and uniformly based on the ISCO 2008 classification for all time periods. The specialization categories are build up based on the ISCED classification as described above.

[14]$Prob(Match_{itcm} = 1) = F(\gamma_{0cm} + \gamma_{1cm}t + \gamma_{2cm}t^2 + \gamma_{3cm}t^3 + H_{it}\gamma_{cm} + region_{it})$, where i, t , c and m correspond to individual, time, cohort, and major subscripts; H_{it} is a matrix of human capital variables; F denotes normal cumulative density function; $\gamma_{0cm}, \gamma_{1cm}, \gamma_{2cm}, \gamma_{3cm}, \gamma_{cm}$ are the regression parameters.
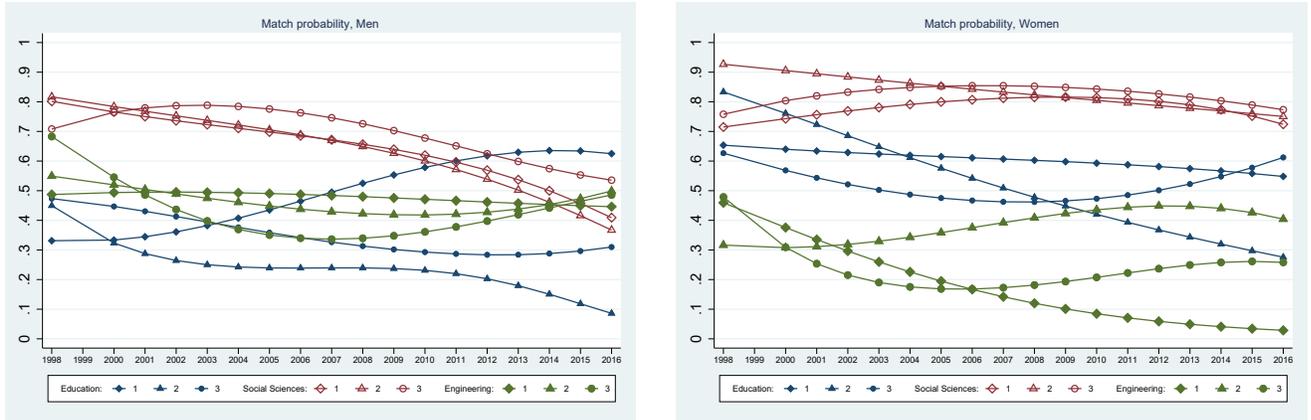
Figure 9: Specialization-occupation match probabilities by major and birth-cohorts. 1: 1956-1965; 2: 1966-1975; 3: 1976-1995

Despite an increasing fraction of *Social sciences* graduates, this profession has the highest match rates over the period of 1998-2016 (about 70%). However, the match rates are decreasing over time. This is particularly true for men. Their match rate falls from 80% to 40% with some minor differences across the cohorts. The decrease accelerates starting in 2007, while the rising fraction of graduates in *Social sciences* peaked in 2010. This is in line with Rudakov et al. (2019) using 2016 data and reporting a particularly strong mismatch for graduates in the fields contributing to the accumulation of general human capital, such as in social sciences, rather than specific human capital, such as in engineering. The depicted dynamics implies that the rising supply of *Social sciences* majors was a response to the greater demand for these graduates in the labor market until the market became saturated in the 2000s.

The *Education* category is dominated by female workers. Their high match rates imply that many female graduates take jobs in the educational sector in difference with men showing low match in this category. However, women who had graduated in the 1990s faced a sharp decrease in their match rates over the period of 1998-2016. This might be related to particularly low wages offered by the public sector since the transition period, rather than to a limited demand on the labor market. As shown in the next section, wage rates were indeed the lowest among *Education* graduates. Students who graduated before or early in

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the economic transition period were not able to anticipate the market wages, their choices of major are therefore unlikely to be based on expected wages. On the other hand, early-transition graduates were the new entrees to the labor market in the 2000s and therefore more mobile in terms of job market transitions as compared to later cohort graduates in *Education* showing more stable match.

In contrast to the *Education* category, the *Engineering*-related professions are disproportionately male; the match rates are higher for male workers in this category. They are relatively stable over the period of 1998-2016 and slightly increasing from earlier to later cohorts. This might be related to a decreasing supply of graduates with technical background and the engineers' wages growing to the same level or above the wages of social sciences graduates since 2008.

4 Wage Structure: Conceptual and Empirical Frameworks

The changes in the supply and demand for skills in different fields of specialization, as described above, are likely to cause changes in equilibrium wage distributions in the labor market within and across the groups of workers specialized in different fields. The basic channels of redistribution and the parameters of the wage dynamics are sketched by the conceptual framework in this section.

From an empirical perspective, the evolution of the underlying wage distribution is not directly observable because random economic shocks also produce changes in observable wages. The empirical wage structure presented next allows then for discriminating between wage dynamics related to the evolution of labor market prices for skills and wage dynamics related to the transitory labor market shocks and instability.

4.1   Conceptual Framework

The wage distribution changes over time according to 1) changes in the composition of skills and ability in the labor force, and 2) changes in the corresponding prices for skills in the labor market. Skills' composition is defined by the graduates' supply on the labor market. Skill prices result from the interaction of skill demand and supply.

1) Changes in the composition of workers with a higher education. The expansion of the higher education occurring unbalanced across fields increases the supply of skilled workers and transforms the sets and distributions of individual abilities and skills acquired from higher education that the workers offer in the labor market. Indeed, a larger pool of students is likely to have a larger dispersion of individual abilities, with perhaps more density in the lower range of ability: weaker selection on abilities is likely to facilitate the access to higher education for individuals with lower abilities.

Further, worker's skills acquired in the university build on the academic major and quality of the higher education programs. Under the expansion, the greater body of students get hosted by a larger number of colleges. Within-major skill heterogeneity might therefore grow from one cohort of graduates to another with disparities in quality and type of the skills provided by the expanding graduate programs.

Let us $\mathcal{A}_t$ be the set of individual abilities and skills acquired from the university and offered by the labor force with higher education at time t; and $\mathcal{A}_t^{mc}$ be its subset corresponding to major m and birth-cohort c. Since the workers belonging to the same birth-cohort, c, and having graduated from the same major, m, are endowed with the same set of abilities and university-acquired skills through their life cycle, $\mathcal{A}_t^{mc}$ is time-invariant:

$$\mathcal{A}_t^{mc} = \mathcal{A}^{mc} \text{ for } \forall t$$

Therefore, a transformation of the labor force set $\mathcal{A}_t$ under the structural change of the higher education is entirely driven by the changing composition of the labor force in terms

of the majors, $\mathcal{M}_t$, and birth cohorts, $\mathcal{C}_t$:

$$\mathcal{A}_t = \bigcup_{m,c \in \mathcal{M}_t \times \mathcal{C}_t} \mathcal{A}^{mc}$$

Additionally, workers can accumulate more skills with working experience and more education (job training, getting a post-graduate or second university degree). Under the higher education expansion, this accumulation, might (but not need to) be cohort- and major-specific.

Wage dynamics implication (a). Conditional on the skill prices, the implication of the evolving $\mathcal{A}_t$ on the wage dynamics is a greater dispersion of wages. Indeed, the increasing set of abilities and university-acquired skills under higher education expansion might diversify the set of skill prices, $p(\mathcal{A}_t, \cdot)$, set on the market over time. This *diversification* effect, $p_{\mathcal{A}_t} : p_{\mathcal{A}_t}(\bigcup_{m,c \in \mathcal{M}_t \times \mathcal{C}_t} \mathcal{A}^{mc}, \cdot) \to p_{\mathcal{A}_{t''}}(\bigcup_{m,c \in \mathcal{M}_{t'} \times \mathcal{C}_{t'}} \mathcal{A}^{mc}, \cdot)$ is due to the changing major and cohort composition of the labor force, $\mathcal{M}_t \times \mathcal{C}_t$, between time t and t'. Important from the empirical perspective, the effect is zero for a given cohort within a given major since $\mathcal{A}^{mc}$ is time-invariant. It might only induce time-invariant differences of the wage variance across different major and cohort groups.

2) Price evolution. The adjustment of skill prices to the changing skill supply and demand is a classical equilibrium mechanism. Such an adjustment translates into changes in workers' wages and eventual unemployment of the oversupplied group. It also comes from the supply side via reallocation of workers across types of jobs and underemployment or mismatch between specialization and professional occupations of workers with higher education. The wage dynamics are then conditioned not only by the race between the demand and supply of skills but also by the substitution rates between workers with different specialization and workers' reallocation across a larger set of jobs compared to the jobs corresponding to the fields of specialization.

Given the multiple composition effects affecting the pool of workers with higher education over time, the resulting wage dynamics are likely to be subjected to composition effects and

variance transformation rather than be limited to some shifts in wage levels. Different re-equilibrium channels might be associated with different traits of the dynamics:

Wage dynamics implication (b). In addition to the *diversification* effect, the increasing heterogeneity can also yield within-major cohort wage polarization in the case of the increasing substitution rate between skills of younger cohorts vs skills of older cohorts (for instance, higher value of workers whose skills are complementary with more recent technologies; or workers trained with stronger market and business orientation as could be the case of later graduates or workers; or workers with deeper and quantitatively more advanced training in the field of specialization as could be the case of older graduates, etc.). Should the substitution rate between the graduates from different cohorts c and c', differ from one, $r_{cc'} \neq 1$, a between-cohort wage gap would also gradually shrink or widen depending on the comparative advantages of earlier vs later cohorts and the race between demands for cohort-specific skills. The changing substitution rate between workers from the same field of specialization but different cohorts, would also induce reordering of the major graduates in the wage distribution, $G_t^{-1}(\cdot)$ with $G_t(\cdot)$ representing graduates distribution based on earnings.

The *within-major within-cohort* time evolution of skill price levels and variance under this *substitution* effect, $p_{\mathcal{C}_t} : p_{\mathcal{C}_t}(\mathcal{A}^{mc}, \mathcal{C}_t, \cdot) \to p_{\mathcal{C}_{t'}}(\mathcal{A}^{mc}, \mathcal{C}_{t'}, \cdot)$, would be monotonic in time. Indeed, the *substitution* effect should be tuned with later cohorts of graduates gradually replacing the earlier cohorts, the corresponding price dynamics should be very gradual and monotonic over time: it would go along with the cohort re-composition of the graduates. Under this dynamics, the *within-major* wage dispersion would be *gradually monotonously increasing* following the expansion period.

Wage dynamics implication (c). In the case of supply outpacing the demand for graduates from a specific field, the demand side would devalue the field-specific skills. Should the devaluation be heterogeneous, it would yield within-major wage *polarization* depending on the substitution rate r_a between workers with higher abilities and skill level and workers with lower ones, $p_m : p_m(\bigcup_{m,\, c \in \mathcal{C}_t} \mathcal{A}^{mc}, \cdot) \to p_m(\bigcup_{m,\, c \in \mathcal{C}_{t'}} \mathcal{A}^{mc}, \cdot)$: under disproportional supply

of workers from a given field, the firms might strengthen the selection on individual skill levels and abilities. Should the supply rise because of the growing lower tier of the ability distribution among the field graduates, the polarization would be associated with devaluation of the lower level skills. The *within-major wage* dispersion would rise with no specific time pattern unlike the gradual monotonous increase under the *substitution* effect.

The supply side would adjust by workers' reallocation across a larger set of jobs including the jobs outside the field of specialization. The *reallocation* effect would be associated with a larger within-major wage dispersion and deterioration of the match between the field of specialization and professional occupation contributing to the polarization. It would eventually contribute to the reordering $G_t^{-1}(\cdot)$ of workers in the wage distribution.

The effects described above each operate to determine the overall wage set in each period $\mathcal{W}_t$, reflecting demand fluctuations and adjusting skill prices under the following composition:

$$p_{\mathcal{C}_t} \circ p_m \circ p_{\mathcal{A}_t} : \mathcal{W}_t \to \mathcal{W}_{t'}$$

The resulting dynamics is major-specific unless graduates from different majors are perfect substitutes. Aside from the diversification and substitution effects, greater within-major dispersion and its variation are associated with greater dis-balance between demand and supply for the field-specific skills and stronger devaluation of the field skills offered by the workers from the lower tier of the ability distribution. Cross-field average wage gaps depend on adjustments of field-specific skill prices, intensity of reallocation effect, and the substitution rate between workers "migrating" into professional occupation unrelated to their academic majors and "natives" to the occupation. Graduates from the fields with a greater number of mismatches would face greater polarization and a more volatile dispersion in wages.

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4.2 Empirical Framework

To empirically trace the mechanisms underlying wage dynamics as discussed above, we analyze the variance of the residuals from the Mincerian wage equation by decomposing them into permanent and transitory components with a flexible parametrization of each component. Below we present the empirical model and show the links between the model parameters and the effects of changing skill supply and demand in the labor market on wage dynamics.

The explained part of the wage distribution is based on the classical Mincer equation with hourly wages in log-form modeled as a function of years of education and age (in a quadratic form), the controls proxy for workers' human capital (summarized by a vector of individual human capital H_{it}). Wages and the time path for wages are allowed to differ across academic majors, m, and birth cohorts of the graduates, c. Cubic time trends capture business cycles, and regional dummy variables reflect differences across local labor markets:

$$ln(W_{itcm}) = \beta_{0cm} + \beta_{1cm}t + \beta_{2cm}t^2 + \beta_{3cm}t^3 + H_{it}\delta_{cm} + region_{itc} + e_{itcm} \tag{1}$$

where W_{itcm} is the hourly wage of an individual i from cohort c, graduated in major m, and observed in the labor market at time t; e_{itcm} is the error term; $\beta_{0cm}, \beta_{1cm}, \beta_{2cm}, \beta_{3cm}, \delta_{cm}$ are the regression parameters

The unexplained part of the wage variation related to the residual wage e_{itcm}, is decomposed into permanent and transitory components by extending the model from Baker and Solon (2003). When adopting the model from Baker and Solon (2003), we additionally allow the time path of e_{itcm} to differ across majors, m, and birth cohorts of the graduates, c:

$$e_{itcm} = p_{mt}q_{cm}(\alpha_{mi} + u_{mit}) + l_{mt}s_{cm}v_{mit} \tag{2}$$

where α_{mi} represents time-invariant individual heterogeneity, u_{mit}, and v_{mit} denote idiosyncratic permanent and transitory wage shocks, q_{cm} and s_{cm} are the major-cohort-specific multipliers relating to the permanent and transitory shocks; p_{mt} and l_{mt} are the corresponding

major-specific time loading parameters.

Individual heterogeneity α_{mi} captures the true, unobserved value of the individual's abilities and skills. The size of the individual heterogeneity, $\sigma_{m\alpha}^2$, might differ across majors and birth cohorts, and $q_{cm}^2 \sigma_{m\alpha}^2$ accommodates cross-major and cross-cohort variation via q_{cm}. q_{cm} above (below) 1 is associated with greater (less) within-major within-cohort heterogeneity compared to the reference group of the graduates. It captures cross-major and cross-cohort change over time in graduates' skills and abilities, which come from the changes in the composition of students and schools induced by the expansion of the higher education. q_{cm} is therefore associated with the *diversification* effect, $p_{\mathcal{A}_t}$.

As discussed in the section above, individual heterogeneity might evolve with working experience and further training. This is modeled by allowing for highly-persistent idiosyncratic random shocks w_{mit} with variance σ_{mw}^2. In addition to growing individual skills, this term picks up the shocks related to workers' *reallocation* on the labor market, $\Delta G^{-1}(\cdot)$, with potential revaluation of their skills or abilities. The resulting permanent shocks u_{mit} allow for long-term reordering of workers in the wage distribution. They are modeled to follow a random walk:

$$u_{mit} = u_{mit-1} + w_{mit} \tag{3}$$

To differentiate skills' revaluation in the labor market from the transitory wage shocks related to labor market instability, we also allow for idiosyncratic transitory wage shocks v_{mit}. The transitory shocks v_{mit} are serially correlated following an AR(1) process. The AR process allows for a transitory shock to have some lasting impact. The persistence of the shock depends on the major-specific autocorrelation, ρ_m, implying that graduates from different fields might face micro-level labor market shocks with different magnitudes and persistence:

$$v_{mit} = \rho_m v_{mit-1} + \varepsilon_{mit} \tag{4}$$

with ε_{mit} standing for idiosyncratic random shocks with variance $\sigma^2_{m\varepsilon}$. As with individual heterogeneity, transitory variance might differ across majors and cohorts because of different labor market sectors or types of jobs. Greater (less) instability of the corresponding sectors/jobs is reflected by the major-cohort-specific multiplier s_{cm} of the transitory shocks, v_{mit}: $s_{cm}v_{mit}$, taking on a value great than (less than) 1.

Finally, as in Baker and Solon (2003), the group-specific loading parameters, p_{mt} and l_{mt}, allow for the group-level time evolution in the permanent and transitory components of the wage variance respectively.

In our context, p_{mt} represents the major-level evolution of the variance which is irrelevant to changing educational quality or ability levels of the graduates as well as their reallocation on the labor market. p_{mt} greater than 1 corresponds to greater inequality in the wage distribution of graduates in major m at time period t, and p_{mt} less than 1 corresponds to greater wage compression over time. The evolution of p_{mt} over time is associated with changing skill prices in the labor market induced by the *substitution* or *polarization* effects, $p_{\mathcal{C}_t}$ and p_m, related to the balancing of supply and demand for a given type of skills as defined in section 4.1. The prevalence of one over another effect drives the time pattern of p_{mt}.

As with p_{mt}, l_{mt} parameters relate to the overall evolution of the wage variance of major m graduates. However, these parameters apply to the transitory variance term $s_{cm}v_{mit}$. Their evolution over time tracks the instability of the labor market sectors hosting the graduates from the same field of study. Their trend relates to the macro shocks and changing business cycles of the economy. Cross-field differences of l_{mt} parameters are associated with major-specific allocation of workers across field-specific sectors or job types.

5 Empirical Wage Dynamics by Major Categories

5.1 Estimation

In line with the empirical framework presented in section 4.2, this section explores descriptive estimates of wage returns to various majors over time and provides a structural analysis of wage variance. We do not model selection into the labor market as we did not find evidence of the selection effect.[15] This is not surprising given high participation rates of both men and women in the Russian labor market as shown in Section 3. Additionally, given that Russian students make their major choices before entering colleges[16] while their labor market outcomes are first realized five years later, eventual selection into different majors is of lower concern and remains beyond the scope of this paper.[17]

Wage equation (1) is estimated by 5-year cohort groups using the OLS. To avoid age and time effects confusion, we use different parametric terms: the cubic time trend (allowing us to capture the multiple business cycles) and the quadratic function of age (classical for the Mincer's equation).

Model (3-2) is estimated by the general method of moments, GMM. The GMM procedure matches sample variances and covariances with their population counterparts. The model yields the following moments.

Variances:

$$Var(e_{tcm}) = q_{cm}^2 p_{mt}^2 \left(\sigma_{m\alpha}^2 + t\sigma_{mw}^2\right) + s_{cm}^2 l_{mt}^2 \frac{\sigma_{m\varepsilon}^2}{1 - \rho_m^2} \tag{5}$$

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[15]The estimates of the likelihood corresponding to the Heckman selection model are not reported but available upon request.

[16]In contrast to the USA and other countries, where students choose their majors later during their studies in college.

[17]Altonji et al. (2016), Altonji et al. (2012), and Kirkeboen et al. (2016) acknowledge multiple challenges related to analyzing the payoffs to different majors: selection may be correlated not only with workers' heterogeneity across fields and essential heterogeneity associated with idiosyncratic gains from preferring one specific field over multiple unordered alternatives, but it is also correlated with non-monetary gains from different occupations conditioned by workers' specialization. Causal analyses of return to major offered by Kirkeboen et al. (2016), Hastings and Zimmerman (2013), and Beffy et al. (2012) are very demanding in terms of institutional and data features.

with loading parameters p_1, l_1, q_{11}, s_{11} normalized to one.

Co-variances:

$$Cov(e_{tcm}, e_{(t+s)cm}) = q_{cm}^2 p_{mt} p_{m,t+s} \left(\sigma_{m\alpha}^2 + t\sigma_{mw}^2 \right) + s_{cm}^2 l_{mt} l_{m(t+s)} \frac{\rho_m^s \sigma_{m\varepsilon}^2}{1 - \rho_m^2} \qquad (6)$$

with $\sigma_{m\alpha}^2$, σ_{mw}^2, and $\sigma_{m\varepsilon}^2$ representing within-major variances of individual heterogeneity α_{mi}, highly-persistent idiosyncratic random shocks w_{mit}, and transitory random shocks ε_{mit} respectively and ρ_m denoting autocorrelation of the transitory wage shocks v_{mit} as defined by equation (4).

5.2 Wage conditional means

The estimation results of equation (1) suggest that the wages by college major (*Education*, *Social Sciences*, and *Engineering*), follow similar business cycle trends: wages decline during the recession and post-financial crisis of 1998 and rise over 2003-2013. However, there are differences among graduates with different majors and workers from different birth cohorts. Figure 10 shows the trends in the predicted wages by birth cohorts and majors. The left graph shows the trends for two oldest 10-year birth cohorts, 1956-1965 and 1966-1975; the right graph shows the trends for two younger 10-year cohorts, 1976-1995, pooled together.

The oldest cohort (1956-1965) graduated before the transition period. This group faces the lowest returns to *Social sciences* majors and the highest returns to *Engineering* majors in the most recent period, corresponding to a growing supply of graduates in *Social sciences* and declining supply of those in *Engineering*. For the cohort of workers graduated by the early 1990s (born in 1966-1975), *Social sciences* majors show the highest returns in the early 2000s; but from the late 2000s the returns to *Engineering* majors outpace those to *Social sciences*. This is further evidence of wages in this setting being responsive to an oversupply of *Social sciences* graduates. The youngest cohorts, born 1976-1985 and 1986-1995, and entering the labor market in the 2000s, benefit the least from majoring in *Education* and the most from majoring in *Engineering*.
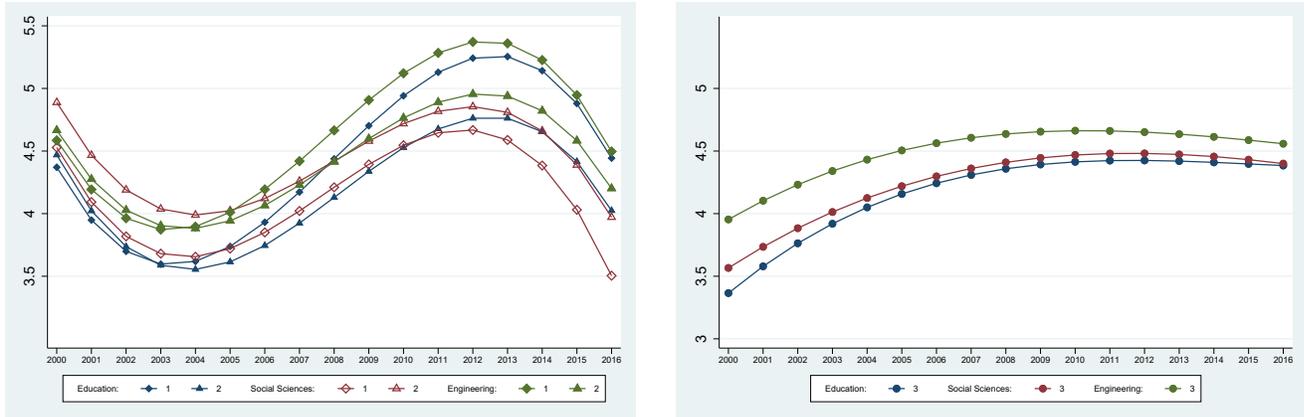
Figure 10: Predicted wage trends net of variation by region, age, and years of education (cubic trends from equation (1)).

Tables 4-5 report the output of wage regressions run by five 5-year cohorts. Smaller cohorts are assumed to be homogenous in terms of abilities and skills within majors. Following Lacroix and Radchenko (2011) showing different wage formation between men and women, these estimations are also run separately by gender group. A new trend observed among female workers (Table 4) having graduated after the transition period is higher returns to *Engineering* as compared to *Social sciences*. This may be a signal of a changing equilibrium in the labor market, while among male recent entrees there is no evidence for differences in the returns. The key output of the wage regressions is the residual term which is analyzed in section 5.4.

5.3 Wage residual variance

Figure 11 shows the evolution of the residual variances of wages by majors (solid lines). The dashed lines show autocovariances of order 4, corresponding to the permanent part of the variance as suggested by Moffitt and Gottschalk (2002). The vertical distance between the solid and dashed lines approximate the transitory part of the variance over time for a given category of workers.

Permanent and transitory variances of wage residuals
sample counterparts
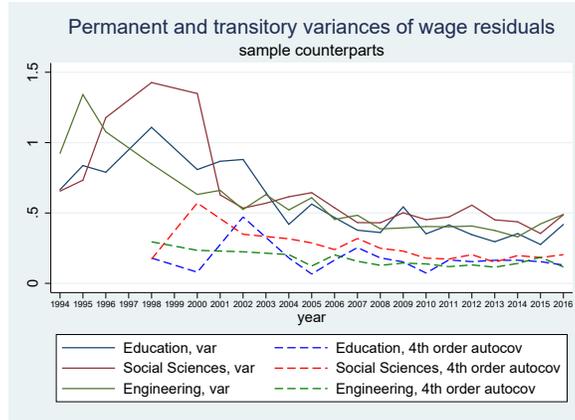
Figure 11: Residual wage trends

The graph shows evidence consistent with an increase in variance during the economic downturn related to the transition period (1990s) and the financial crisis of 1998. The variance decreases and remains at a steady, relatively lower level in the 2000s with approximately equal contributions of the permanent and transitory components. There are differences in the timing between workers educated in different fields. The graph also shows that wage disparity is larger among workers specialized in *Social sciences* compared to workers specialized in *Education* and *Engineering*. We next provide a structural analysis of the variance dynamics by parameterizing the permanent and transitory components as well as their time paths and by adopting the model from Baker and Solon (2003).

5.4 Variance structural parameters

The key results are reported by Table 2 and Figures 12-14. Table 2 reports the major-specific baseline variances of the reference parameters of equations (2)-(4); Figures 12 and 14 display the estimated cohort- and time-variant parameters respectively (along with 95% confidence intervals); Figure 13 shows the estimated trends of the total variance estimated by major and cohort.

Table 2: GMM estimates of the wage variance structure: individual heterogeneity and transitory shocks

	Education	*Social sciences*	*Engineering*
Permanent			
$\sigma^2_{m\alpha}$	0.145***	0.146***	0.144***
	(0.019)	(0.022)	(0.021)
σ^2_{mw}	0.033*	0.007***	0.064
	(0.017)	(0.002)	(0.050)
Transitory			
$\sigma^2_{m\varepsilon}$	0.353***	0.313***	0.336***
	(0.050)	(0.044)	(0.077)
ρ_m	0.195***	0.521***	0.168***
	(0.046)	(0.040)	(0.047)

Standard errors in parenthesis. ***$p < 0.01$,**$p < 0.05$,*$p < 0.1$

Heterogeneity within majors and cohorts

Table 2 reports $\sigma^2_{m\alpha}$ and $\sigma^2_{m\varepsilon}$, the variances associated with individual heterogeneity α_{mi} and the idiosyncratic transitory shocks ε_{mit}, respectively. They are major-specific and correspond to 2002 wages of the workers of the oldest cohort of 1956-1960. The estimates imply that the baseline heterogeneity is relatively weak ($\sigma^2_{m\alpha}$=0.14) and uniform across the fields of specialization for the reference workers.

The blue squares on figure 12 show the estimates of the cohort multipliers q_{cm} corresponding to the permanent variance components, with the reference group (cohort 1) multipliers scaled to 1. *Engineering* cohorts show a slight monotonic increase in wage dispersion for the younger cohorts having graduated under the expansion of the higher education. This is a signal of the *diversification* effect $(p_{\mathcal{A}_t})$, related to the expanding set of workers' skills and abilities induced by the expansion.
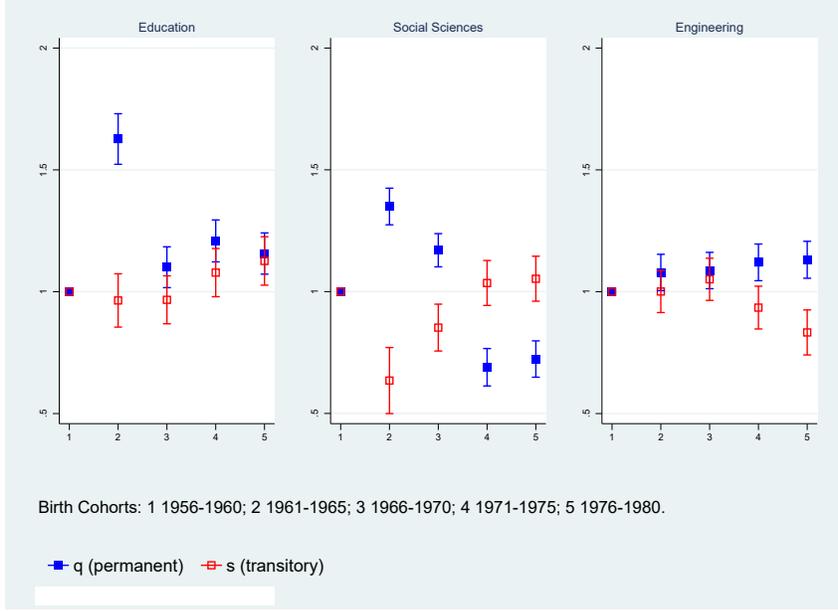
Figure 12: Cohort multipliers q_{cm} (blue) and s_{cm} (red)

Despite *Soial sciences* experiencing the largest expansion, the cross-cohort comparison of q_{cm} does not provide evidence for the *diversification* effect for this major. Indeed, q_{cm} scales for graduates born in 1961-1970 (cohorts 2-3) and having graduated before the higher education expansion while the multiplier is below 1 for the cohorts having graduated later. Their high wage dispersion cannot therefore be associated with the increasing heterogeneity induced by the expansion but should be attributed to the transition shocks of the 1990s faced by these cohorts at their entry in the labor market and their allocation to more diverse jobs in the early 1990s.

Further, the within-major heterogeneity experiences little change over time, as demonstrated by the low variance σ^2_{mw} (Table 2) of the permanent shocks w_{mit} among all the graduates (about 0.03 in *Education*, 0.06 in *Engineering* and 0.01 in the *Social sciences* group). A low estimate for σ^2_{mw} is evidence against the heterogeneous accumulation of human capital or substantial arbitrary reallocation of the graduates towards jobs of higher or lower ranks in the wage distribution. Yet, the results apply to the cohorts having entered the labor market by 2002.

On the other hand, idiosyncratic transitory shocks among the workers with *Social sciences*

specialization have a relatively high time persistence ($\rho = 0.52$). Given the unbalanced structure of the panel used, the high correlation between the shocks of the successive time periods can be to some extent related to more persistent reordering in the wage distribution of the *Social sciences* graduates.

Dynamics

The trends in total variance estimated by major and cohort are in line with the descriptive findings; total variance follows business cycles with higher variance during the recession of the early 2000s and weaker and more regular wage variance in the later growth period. The total variance oscillates around 0.5 (Figure 13) among *Social sciences* and *Engineering* graduates regardless of their birth cohort. It is lower for some cohorts having graduated in *Education*.

The trend for *Engineering* graduates differs by showing a rise in the last two years of our sample. This is entirely driven by the transitory shocks as can be seen in Figure 14 (red) corresponding to the time loading l_{mt} of the transitory variance components. The baseline transitory shocks ε_{mit} faced by the oldest cohort have the same dispersion of $\sigma^2_{m\varepsilon} = 0.3$ across the majors. These shocks are random and relate to instability of the labor market. Their distribution varies across younger cohorts by major.

The group with the lowest transitory variance are *Education* graduates, and their transitory variance is decreasing over time. They are mostly women with a relatively high probability of specialization-occupation match (about 0.65 in 2002). While expanded by private educational institutions, the education sector remains predominantly public. Compared to other sectors, the education sector provides low wages but high job security which explains the comparatively low degree of transitory shock dispersion.
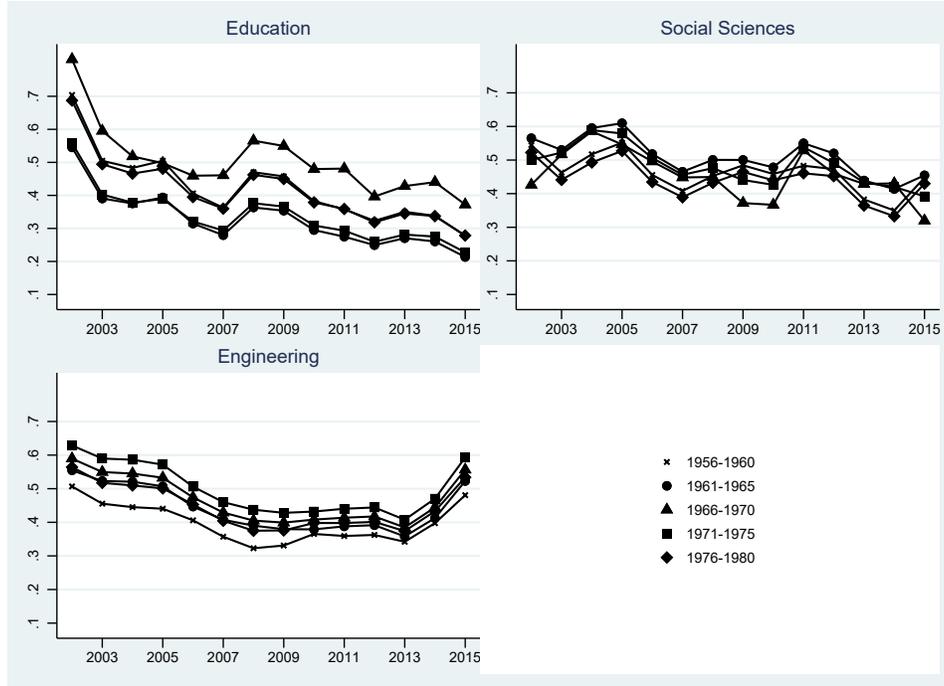
Figure 13: Total variance estimated

The estimates of the structural parameters discussed below imply that the downward trends, while common across majors, are driven by different processes in different fields. Figure 14 shows the estimates of the major-specific time loadings, p_{mt} (blue) and l_{mt} (red), corresponding to the permanent and transitory variance components respectively. Recall that these parameters are associated with time-variant factors of the variance which are common across cohorts.

Among workers with the *Education* degree, the wage dispersion is steady over the period of 2005-2015 with almost equal contributions from the permanent and transitory components. Workers with the *Education* degree are the least concerned with transitory shocks and instability as evidenced by the relatively small transitory loadings l_{mt}. Their wage dispersion seems also not to be impacted by the expansion of higher education.
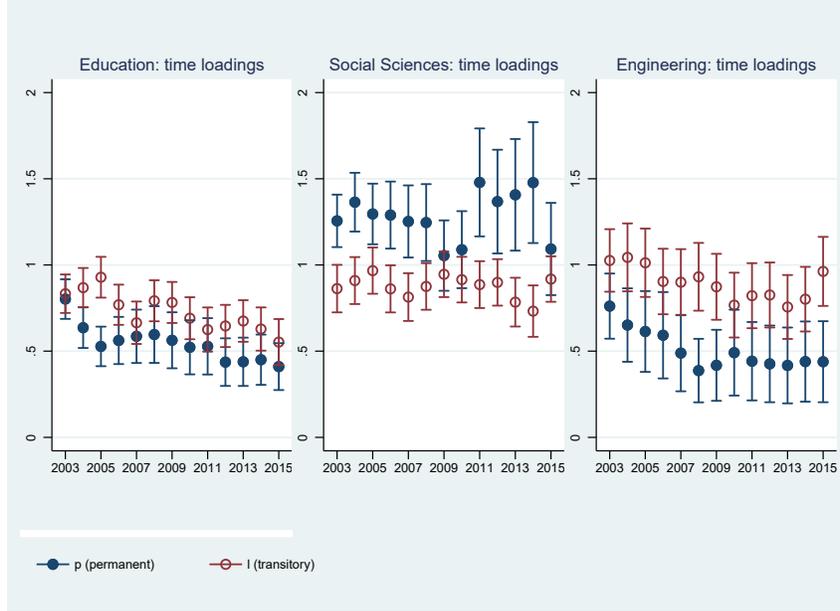
Figure 14: Time loadings, p_{mt} (blue) and l_{mt} (red)
Birth Cohorts: 1 (1956-1960), 2 (1961-1965), 3 (1966-1970), 4 (1971-1975), 5 (1976-1980).

For the graduates in *Engineering*, the permanent component of the wage dispersion decreases in the beginning of the 2000s and remains steady over the later years. This is quite similar to the dynamics observed among the *Education* graduates. However, the engineers' trend is more strongly synchronized with the expansion of higher education and the business cycle: the permanent variance shrinks until 2008 which marks the end of the expansion of higher education as well as the end of strong economic growth.

While the trend seems cyclical, the pattern followed by the engineers' wage dispersion does not show evidence of the deindustrialization impact. Under deindustrialization and the outflow of moderate wage laborers from the manufacturing sector to the trade and services in the 2000s, the dispersion is expected to increase because of wage polarization in manufacturing and the mismatch between specialization and professional occupation of the *Engineering* graduates. The impact of deindustrialization is therefore outweighed by the reduced relative supply of engineers in the labor market. The higher mean wage compared to the payoffs in other fields in the second part of the period is also in line with increasing prices for *Engineering* skills in the market despite the decreasing demand. The decrease of

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the relative supply therefore outweighs the demand decline.

The cyclical phenomenon is rather captured by the transitory component trend (Figure 14) which also contributes to the reducing wage dispersion among engineers during the growth period and steady variance after that; however, the older cohorts face more various shocks (Figure 12) while the younger cohorts experience a slightly greater stability but larger skill price disparity. The diversification effect along with the greater stability might signal greater inter-sector mobility and occupational flexibility of younger *Engineering* graduates facing a lower demand in the field in the 2000s. This is in line with the match rates implying that the younger *Engineering* cohorts are slightly less likely to work in the field of specialization compared to the older cohorts.

Wage dispersion among *Social sciences* graduates markedly differs from the patterns observed in other fields. The permanent variance component is systematically the main driver of the wage variance evolution for these workers. Unlike trends in other fields, it is particularly high in the second part of the period (about a 50% rise compared to 2002) where the expansion of higher education ends and the supply of *Social sciences* graduates stabilizes. This is consistent with the accelerated decrease of the professional match rates also observed in the second part of the period as noted in Section 3. These findings signal market saturation following disproportional expansion of higher education in this field.

The irregular time pattern and non-monotonic growth of the permanent variance of wage variance among *Social sciences* graduates is evidence against the *substitution* effect ($p_{\mathcal{C}_t}$) as the main driver of the changing variation in skill prices: under the substitution effect, the change would be monotonic in line with the gradual substitution of the older cohorts by the younger cohorts of workers trained under the expansion.

The pattern observed for *Social sciences* graduates is therefore associated with the effects resulting from the field supply outpacing the corresponding demand − within-major wage *polarization* and *reallocation*. Indeed, the deteriorating specialization-profession match among *Social sciences* graduates documented above is in line with the graduates' allocation

across a larger set of jobs. It is then likely that the selection on individual skill levels and abilities in the labor market is growing and boosting the polarization effect. However, the *reallocation* effect does not seem to have long-term re-distributive effects among the graduates given the weak variance of the permanent shocks ($\sigma_{mw}^2 \approx 0.01$) along with the high time persistence only detected for the transitory wage shocks of the *Social sciences* graduates ($\rho = 0.52$).

Overall, the results imply that dynamics of inequality among university graduates relates to both changing prices of skills in the labor market and wage shocks induced by economic fluctuations. The price variation is due to the equilibrium effects related to changing supply of graduates specialized in different fields as implied by trends observed for wages, match between workers' specialization and profession, and composition of academic majors.

6   Conclusions

Using the Russian Longitudinal Monitoring Survey, this paper examines the evolution of the distribution of academic majors among university graduates and the dynamics of their wages across major and birth cohorts. The structural analysis of the residual wage variance and its evolution allows us to distinguish between permanent variance parameters relating to the distribution of skill prices in the market and transitory shocks induced by labor market instability and business cycles.

As in many countries, Russian tertiary education expanded and experienced changes in the composition of graduates by academic major: the fraction of college students majoring in the sciences and technical fields declined while the fraction of those graduating in socio-economic majors increased. Analyzing parameters that describe the wage dynamics of workers with higher education specialized in one of three major fields (Education, Engineering, manufacturing and construction, and Social sciences, business and law), we find evidence of skills price re-equilibrium related to the changing supply of college graduates in

the labor market. Re-equilibrium channels differ across fields of workers' specialization. The findings indicate that uneven expansion of certain majors induces labor market saturation and a changing equilibrium.

Specifically, the results suggest that despite the country's deindustrialization and a shift of the middle wage labor force from manufacturing to trade and services in the 2000s, the decreasing demand for engineers is outweighed by the reduced relative supply of graduates from Engineering, manufacturing and construction majors in the labor market: the prices for skills gained in these majors rise while the dispersion of those prices shrink over time. Later cohorts of graduates from Engineering, manufacturing and construction majors adjust to a lower demand for their field in the 2000s by exhibiting greater inter-sector mobility and occupational flexibility. This is evidenced by an increasing heterogeneity of prices among later cohorts and a steady, non-increasing distribution of the transitory shocks that accompany a decreasing probability of the specialization-occupation match.

The highest wage variance found among Social sciences, business and law graduates is associated with the effects resulting from the field supply outpacing the corresponding demand. Irregular fluctuation over time and non-monotonic growth of the permanent wage variance along with the deteriorating specialization-profession match among these graduates suggests (a) an allocation of college graduates across a larger set of jobs, (b) a growing selection on individual skill levels and abilities in the labor market, and (c) a wage polarization effect. However, we do not find evidence of long-term re-distributive effects in the wage distribution of graduates with the specialization in Social sciences, business and law: according to our results, rising inequality among them is not associated with workers' moving toward better or worse paying jobs. We also do not find evidence of the cohort substitution effect under which the widening of the price dispersion would be driven by the evolution of the quality of skills from earlier to later cohorts of the graduates from these rapidly expanding majors.

Our results apply to the cohorts having entered the labor market by 2002. A limitation of our analysis is the focus on the cohorts present on the labor market over the whole time

period under consideration. Further analysis should extend the empirical model and allow different periods of observations for different cohorts.

Further research would develop a structural model of major choice, specialization-occupation match, and wage dynamics to shape interactions and causal mechanisms between those outcomes. It would also integrate multiple selection mechanisms related to workers' heterogeneity as well as the heterogeneity of their gains from different specializations in order to identify the payoffs to majors. High variation in education and labor market outcomes within a relatively short time period, as observed in the Russian context, has the potential to yield numerous quasi-natural experiments and identification tools.

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Appendix

Table 3: Occupation-Major Match

		Education	Social Sciences	Engineering
0	Armed Forces			X
1	Managers	X	X	X
2	Professionals	X	X	X
3	Technicians and Associate Professionals			X
5	Services and Sales Workers		X	
8	Plant and Machine Operators and Assemblers			X
11	Chief Executives, Senior Officials and Legislators	X	X	
12	Administrative and Commercial Managers Production and Specialized Services Managers		X	
13	Production and Specialized Services Managers		X	
14	Hospitality, Retail and Other Services Managers		X	
21	Science and Engineering Professionals			X
23	Teaching Professionals	X		
24	Business and Administration Professionals		X	
25	Information and Communications Technology Professionals		X	
26	Legal, Social and Cultural Professionals			X
31	Science and Engineering Associate Professionals			X
33	Business and Administration Associate Professionals		X	
34	Legal, Social, Cultural and Related Associate Professionals		X	
35	Information and Communications Technicians			X
52	Sales Workers		X	
71	Building and Related Trades Workers (excluding Electricians)			X
72	Metal, Machinery and Related Trades Workers			X
73	Handicraft and Printing Workers			X
74	Electrical and Electronic Trades Workers			X
75	Food Processing, Woodworking, Garment			X
93	Labourers in Mining, Construction, Manufacturing and Transport			X

Table 4: Wage differentials by majors and cohorts

	Men					Women				
	1	2	3	4	5	1	2	3	4	5
t	-2.209***	-2.068***	-2.099***	-2.158***	0.427	-2.527***	-1.979***	-2.176***	-1.600***	0.904***
	(0.187)	(0.138)	(0.164)	(0.146)	(0.353)	(0.083)	(0.072)	(0.074)	(0.103)	(0.235)
Education × t	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
Social × t	0.085	-0.094	-0.358*	0.578***	-0.096	0.172*	0.020	0.156	0.263*	-0.676**
	(0.239)	(0.194)	(0.213)	(0.200)	(0.398)	(0.104)	(0.104)	(0.096)	(0.147)	(0.280)
Engineering × t	0.162	-0.025	0.158	0.540***	-0.426	0.196*	-0.036	0.200*	-0.291**	-0.333
	(0.188)	(0.145)	(0.178)	(0.164)	(0.383)	(0.103)	(0.093)	(0.109)	(0.142)	(0.355)
t × t	0.199***	0.167***	0.155***	0.158***	-0.016	0.208***	0.160***	0.174***	0.123***	-0.051***
	(0.020)	(0.013)	(0.015)	(0.012)	(0.023)	(0.009)	(0.006)	(0.006)	(0.008)	(0.016)
Education × t × t	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
Social × t × t	-0.030	-0.008	0.045**	-0.034**	0.002	-0.012	-0.010	-0.016*	-0.024**	0.046**
	(0.026)	(0.019)	(0.021)	(0.017)	(0.026)	(0.012)	(0.010)	(0.009)	(0.011)	(0.018)
Engineering × t × t	-0.028	0.002	-0.000	-0.036***	0.023	-0.013	0.005	-0.010	0.013	0.024
	(0.021)	(0.014)	(0.017)	(0.014)	(0.025)	(0.011)	(0.009)	(0.010)	(0.012)	(0.024)
t × t × t	-0.005***	-0.004***	-0.004***	-0.004***	0.000	-0.005***	-0.004***	-0.004***	-0.003***	0.001***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Education × t × t × t	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
Social × t × t × t	0.001	0.000	-0.002***	0.001	-0.000	0.000	0.000	0.000*	0.001**	-0.001**
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Engineering × t × t × t	0.001	-0.000	-0.000	0.001*	-0.000	0.000	-0.000	0.000	-0.000	-0.001
	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Education × Age	0.025	-0.035	-0.071	0.435***	-0.051	0.355**	-0.067	-0.036	0.369***	-0.113
	(0.177)	(0.168)	(0.145)	(0.098)	(0.138)	(0.146)	(0.121)	(0.105)	(0.091)	(0.106)
Social × Age	-0.067	-0.072	-0.117	0.264***	0.006	0.434***	-0.090	-0.025	0.293***	0.043
	(0.180)	(0.157)	(0.146)	(0.097)	(0.098)	(0.146)	(0.123)	(0.106)	(0.093)	(0.088)
Engineering × Age	0.016	-0.013	-0.081	0.238***	0.111	0.369**	-0.048	0.021	0.469***	-0.074
	(0.171)	(0.157)	(0.140)	(0.087)	(0.095)	(0.147)	(0.122)	(0.107)	(0.092)	(0.115)
Education × educ	0.079	0.083*	0.085*	-0.012	0.036	0.139***	0.007	0.030	0.016	-0.043**
	(0.053)	(0.050)	(0.048)	(0.032)	(0.026)	(0.026)	(0.018)	(0.022)	(0.018)	(0.018)
Social × educ	-0.081*	0.067*	0.116***	-0.051**	0.036**	0.049*	-0.013	0.022	0.045***	0.014
	(0.045)	(0.039)	(0.037)	(0.021)	(0.015)	(0.028)	(0.023)	(0.021)	(0.014)	(0.012)
Engineering × educ	0.029*	0.049***	0.032*	0.003	0.059***	0.067***	0.028	-0.014	-0.029	0.038*
	(0.017)	(0.018)	(0.019)	(0.014)	(0.012)	(0.021)	(0.019)	(0.021)	(0.024)	(0.021)
Observations	1316	1451	1144	1766	1813	2098	2167	2212	2529	2388

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
1-5 denote five cohorts. t and its power denote the polynomial terms of the time trend.
"educ" denotes the years of education.

Table 5: Wage differentials by majors and cohorts, continued

	Men					Women				
	1	2	3	4	5	1	2	3	4	5
Moscow-St Petersburg	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
Central	-1.029	-0.208	-0.005	-0.101	0.111	-0.130	-0.042	-0.312***	-0.394***	-0.284***
	(0.736)	(0.149)	(0.199)	(0.104)	(0.072)	(0.116)	(0.095)	(0.095)	(0.067)	(0.066)
Volga	-0.525***	-0.605***	-0.688***	-0.487***	-0.298***	-0.591***	-0.490***	-0.673***	-0.747***	-0.625***
	(0.092)	(0.091)	(0.118)	(0.074)	(0.061)	(0.073)	(0.073)	(0.066)	(0.060)	(0.055)
Caucase	-0.860***	-0.855***	-0.750***	-0.789***	-0.594***	-0.852***	-0.960***	-0.921***	-0.816***	-0.851***
	(0.101)	(0.093)	(0.113)	(0.068)	(0.062)	(0.081)	(0.072)	(0.073)	(0.060)	(0.056)
Ural	-0.613***	-0.873***	-0.790***	-0.733***	-0.820***	-0.775***	-0.705***	-0.865***	-1.069***	-0.739***
	(0.118)	(0.119)	(0.145)	(0.088)	(0.069)	(0.104)	(0.089)	(0.090)	(0.074)	(0.065)
Western Siberia	-0.500***	-0.898***	-0.742***	-0.657***	-0.724***	-0.611***	-0.793***	-0.648***	-0.828***	-0.826***
	(0.120)	(0.096)	(0.130)	(0.078)	(0.069)	(0.088)	(0.085)	(0.079)	(0.064)	(0.061)
Eastern Siberia	-0.732***	-0.656***	-0.757***	-0.608***	-0.508***	-0.622***	-0.585***	-0.833***	-0.652***	-0.585***
	(0.129)	(0.107)	(0.123)	(0.082)	(0.071)	(0.092)	(0.083)	(0.074)	(0.071)	(0.061)
North-Est	-0.446***	-0.426***	-0.409***	-0.315***	-0.319***	-0.394***	-0.572***	-0.665***	-0.644***	-0.578***
	(0.120)	(0.119)	(0.131)	(0.090)	(0.065)	(0.090)	(0.082)	(0.108)	(0.074)	(0.068)
Observations	1316	1451	1144	1766	1813	2098	2167	2212	2529	2388

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
1-5 denote five cohorts.
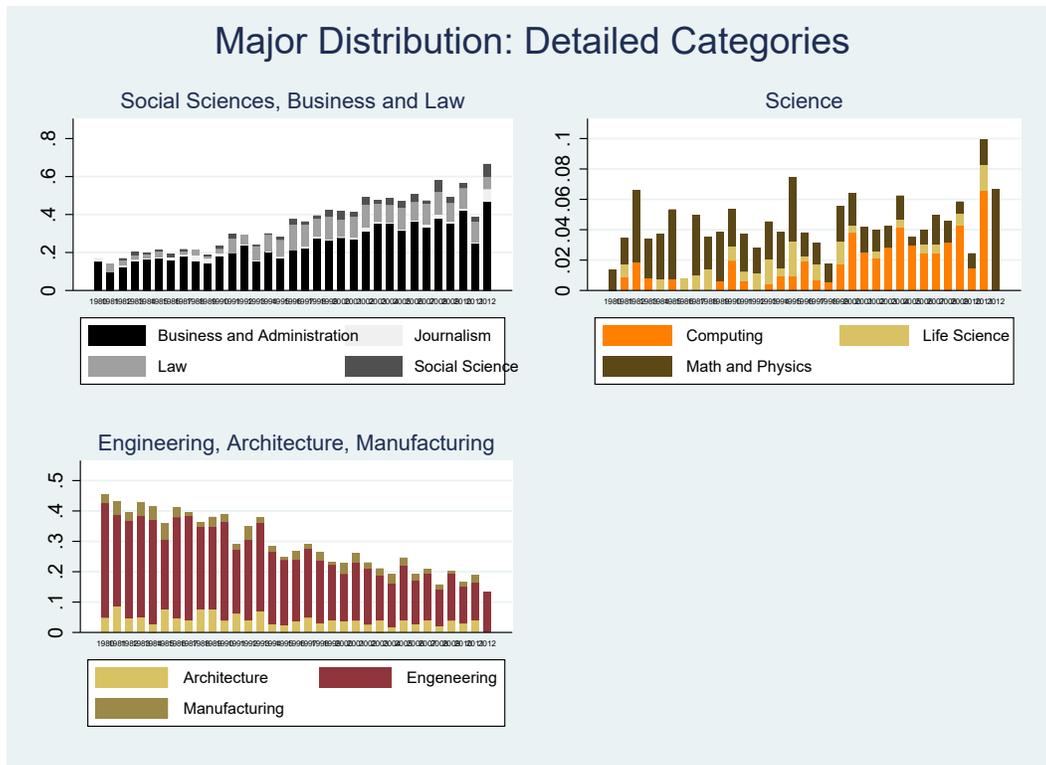
Figure 15: Distribution of majors (detailed categories for the main aggregated groups).