Task-Warranted Graduate Jobs and Mismatch

Francis Green and Golo Henseke

Singapore Economic Review, 2021

https://doi.org/10.1142/S0217590821500399

Final accepted version before publication.

Abstract

We distinguish between 'task-warranted' and 'task-unwarranted' graduate jobs. For both types a degree is required, but task-warranted graduate jobs involve carrying out typical graduate-level tasks. We operationalise the distinction, using representative surveys of resident Singapore workers. We find that the ongoing fast expansion of higher attainment between 2013 and 2017 was met by a similarly-strong growth in task-warranted graduate jobs. Compared with matched graduates, the graduates in task-unwarranted graduate jobs and in non-graduate jobs both perceive lower skills utilisation. There is a negative wage gap of 18% for graduates in task-unwarranted graduate jobs, and of 31% for underemployed graduates.

Keywords: wages, skills utilisation, underemployment, Singapore, task-based analysis.

JEL Classification: J23, J24, J31.

1 Introduction

Around the developed world, graduate labour markets have been evolving in response to two major trends: the 'massification' of higher education that began in the late 20th century led by the United States, and the ongoing rise in the demand for graduates. A concern in many countries is that the expansion of graduate jobs has not been fast enough to match the rising numbers of young graduates, each with their elevated aspirations for high-skilled employment (Verhaest and Van der Velden, 2013; Kiersztyn, 2013; Green and Henseke, 2016a; Holmes and Mayhew, 2016; Mok and Neubauer, 2016). One recent paper suggests that the demand for higher level skills in the United States has entered a 'reversal' with skills stagnating (Beaudry et al., 2016). Yet this pattern does not appear to be universal. In Germany, for example, graduate jobs are expanding faster than the supply of graduates and the graduate wage premium has been rising (Green and Henseke, 2021).

The source of rising demand for graduates is typically credited to the skill-biased technological transformation of work and specifically to the increasing importance of non-routine tasks (Autor et al., 2003). However, the demand for entry-level graduates has often also been attributed to the signalling value through college of otherwise unobserved abilities and attributes (Bordón and Braga, 2020). In this paper we use task-based analysis to study the relevance or otherwise of required tasks for the rise in graduate jobs. We consider that among graduate jobs there is considerable heterogeneity in the intensity and range of tasks requiring prior higher education. It is possible that a degree qualification is required to access a job even though the observed tasks are not at an expected graduate level. This state occurs if there are unobserved tasks requiring high skill levels, and the relevant unobserved abilities are signalled by the achievement of a university degree. University qualifications may serve as an indicator of either absolute ability or rank in the ability spectrum. As the prevalence of degree-holders in the population rises, more employers may require a degree qualification when recruiting, even in the absence of changes in task requirements.

To capture this dimension of the variation within graduate jobs, we distinguish between *task-warranted* graduate jobs --- which require degree qualifications to get and utilise a high level of observable graduate skills as measured by tasks performed – and *task-unwarranted* graduate jobs, where a degree is required to get the job, even though a degree is not warranted by the observed constellation of tasks. Both these categories are distinguished from non-graduate jobs, that do not require higher education to access the job. Correspondingly, we distinguish three categories of job-match for graduates: Matched Graduates (MGs), i.e. graduates in task-warranted graduate jobs; Matched but Underutilized Graduates (MUGs), i.e. graduates in task-unwarranted graduate jobs; and Underemployed Graduates (UGs), i.e. graduates in non-graduate jobs. These classifications can then be used to elucidate differentials in outcomes (such as for pay and skills utilisation) and to characterise changes in the graduate labour market. Where the expansion is through task-warranted graduate jobs, it can also be asked whether that rise derives from changes within jobs or shifts in the occupational composition.

We apply these novel distinctions in a study of the changing share of graduates and of graduate jobs in Singapore, a small but affluent knowledge economy where it could be expected, if only from its continued high growth rate, that the proportion of graduate jobs in the labour force would be rising. We operationalise the distinctions by applying a task-based analysis to survey data, and develop the new classification for qualifications and skills matching. We study whether graduates in task-warranted graduate jobs differ systematically in their pay and perceived skills utilisation from those in task-unwarranted jobs; and build a picture of the changing shares of task-warranted and task-unwarranted graduate jobs in Singapore's economy. Our paper thus brings together the literatures on task-based analysis, education signalling, higher education massification and graduate underemployment. We find that the period between 2013 and 2017 in Singapore was a time of substantive upskilling, with graduate jobs expanding at broadly the same rate as the proportion of graduates in the labour market. Moreover, the expansion was primarily in task-warranted graduate jobs, and there was a rise in the proportion of Matched Graduate jobs. Matched but Underutilised Graduates earned less pay than Matched Graduates, though more than Underemployed Graduates.

2 Task heterogeneity among graduate jobs, and the classification of mismatch among graduates: MGs, MUGs and UGs.

Studies of the growth of higher education find that the ‘massification’ has been universal across all the world’s regions. It is judged that, for the foreseeable future, this growth is unlikely to be reversed owing to the deeply embedded social and economic forces behind it (Marginson, 2016). Our paper draws on and contributes to the literatures surrounding the demand for graduate labour, and on the potential mismatch in market outcomes.

To examine the demand for graduate labour, studies of the changing shares of ‘graduate jobs’ are an alternative, or complement, to imputing demand from movements in the higher education wage premium alongside supply trends (e.g. Elias and Purcell, 2013; Figueiredo et al., 2011; Green and Henseke, 2016b). A graduate job is defined as one where “.. a substantial portion of the skills used are normally acquired in the course of higher education, including many of the activities surrounding it, and of its aftermath—the years after higher education when skills are acquired in work through graduates’ acquired faculty for learning them” (Green and Henseke, 2016b: p.3). Alternative approaches to measurement that spring from this concept derive either from job-holders’ self-reports of the educational requirements for the jobs they themselves hold, or follow expert-based assessments of required qualifications, or deploy a statistical approach based on task-based analysis of jobs. The growth in the share of graduate jobs varies considerably across countries, and is not always positive.

The potential mismatch of graduates is a long-standing and ongoing issue (e.g. Freeman, 1976; Allen and van der Velden, 2001; McGuiness and Bennett, 2007; Green and Zhu, 2010; Kiersztyn, 2013; Verhaest and Van der Velden, 2013; Meroni and Vera-Toscano, 2017; Green and Henseke, 2016a; Wu and Wang, 2018; Turmo-Garuz et al., 2019). A graduate is said to be ‘matched’ if they are doing a graduate job, and to be ‘under-employed’ (or ‘overeducated’ or ‘overqualified’) if they are doing a non-graduate job. Graduate underemployment is found to be a persistent state in many countries. It is highest in countries with higher relative oversupply of graduates. Underemployed graduates normally earn less than matched graduates, and experience lower job satisfaction. Some studies have extended the category of ‘underemployment’ to take account of graduates’ skills heterogeneity (e.g. Wu and Wang, 2018). Nevertheless, including measures of skills heterogeneity does not eliminate the pay gaps and job satisfaction gaps associated with underemployment; and 'underemployment' has largely retained its place as a useful concept with explanatory value in labour markets in many countries.

The division of graduate jobs into task-warranted and task-unwarranted, however, is novel. Moreover, we propose that this classification matters potentially both for skills utilisation and for pay. We expect, given the tasks they must perform, that MUGs are more likely to perceive that their skills are underutilised, compared with MGs. However, the perceived skills utilisation of MUGs would be greater than for UGs, if the degree requirement for the job reflects the need for skills that are not shown in generic task requirements.

$$SU_{MG} > SU_{MUG} > SU_{UG} \tag{1}$$

Previous research has demonstrated a relationship, as predicted, between pay and high-level cognitive task requirements in jobs (Autor and Handel, 2013; Dickerson and Green, 2004; Henseke and Green, 2020). Thus we expect graduates in task-warranted graduate jobs to receive higher pay than those in task-unwarranted jobs. We also expect to re-confirm the well-established pay penalty for underemployment.

$$Pay_{MG} > Pay_{MUG} > Pay_{UG} \tag{2}$$

To our knowledge, Kracke et al., 2018 and Kracke and Rodrigues (2020) are the only previous studies to bring task-based analysis to bear on the study of labour market mismatch for graduates. Using data from the German labour market where occupational tasks and skills are relatively well-defined, Kracke and Rodrigues (2020) find that young workers trained in occupations that require the performance of analytical non-routine, interactive non-routine and cognitive routine tasks, suffer a wage penalty if they then work in occupations requiring the performance of manual tasks.

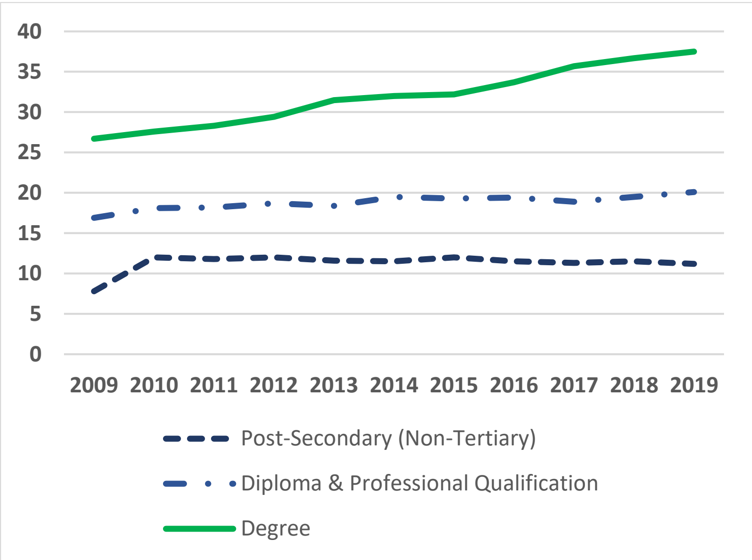
The context of Singapore's graduate labour market.

In our analysis below we apply this classification to the jobs of Singapore residents, and test our predictions on the residents' pay and perceptions of skills utilisation. Singapore is a case study of considerable interest elsewhere, an example of a small state which has been able over the long term to keep a balance between skills supply and demand throughout successive stages of development (Ashton et al., 1999). Its 15-year old school pupils score very highly in the PISA tests (OECD, 2019, p.15), and its GDP grew at an annual rate of 4.2% between 2010 and 2018. As an advanced knowledge economy, it could be expected that there would be a high and growing demand for high-skilled labour. We first, therefore, provide some context.

Previous literature on Singapore's higher education has mainly focused on the issues of how far its universities are succeeding in becoming a global education hub and in managing the massification of HE without lowering standards, and on related issues of governance (Ng, 2013; Lee, 2016; Mok and Neubauer, 2016). Studies of Singapore's high skills labour market, however, are scarce. Appold (2005) analyses changing occupation structures in the 1990s alongside the growing university participation and subsequent supply of graduates. Habibi (2019) singles out Singapore and Hong Kong, in contrast with Middle Eastern states, for having powerful political leaders with the strength and will to push back against middle-class pressure to over-expand access to universities. The consequence, Habibi argues, is that Singapore achieves a balance between the skill composition of jobs and that of the workforce. A complementary study by Sim (2015) reports a substantial average higher education premium above all other workers of around 72 to 78% in 2010.

Since then those educated to degree level are becoming an increasingly important segment of Singapore's tertiary labour force. With its eye on labour market trends, in 2012 the government announced its intention to raise the Cohort Participation Rate in university education to 40%, a goal that was achieved in 2020 (Davie, 2020). Moreover, the government has recently altered its approach to promoting skills development, inaugurating generously-funded 'SkillsFuture' programmes in 2015 to promote 'skills deepening' through lifelong learning. This shift of policy emphasis has naturally led to an increased emphasis on the sort of high-skills flexibility for which university education is most suited. There are now six autonomous universities in this small city state: the National University of Singapore, Nanyang Technological University, Singapore Management University, Singapore University of Technology and Design, Singapore Institute of Technology and Singapore University of Social Sciences with a collective enrolment of more than 100,000. The combined intake at these universities grew by 4% per year since 2008, while the total intake at polytechnical institutions and the Institute of Technical Education remained largely unchanged. These universities run annual surveys of graduate employment 6 months after graduation, which reveal relatively high levels of employment (Ministry of Education, 2020). In addition, there are many private, transnational campuses offering qualifications from foreign universities. A 'talent gap' at the high end of the economy has been partly filled by an influx of ex-patriate graduates: professionals, managers and executives with Employment Passes make up about one in ten non-resident workers; a similar proportion hold S Passes for degree or diploma holders concentrated in healthcare and social services. The analysis below perforce applies solely to the resident workforce, since the skills data do not cover the other components of the workforce. Even without the rising enrolments in higher education, a growth in the supply of graduate labour is expected due to the large education gap between Singapore's old and young workforce. For all these reasons, higher education has become the fastest growing attainment level in Singapore's resident workforce, as shown in Figure 1.

Figure 1 Post-secondary educational attainment of Singapore's resident labour force, 2009-2019 (%)



Source: https://stats.mom.gov.sg/Pages/Labour-Force-Summary-Table.aspx

Research Questions

In this context of rapidly rising graduate supply, we deploy the classification of graduate job types to help to characterise the recent state of the graduate labour market for Singapore residents, posing the following questions:

RQ1: has the rise in graduate jobs matched the growth in the supply of graduates?

RQ2: what are the shares of task-warranted and task-unwarranted graduate jobs, and how have these been changing in this period of substantive economic growth?

R3: among graduates, what are the shares of MGs, MUGs and UGs; and how have these shares been changing? How does this breakdown differ among socio-economic groups (defined by age and gender)?

R4: Are the differences in perceived skills utilisation between MGs, MUGs and UGs consistent with expectations (1)?

R5: Are the pay gaps between MGs, MUGs and UGs consistent with expectations (2)?

3. Data, Measures and Methods

Data

Our sources of data are the Skills Utilisation 2 Survey 2013 (SU2) and the Singapore Skills and Learning Study 2017 (SLS). SLS and SU2 are the second and third iterations of the Skill Utilisation series which aims to track skills utilisation in Singapore in the resident population. While the gap between survey years is relatively short this was, as noted above, a period of high economic growth and of rapid change on the supply side of the graduate labour market. Both surveys drew part of their design and question wording from the British Skills and Employment surveys (Felstead et al., 2019). They collected rich, comparable data on job tasks and qualification requirements alongside job-related learning from a sample of workers; in the case of SLS this was for workers aged 20-70 years, but since SU2 covered ages 20-65 we also restrict our SLS sample to that age range. SU2 is a quota sample of 3,422 Singapore citizens and permanent residents who had been in paid work in the last seven days before the time of the interview. Quotas were based on ethnicity, gender, age, and dwelling type. SLS used the more satisfactory method of random probability sampling of adult citizens and permanent residents; the achieved sample was 6,298, of whom 77% were in paid work. In both cases, interviews were conducted face-to-face with self-completion modules for the job tasks requirements and wellbeing sections. We combined the surveys into a pooled file of employed workers (n = 7971). All analyses below use provided survey weights to represent the population of interest.

Educational Requirements

Following many earlier papers (e.g. Battu et al., 2000), our graduate job indicator is derived from the self-reported educational requirements for the job. To measure these educational requirements, SU2 and SLS asked workers "If they were applying today, what qualifications, if any, would someone need to get the type of job you have now?". Workers can select all applicable qualifications from a list of nationally recognised qualifications. The question wording was identical across surveys, but the list of qualifications changed. Although some measurement error is conceivable, workers are generally well placed to assess the qualification requirements to get their jobs (Verhaest and Omey, 2006, 2012; Green and James, 2003). Table 1 maps responses by survey wave into five qualification levels and their breakdown in the labour force aged 20-65 years in 2013 and 2017. In practice this raised no serious problems for reliable identification of degree-level jobs.

Table 1: Qualifications map and the breakdown of educational requirements in 2013 and 2017.

Level	SU2 (2013)		SLS (2017)	
	%	Detailed Qualifications	%	Detailed Qualifications
No qualifications	7.8	None/No qualifications	10.5	No formal qualification/ Pre-primary/ Lower primary
Secondary	31.7	PSLE or below Lower secondary Workplace literacy and numeracy statement of attainment (WPLN SOA) Secondary / 'O' level or equivalent	19.9	PSLE or equivalent Lower secondary Secondary ('O'/ 'N' Level or equivalent)
Post-secondary	10.6	Workforce skills qualifications (WSQ) certificate 'A' level or equivalent ITE certificate	5.0	Post-secondary (non-tertiary): General ('A' level or equivalent) Post-secondary (non-tertiary): Vocational (ITE)
Short tertiary	21.0	Polytechnic Diploma Workforce skills qualifications (WSQ) diploma Professional Qualifications & Other Diploma	26.2	Polytechnic diploma Professional qualification and other diploma
Higher education	29.0	Bachelor's degree Workforce skills qualifications (WSQ) graduate diploma Master's degree PhD	38.4	Bachelor's or equivalent Postgraduate diploma/ Certificate Master's or equivalent Doctorate or equivalent

Job tasks

We draw on the task-based approach to labour market analysis, which distinguishes between routine and non-routine job task (Autor et al., 2003). The former are automatable tasks which can be feasibly carried out by machines or algorithms, whereas the latter are bottlenecks for automation. University graduates are assumed to have a competitive advantage in carrying out non-routine cognitive and interpersonal tasks that require creative and social intelligence (Acemoglu and Autor, 2011; Frey and Osborne, 2017). Job task profiles therefore shape graduate skills requirements (Green, 2012; Green and Henseke, 2016a,b). Thus, to classify the different types of graduate jobs in Singapore we use the self-reported education requirements data in conjunction with data on work tasks carried out by those working in each job. It matches those tasks to the skills typically acquired in the course of a university education and associated work experience.

The definition and selection of job task items follows earlier task-based research (e.g. Autor, 2013; Autor and Handel, 2013; Green, 2012; Spitz-Oener, 2006) and previous articles by the authors (Green and Henseke, 2016a,b; Henseke and Green, 2017). SLS and SU2 ask survey participants about the importance of more than 45 job tasks including manual, literacy (reading and writing short/long documents), numeracy (calculations using addition/ fractions/ statistics), problem-solving (spotting problems, working out solutions), orchestrating others (planning others, persuading, negotiating) or computer use (importance and complexity). Each item measures the importance of the job task in the respondent's job in five steps from "essential" to "not all important/ does not apply". To study the demand for graduate skills, we concentrate on job tasks around high-level information processing, orchestration, interpersonal tasks and computer use. Each task variable is dichotomized with a value of one if a job task is deemed essential and zero otherwise.

Additional variables

SU2 and SLS assess perceived skills utilisation through a single-item Likert-type scale, but the questions changed between surveys. SU2 asked respondents to assess "How much of your past experience, skill and abilities can you make use of in your present job?" (very little, a little, quite a lot, almost all). In SLS respondents reported how much they agree or disagree with the statement "In my current job I have enough opportunity to use the knowledge and skills that I have" (Strongly agree, agree, disagree, strongly disagree). We recode the variable so that higher values indicate better skills use and normalise the responses to the [0,1] range. These two indicators of skills utilisation are known from the British Skills and Employment Survey series to be significantly but imperfectly correlated. In what follows we make no comparisons of the skills utilisation data between the two surveys.

We also draw as appropriate on survey information to derive variables on higher educational attainment, gross hourly pay (deflated to 2019 using the Consumer Price Index), and some additional variables covering occupation, age, gender, marital status, presence of dependent children in the household, parents' educational attainment and information on the place of birth. The hourly pay data is derived as a continuous variable in 2017, but is only available as a banded variable in 2013.

The available basic statistics for these are shown in Table 2. They confirm the rapid change in educational attainment during this interval, already seen in the government data (Figure 1). They show that graduate pay rose very substantially, and by more than the pay of non-graduates, again suggesting that this was a period of considerable change for graduates. Nevertheless, the occupational structure remained relatively stable, as did the socio-economic composition.

Table 2: Descriptive Statistics:

	(1) SU2	(2) SLS
Graduates	0.32	0.39
Hourly pay (S$)		
Total	17.71	23.43
Graduates	27.68	36.61
Non-graduates	13.22	15.96
Skill use 2012	0.58	
Skill use 2017		0.73
Age	42.14	41.76
Female	0.51	0.48
Foreign-born		0.25
Graduate parents		0.11
Occupation shares:		
Professionals, Managers, Executives and Technicians	0.57	0.59
Clerical, Sales and Service Workers	0.24	0.25
Production & Transport Operators, Cleaners & Labourers.	0.18	0.16

Descriptive Statistics from SU2 and SLS for the employed resident workforce 20-65 years (SU2: N=3353, SLS: N=4391).

Analysis Methods

To specifically address our research questions, we will first present a description of the changes between 2013 and 2017 in the job tasks and degree requirements, including results of a standard decomposition that measures how changes occur either within or between 2-digit occupations. We then investigate whether the change in degree requirements can be accounted for by the changes in job tasks, using the non-linear decomposition proposed by Fairlie (2005):

$$\overline{D_t} - \overline{D}_{t-1} = \left[\Delta(\hat{\beta}^t - \hat{\beta}^{t-1}) \cdot \overline{jbtsk}^t\right] + \left[(\overline{jbtsk}^t - \overline{jbtsk}^{t-1}) \cdot \hat{\beta}^{t-1}\right] \qquad (3)$$

where $\overline{D}_{t,t-1}$ is the share of jobs that require a degree at entry in t or $t-1$. The term $\overline{(jbtsk)}^p$ describes the sample means of the job task scales by period $p = t, t-1$. β^p are the regression coefficients. Equation (3) splits the total change in the share of jobs that require a degree between t and t-1 into a coefficient effect, the first term in brackets, and a job task effect, the second term in brackets in equation.

To distinguish between task-warranted and task-unwarranted jobs, we first re-estimate a probit model of self-reported degree requirements on job tasks using the pooled sample. Second, from the estimates, we predict a *graduate skills requirement score* as the probability of degree requirements conditional on job task content.

$$\Pr\left(D_{i,t} = 1 | jbtsk_{i,t}\right) = \Phi(jbtsk_{i,t}\beta) \qquad (4)$$

Next, we dichotomise the graduate skills requirement score into a low and high value range. We distinguish jobs with a low task-based probability of requiring a degree (threshold at probability of 0.3) from other jobs.[1] In sensitivity analysis, we increase the threshold to a probability of 0.5.

Our remaining research questions concern the graduate match types (MGs, MUGs and UGs). We present a description of the changes in shares of graduate match types between 2013 and 2017. We then report the gaps in skills utilisation and in pay between each type. For these, we run weighted regression analyses, including standard controls for skills utilisation and for 2017 log wages; for the 2013 wage data we use interval regression for hourly earnings bands.

[1] Although any dichotomisation is necessarily arbitrary around the cut-point, the probability cut-off of 0.3 is close to an 'optimal' threshold based on the Youden's J statistic which maximizes the sum of sensitivity and specificity using self-reported degree requirements as the test outcome (Youden, 1950). The derived 'optimal' cut-point is 0.28.

4 Findings

a) The Changing Share of Graduate Jobs

Our first research question is answered in Table 3, which summarises the percentage of self-reported graduate jobs in the resident workforce 20-65 years, and average task intensities as well as their change from 2013 to 2017.

The first row shows that the sharp increase in graduate educational attainment seen in Table 2 is quite closely matched in magnitude by a substantive change in the share of self-reported graduate jobs. This finding is consistent with the picture of Singapore's knowledge economy going through an exceptional dynamic period of growth in recent years. There has been a surge of jobs that require a bachelor's degree or above from 29% to 38% over just four years between surveys. The 9-point jump comes after a period of slow GDP growth in the aftermath of the 2008-09 financial crisis. There is a parallel here with evidence from the United States, which suggests that periods of economic downturn might spur educational upgrading (Blair and Deming, 2020).

The rest of the table shows rising job task intensities across fourteen domains, but falling in two domains. The fall in task discretion is consistent with some international trends, (Freeman et al., 2020; Gallie et al., 2018). Secondly, as shown in the final column, almost all of the changes happened *within* 2-digit occupations rather than *between* those 2-digit occupations. This has important implications for our understanding of how technological and organisational changes are manifested in the labour market. Rather than replacement or growth of whole occupations, we see changes in the job task mix and education requirements within occupations. In all, the descriptive statistics on job tasks suggest that the predominance of job upskilling has the potential to account for the surge in employers' degree requirements.

Table 3: Changes in degree requirements and job task profiles, 2013-2017

	(1) 2013	(2) 2017	(3) Δ.(2013-2017)	(4) Δ.(Within)
Self-reported graduate job	0.288	0.383	0.095***	0.092
	(0.008)	(0.007)	(8.85)	
Literacy	0.104	0.156	0.052***	0.049
	(0.005)	(0.005)	(6.82)	
Numeracy	0.120	0.171	0.052***	0.048
	(0.006)	(0.006)	(6.47)	
Dealing with people	0.823	0.813	-0.009	-0.021
	(0.007)	(0.006)	(-1.06)	
Giving speeches	0.288	0.341	0.052***	0.049
	(0.008)	(0.007)	(4.94)	
Persuading	0.455	0.537	0.081***	0.076
	(0.009)	(0.007)	(7.12)	
Analyzing	0.196	0.303	0.108***	0.104
	(0.007)	(0.007)	(11.02)	
Learning new things	0.371	0.526	0.154***	0.146
	(0.006)	(0.005)	(20.64)	
Continuous learning requirements	0.342	0.434	0.093***	0.080
	(0.008)	(0.007)	(8.34)	
Non-repetitive	0.204	0.085	-0.119***	-0.116
	(0.007)	(0.004)	(-14.56)	
Planning own work	0.237	0.292	0.055***	0.053
	(0.007)	(0.007)	(5.41)	
Concentrating on details	0.396	0.445	0.049***	0.038
	(0.009)	(0.007)	(4.29)	
Managing/ supervising	0.198	0.276	0.078***	0.087
	(0.007)	(0.007)	(8.04)	
High-level task discretion	0.274	0.215	-0.058***	-0.061
	(0.008)	(0.006)	(-5.87)	
Computer use	0.436	0.523	0.087***	0.074
	(0.009)	(0.007)	(7.60)	
N	3,402	4,569	7,971	

Secondary analysis of SU2 and SLS for the resident workforce 20-65 years. Columns (1) and (2) report mean of self-reported graduate jobs in 2013 and 2017, respectively. Column (3) gives the mean differences and p-values from t-test. Column (4) calculates the changes within occupation as opposed to between occupations from a shift-share analysis.

Table 4 shows the results from applying the decomposition (3). Results from the regression of degree requirement on task intensities in each year are given in Appendix, Table A1, showing that, as hypothesized, degree requirements are closely linked to requirements to carry out cognitive work tasks. The decomposition splits the change in degree requirement into a component that is accounted for by changes in the job task mix and an unexplained, residual component. We find that the overall change in the share of jobs with degree requirements is to 80% accounted for by the greater job task intensities. The unexplained component, which measures changes in degree requirements that are unrelated to job skills, is small but different from zero at the 10% significance level. In short, we find that the substantial growth of jobs that would require a degree qualification to obtain, over this relatively short period, is largely accounted for by job upskilling (that is, increased intensity of use of typical graduate job tasks).

Table 4: A decomposition of the rising self-reported graduate jobs in Singapore.

	Overall Change	Job task change	Unexplained
Coefficient	0.096***	0.076***	0.020*
se	(0.011)	(0.007)	(0.011)

Results from a non-linear decomposition using SLS and SU2 job task data and self-reported degree requirements for employed residential workers 20-65 years. Bootstrapped standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

b) Distinguishing types of graduate jobs

To distinguish between task-warranted and task-unwarranted graduate jobs, following (3) we re-estimate the probit regression of self-reported degree requirements in the pooled sample. From the estimates, we predict the graduate skills requirement score, which is the probability of a degree requirement, conditional on job task content. Figure A1 in the Appendix plots the density distribution of the graduate skills requirement score by jobs that require a degree at entry and those that did not. According to the estimates, a quarter of jobs that require a degree on entry scored 0.32 or less on the graduate skills requirement score and half of the jobs with degree requirements scored 0.50 or less. Next, we dichotomise the graduate skills requirement score into a low and high value range as described above. .

Table 5 shows the results for the employed workforce of ages 25-65 years.[2] The earlier observed expansion of graduate jobs shown is broken down into the changed shares of task-unwarranted and task-warranted graduate jobs. Whereas the former shrinks significantly from 9% to 6%, employment in the latter surges from 21% to 32%. In short, according to these estimates more Singapore citizens and permanent residents were being employed in task-warranted graduate jobs.

[2] This age range is chosen assuming the vast majority have completed their FT education by 25.

c) MGs, MUGs, and UGs.

Given the fast expansion of graduates in the labour force, it is not surprising that the rising share of graduate jobs did not significantly reduce the proportion of graduates who were underemployed: this share stood at 23% in 2013 and 21% in 2017 (Table 5). The subclassification of graduate jobs now permits the sub-classification of graduate mismatch, as described above, into Matched Graduates (MGs), matched but underutilised graduates (MUGs) and Underemployed Graduates (UGs). The trend towards greater skill use is evident in a sharp reduction in the share of MUGs from 21% to 13%, while the proportion of MGs rose from 57% to 66%.

Despite these positive changes from the perspective of Singapore resident graduates, it remains the case that about one in three employed graduates were still not able to fully utilise their skills in 2017, suggesting that, despite labour market frictions, there may remain some potential to improve graduate skills utilisation.

Table 5: Graduate Labour Market Trends in %, 2013-2017

	(1) Task-unwarranted graduate job share	(2) Task-warranted graduate job share	(3) Underemployed graduates (UG)	(4) Matched but underutilised graduates (MUG)	(5) Matched graduates (MG)
2013	8.4	21.2	23.2	20.3	56.5
	(0.50)	(0.73)	(1.33)	(1.26)	(1.56)
2017	6.8	31.8	21.2	12.5	66.3
	(0.39)	(0.73)	(1.03)	(0.83)	(1.20)
Difference	-1.6*	10.6***	-2.1	-7.8***	9.8***
	(0.64)	(1.04)	(1.68)	(1.51)	(1.96)

Secondary analysis of SU2 and SLS data for the employed workforce aged 25-65 in Singapore. Employment rate of task-unwarranted and task-warranted graduate jobs, the percentage of underemployed graduates, matched but underutilized graduates, and the percentage of matched graduates. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

d) Skill Utilisation by Match Status

As noted in (1) we expected graduates' perceptions of the extent to which they utilise their skills to vary according their classification as MGs, MUGs or UGs. To test this, we ran conventional regression models of the determinants of skills utilisation. Because the skills utilisation question changes between survey waves, we are interested only in the differences between match groups within each survey wave. In each case there is a potential bias from endogenous job assignment.

Table 6 reveals indeed a significant skills utilisation gap between matched graduates and the other graduates in the workforce with notable variation by age. Graduates outside task-warranted graduate jobs perceive that they can apply less of their skills set in their current job. Although the item changed between surveys, the patterns are similar across the two surveys. The estimates suggest that in terms of skill use, MUGs and UGs struggle similarly, there being no significant difference between the coefficient estimates for these two groups. The directions of the effects and patterns are consistent among males and females, and among young and older workers. However, young graduates reported smaller skills utilisation gaps by job type.

Table 6: Skills underutilisation by sex and age. 2013 and 2017

	Underemployed Graduates	Matched but Underutilised Graduates	Matched graduates	p-value (UGs = MUGs)	N
Total					
2013	-0.080*** (0.023)	-0.097*** (0.023)	(ref.)	0.545	1042
2017	-0.047*** (0.013)	-0.061*** (0.014)	(ref.)	0.404	1582
Men					
2013	-0.060* (0.029)	-0.112*** (0.029)	(ref.)	0.154	591
2017	-0.051** (0.019)	-0.069*** (0.019)	(ref.)	0.344	822
Women					
2013	-0.103** (0.036)	-0.081* (0.036)	(ref.)	0.622	451
2017	-0.042* (0.019)	-0.058** (0.019)	(ref.)	0.491	760

25-34					
2013	-0.029 (0.034)	-0.052 (0.035)	(ref.)	0.587	443
2017	-0.017 (0.019)	-0.040* (0.018)	(ref.)	0.335	617
35-65					
2013	-0.118*** (0.031)	-0.130*** (0.030)	(ref.)	0.756	599
2017	-0.066*** (0.018)	-0.076*** (0.020)	(ref.)	0.672	965

Weighted OLS regression of self-assessed skills utilization in 2013 and 2017 on indicators for underemployment (non-graduate job) and underutilization (task-unwarranted graduate job) and control variables for employed graduates aged 25–65 years. Control variables comprise 5-year age-groups, sex, indicator for the presence of dependent children under 16 in the household, and cohabitation status. Robust standard errors in parentheses. # $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

e) Pay by Match Status

To contextualise our findings for how pay varies with match status, it is useful to consider the substantial pay advantage enjoyed by graduate workers in Singapore. There is a very substantial hourly pay premium (202%) (as estimated from a conventional Mincer equation, unadjusted for endogeneity bias) among Singapore residents, associated with degree attainment, relative to those who had attained at most secondary-level qualifications.[3] The premium remained stable between 2013 and 2017 despite this being a period of rapid growth; though it should be noted that wages are to an extent regulated across Singapore, with a strong influence coming from the 'going rate' in each industry.

[3] Sim (2015) reports that, as with some other countries, an instrumental variable estimator gives a larger return than is implied by the OLS estimator, a difference attributed to potential measurement error.

Table 7: The graduate underemployment wage penalty by sex and age. 2013 and 2017

	Underemployed Graduates	Matched but Underutilised Graduates	Matched graduates	p-value (UGs = MUGs)	N
Total					
2013	-0.383*** (0.043)	-0.119** (0.038)	(ref)	0.000	1024
2017	-0.377*** (0.052)	-0.197*** (0.044)	(ref)	0.003	1209
Men					
2013	-0.404*** (0.064)	-0.130* (0.058)	(ref)	0.000	580
2017	-0.417*** (0.087)	-0.239*** (0.053)	(ref)	0.054	619
Women					
2013	-0.352*** (0.059)	-0.096* (0.048)	(ref)	0.000	444
2017	-0.327*** (0.062)	-0.145* (0.067)	(ref)	0.018	590
25-34					
2013	-0.220*** (0.052)	-0.065 (0.041)	(ref)	0.006	438
2017	-0.341*** (0.056)	-0.146** (0.047)	(ref)	0.003	503
35-65					
2013	-0.531*** (0.067)	-0.160* (0.066)	(ref)	0.000	586
2017	-0.399*** (0.078)	-0.205** (0.068)	(ref)	0.029	706

Weighted OLS regression of log real gross hourly pay in 2017 and interval regression of log real gross hourly earning bands in 2013 on indicators for underemployment (non-graduate job) and underutilization (task-unwarranted graduate job) and control variables for employed graduates aged 25–65 years. Control variables comprise 5-year age-groups, sex, indicator for the presence of dependent children under 16 in the household, cohabitation status, and housing tenure. Robust standard errors in parentheses. $^{\#}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7 presents our estimates of the mean pay gaps between MGs, MUGs and UGs for resident graduates in Singapore. These estimates also do not adjust for the potential influence of skills differences between graduates on the likelihood of mismatch, and are therefore to be interpreted as wage differentials conditional on selection into these groups. Two key findings stand out. First, underemployment carries a heavier wage penalty than underutilisation on its own. In 2017, average hourly pay for MUGs was about 18% (=1-exp(-0.197)) lower than for MGs, their matched peers. This penalty is notably lower than that experienced by UGs, who earned on average 31% (=1-exp(-0.377)) less than MGs. The declining ranking in earnings from matched over matched but underutilised to underutilised graduates is consistent across demographic subgroups.

Second, the wage penalties associated with underemployment and underutilisation do not change significantly between 2013 and 2017, though the magnitude of the point estimates of the penalties for men and for all in the age-group 25-34 years are greater for 2017 than for 2013. The finding of a comparatively stable underemployment penalty is similar to trends in most European graduate labour markets (Green and Henseke, 2020).

Robustness checks

Bonus payments can form a substantial share of labour earnings in Singapore. SLS introduced a set of questions to collect information on bonus payments. About 70% of employees in the sample received some form of annual bonus payments in 2017. On average for those employees who received bonuses, they amounted to roughly 20% of the basic salary rate. Bonus payments could either have exaggerated or ameliorated the earnings gaps between UGs, MUGs, and MGs. In a robustness check, we therefore re-estimate the earlier earnings model with log total gross hourly pay including bonus as the new dependent variable. The estimation results confirm the earnings ranking from matched over matched but underutilised down to underutilised graduates. Compared with the results in Table 7, the pay gaps in 2017 by job destination widened to 35 % for UGs and 21 % for MUGs. Bonus payments seem to be a more important part of the pay package in job destination for matched graduates. The full estimation results by subgroups are summarised in Appendix Table A1.

Our results suggest significant heterogeneity in jobs with degree requirements which correlate with graduates' skills usage and earnings. For the analysis, we split jobs with degree requirements on entry into a group with task-warranted and a group with task-unwarranted degree requirements. Such a dichotomisation is a simplification for purposes of analysis, which obscures what may be a fuzzy threshold. To assess the sensitivity of our findings to the threshold at which degree requirements are considered task-warranted, we re-estimated the models for skills usage and base gross earning using a cut-off at 0.5 instead of 0.3 on the graduate skills requirement score; i.e. the probability of degree requirements is 50% or less. For brevity, we describe the sensitivity check for the 2017 sample (see Table A2 in the Appendix). The estimates confirm the previous findings. First, there are clear skills utilisation gaps between matched graduates on the one hand, and UGs and MUGs on the other. Second, mean earnings decline from MGs, over MUGs, down to UGs. The higher skills requirement threshold moved average hourly earnings of MUGs closer to those of MGs (with a pay gap of 13%), while the mean pay differential between MGs and UGs widened marginally to 33%. The overall pattern of the results therefore does not depend on the specific cut-point.

5 Discussion

In applying the concept of the 'graduate job' to the circumstances of Singapore's dynamic economy, we have developed a new conceptual distinction between 'task-warranted' and 'task-unwarranted' graduate jobs. For both types of job, a degree is required to get them. Yet, while task-warranted graduate jobs involve carrying out typical graduate-level tasks, task-unwarranted graduate jobs require no or low levels of observed graduate-level tasks. The rationale for the existence of task-unwarranted graduate jobs is that requiring recruits to have a degree may help sort applicants for their hard-to-observe skills and attributes – the logic that lies behind signalling. The distinction implies a new classification of graduate mismatch – by MGs, MUGs or UGs – with expected gaps between groups in both skills utilisation and pay. We have operationalised the distinction using task analysis with two recent surveys.

We find that there has been no tendency, at least in the short period between 2013 and 2017, for an increase in the share of graduates who are underemployed (overeducated), which remains at about one in five graduates. This finding is consistent with Habibi (2019), and with the fact that the graduate pay premium associated with higher education remained very high (more than double that of secondary school leavers) and unchanged between 2013 and 2017. Unlike that study, however, we find no obvious political restraints on the growth of graduate supply in recent years. Rather, the rapidly growing supply of graduates in Singapore's resident labour force was encouraged, and has been matched by an equally fast expansion in the share of graduate jobs. The growth of graduate jobs can be largely explained by upskilling: an increasing use of graduate-level tasks within jobs. The share of task-warranted graduate jobs expanded sharply from 21% to 32% of jobs, while the share of task-unwarranted graduate jobs fell slightly. These patterns of change and continuity are largely consistent across gender and age.

As expected, we find significant gaps in pay and perceived skills utilisation between MGs and MUGs. There is dispersion among graduates' pay, and in particular a wage penalty of 31% for underemployed Singapore graduates in 2017. There is a smaller wage penalty (18%) for being in an task-unwarranted graduate job as opposed to a task-warranted graduate job. Neither of these penalties significantly changed between 2013 and 2017. The existence of this penalty is consistent with the similar findings from Germany (Kracke and Rodrigues, 2020) applied to those who had been through occupational apprenticeships. However, in this paper we have utilised the detailed task specifications of individual jobs, rather than relied on occupation-level task use averages, and have developed the typology for graduate jobs and mismatch categories for graduates.

Moreover, we have been able to test and confirm the expectation that MUGs would report a lower use of their own skills than MGs. Perhaps surprisingly, we find no significant difference between the perceived skill use of MUGs and UGs. This finding poses the question, why do employers require MUGs to have qualified to degree level? If that degree is signalling attributes otherwise unobservable at the point of recruitment, then it seems that they may not be included in the set of attributes that MUGs perceive when they report skills underutilisation. One conceivable answer could be that some employers require workers to have degrees in order to learn and perform future tasks, which would not currently be perceived by the job-holders; such an explanation could be tested using longitudinal task data for workers who stay with their organisations, or with data on employers' expectations, should either become available in the future.

We have subjected our findings to several robustness tests, including specifying a substantively higher threshold between task-warranted and task-unwarranted graduate jobs, finding essentially the same pattern of findings. However, two limitations to our analysis deserve repeating here. First, the data refer only to the resident population. The value of analyses of skills supply and utilisation for Singapore's economy would be enhanced if it becomes possible in future to survey the jobs and job-holders in the remaining segments of the economy. Second, the estimated gaps between match categories among graduates are conditional on selection into those categories. That selection could be endogenous, and dependent on unobserved factors that themselves affect pay or skills utilisation. Sim (2015) finds that the estimated graduate wage premium is higher when using an instrumental variable determining attainment of a place at university, and concluded that omitted ability bias is less of a problem than measurement error. Some studies in other countries of endogenous selection by ability into match categories have shown small reductions in the underemployment wage penalty compared with the OLS estimate (e.g. Wu and Wang, 2018), with the estimated penalty remaining significant. While it is not obvious that omitted ability would select between task-warranted and task-unwarranted job attainment, our estimated coefficients cannot be interpreted as unbiased causal estimates of the effects of moving random graduates between these categories. If it became possible in future surveys to match in cognitive skills tests, for example from successive waves of the OECD's Survey of Adult Skills, this source of potential bias could be studied.

Our findings – the first in-depth analysis of Singapore's graduate labour market of which we are aware -- paint a picture of a dynamic labour market in recent years. While there is a case for ongoing monitoring with future skills utilisation surveys, the rising share of task-warranted graduate jobs, if it should persist, suggests that there was no immediate call, prior to the COVID-19 induced economic crisis, to turn off the higher education tap in Singapore. The distinction between task-warranted and task-unwarranted jobs should also be applicable to all countries and regions with suitable individual-level data on both task use and educational requirements. Incorporating data on skills heterogeneity, such as across subjects or using skills tests, would enrich future research on graduate job heterogeneity, as would separate consideration of the bachelors and post-graduate degree levels.

References.

Acemoglu, D., & Autor, D. (2011) Skills, Tasks and Technologies: Implications for Employment and Earnings, *Handbook of Labor Economics*. https://doi.org/10.1016/S0169-7218(11)02410-5

Allen, J. and R. van der Velden (2001). "Educational mismatches versus skill mismatches: effects on wages, job satisfaction, and on-the-job search." *Oxford Economic Papers* 53(3): 434-452.

Appold, S. J. (2005). The Weakening Position of University Graduates in Singapore's Labor Market: Causes and Consequences. *Population and Development Review*, 31(1), 85-+.

Ashton, David; Francis Green; Donna James and Johnny Sung. (1999). *Education and Training for Development in East Asia the Political Economy of Skill Formation in East Asian Newly Industrialised Economies*. London and New York: Routledge.

Autor, D. H. (2013). The “task approach” to labor markets: an overview. *Journal for Labour Market Research*, *46*(3), 185–199. https://doi.org/10.1007/s12651-013-0128-z

Autor, D. H., & Handel, M. J. (2013). Putting Tasks to the Test: Human Capital, Job Tasks, and Wages. *Journal of Labor Economics*, *31*(2), S59–S95. https://doi.org/10.1086/669332

Autor, D. H., F. Levy and R. J. Murnane (2003). "The skill content of recent technological change: An empirical exploration." *Quarterly Journal of Economics*, 118(4): 1279-1333.

Battu, H., C. Belfield, and P. Sloane (2000), “How Well Can We Measure Graduate Over-Education and its Effects?”, *National Institute Economic Review*, Vo. 171, pp. 82-93.

Beaudry, Paul; David A. Green and Benjamin M. Sand. 2016. "The Great Reversal in the Demand for Skill and Cognitive Tasks." *Journal of Labor Economics*, 34(1 , pt 2), S199-S247.

Blair, P. Q., & Deming, D. J. (2020). Structural Increases in Demand for Skill after the Great Recession. *AEA Papers and Proceedings*, *110*, 362–365. https://doi.org/10.1257/pandp.20201064

Bordón, Paola, and Breno Braga. 2020. “Employer Learning, Statistical Discrimination and University Prestige.” *Economics of Education Review* 77 (May): 101995.

Davie, S. (2020, January 28). Planning for university places needs rethink, Education News & Top Stories - The Straits Times. *The Straits Times*. Retrieved from https://www.straitstimes.com/singapore/education/planning-for-uni-places-needs-rethink

Dickerson, A. and Green, F. (2004) ‘The growth and valuation of computing and other generic skills’, *Oxford Economic Papers* 56 (3), 371-406.

Elias, P. and K. Purcell (2013). Classifying graduate occupations for the knowledge society, Futuretrack. Working Paper(5): 1-37.

Fairlie, R. W. (2005). An extension of the Blinder-Oaxaca decomposition technique to logit and probit models, *Journal of Economic and Social Measurement*, 30(4), 305–316.

Felstead, Alan, Duncan Gallie, Francis Green, and Golo Henseke. 2019. “Skills and Employment Surveys

Series Dataset, 1986, 1992, 1997, 2001, 2006, 2012 and 2017.” UK Data Service. https://doi.org/10.5255/UKDA-SN-8589-1.

Figueiredo, H., Teixeira, P. and Rubery, J. (2011) *Is Mass Higher Education Working? An Update and a Reflection on the Sustainability of Higher Education Expansion in Portugal.* ALMALAUEA Working Papers, 14.

Figueiredo, H., Biscaia, R., Rocha, V., & Teixeira, P. (2017). Should we start worrying? Mass higher education, skill demand and the increasingly complex landscape of young graduates’ employment. *Studies in Higher Education*, 42(8), 1401-1420.

Freeman, R. B. (1976). *The overeducated American.* New York, Academic Press.

Freeman, R. B., Ganguli, I., & Handel, M. J. (2020). Within-Occupation Changes Dominate Changes in What Workers Do: A Shift-Share Decomposition, 2005–2015. *AEA Papers and Proceedings*, *110*, 394–399. https://doi.org/10.1257/pandp.20201005

Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting and Social Change*, *114*, 254–280. https://doi.org/10.1016/j.techfore.2016.08.019

Gallie, D., Felstead, A., Green, F., and Henseke, G. 2018. *Participation at work in Britain. First findings from the Skills and Employment Survey 2017*. London: LLAKES Centre, UCL Institute of Education.

Green, F. (2012). Employee Involvement, Technology, and evolution in job skills: A Task- Based analysis. *Industrial and Labor Relations Review*, *65*(1), 36–67.

Green, F. and D. James (2003). "Assessing skills and autonomy: the job holder versus the line manager." *Human Resource Management Journal* 13(1): 63-77.

Green, F., and Henseke, G. (2016a). Should governments of OECD countries worry about graduate underemployment?, *Oxford Review of Economic Policy* 32(4): 514-537.

Green, F., and Henseke, G. (2016b). The changing graduate labour market: analysis using a new indicator of graduate jobs. *IZA Journal of Labor Policy*, *5*(1), 1–25. https://doi.org/10.1186/s40173-016-0070-0

Green, F. & G. Henseke (2020). Graduate employment and under-employment: Trends and prospects in high participation systems of higher education. *The Future of Higher Education*. C. Callender, W. Locke and S. Marginson. London, Bloomsbury.

Green, F., & Zhu, Y. (2010). Overqualification, job dissatisfaction, and increasing dispersion in the returns to graduate education. *Oxford economic papers*, 62(4), 740-763.

Habibi, N. 2019. "Preventing Overeducation and Graduate Surplus What Can West Asia Learn from Singapore and Hong Kong." *Asian Education and Development Studies*, 8(4), 523-35.

Henseke, G., & Green, F. (2017). Cross-national deployment of “graduate Jobs”: Analysis using a new indicator based on high skills use. *Research in Labor Economics*, *45*, 41–79. https://doi.org/10.1108/S0147-912120170000045002

Henseke, G. and F. Green (2020). The rising value of interpersonal job tasks for graduate pay in Europe. Oxford, Centre for Global Higher Education, Working Paper 53.

Holmes, C., & Mayhew, K. (2016). The economics of higher education. *Oxford Review of Economic Policy*, 32(4), 475-496.

Kiersztyn, A. (2013). Stuck in a mismatch? The persistence of overeducation during twenty years of the post-communist transition in Poland. *Economics of Education Review*, 32, 78-91.

Kracke, N., M. Reichelt and B. Vicari (2018). "Wage Losses Due to Overqualification: The Role of Formal Degrees and Occupational Skills." *Social Indicators Research* 139(3): 1085-1108.

Kracke, N. and M. Rodrigues (2020). "A Task-Based Indicator for Labour Market Mismatch." *Social Indicators Research* 149(2): 399-421.

Lee, M.H. (2016) Researching Higher Education in "Asia's Global Education Hub": Trends and Issues in Singapore, *Education and Society*, 34 (2), 5-25.

Marginson, S. (2016). "High participation systems of higher education." Journal of Higher Education 87(2): 243-271.

McGuinness, S. and J. Bennett (2007). "Overeducation in the graduate labour market: A quantile regression approach." *Economics of Education Review* 26: 521-531.

Meroni, E. C., & Vera-Toscano, E. (2017). The persistence of overeducation among recent graduates. *Labour Economics*, 48, 120-143.

Ministry of Education. (2020). *Graduate employment survey.* Singapore. Retrieved from https://www.moe.gov.sg/docs/default-source/document/education/post-secondary/files/joint-web-publication-ges-2019.pdf

Mok, K. H. and D. Neubauer (2016) Higher education governance in crisis: a critical reflection on the massification of higher education, graduate employment and social mobility, *Journal of Education and Work*, 29:1, 1-12.

Sim, N. (2015). "Astronomics in action: the graduate earnings premium and the Dragon effect in Singapore." *Economic Inquiry* 53(2): 922-939.

Spitz-Oener, A. (2006). Technical Change, Job Tasks, and Rising Educational Demands: Looking outside the Wage Structure. *Journal of Labor Economics*, *24*(2), 235–270. https://doi.org/10.1086/499972

Verhaest, D., & Omey, E. (2006). The Impact of Overeducation and its Measurement. *Social Indicators Research*, *77*, 419–448. https://doi.org/10.1007/s11205-005-4276-6

Verhaest, D., & Omey, E. (2012). Overeducation, Undereducation and Earnings: Further Evidence on the Importance of Ability and Measurement Error Bias. *Journal of Labor Research*, *33*(1), 76–90.

Verhaest, D., & Van der Velden, R. (2013). Cross-country differences in graduate overeducation. *European Sociological Review*, 29(3), 642-653.

Wu, N., & Wang, Q. (2018). Wage penalty of overeducation: New micro-evidence from China. *China Economic Review*, 50, 206-217.

Youden, W. J. (1950). Index for rating diagnostic tests. *Cancer*, 3(1), 32-3.

Appendix to ***Task-Warranted Graduate Jobs and Mismatch***

This appendix presents a graph of the density of the graduate skills requirement score, and the details of two robustness tests reported in the text of the paper.

Figure A1: Kernel density estimation of the distribution of graduate skills requirement score by whether reported as a graduate job

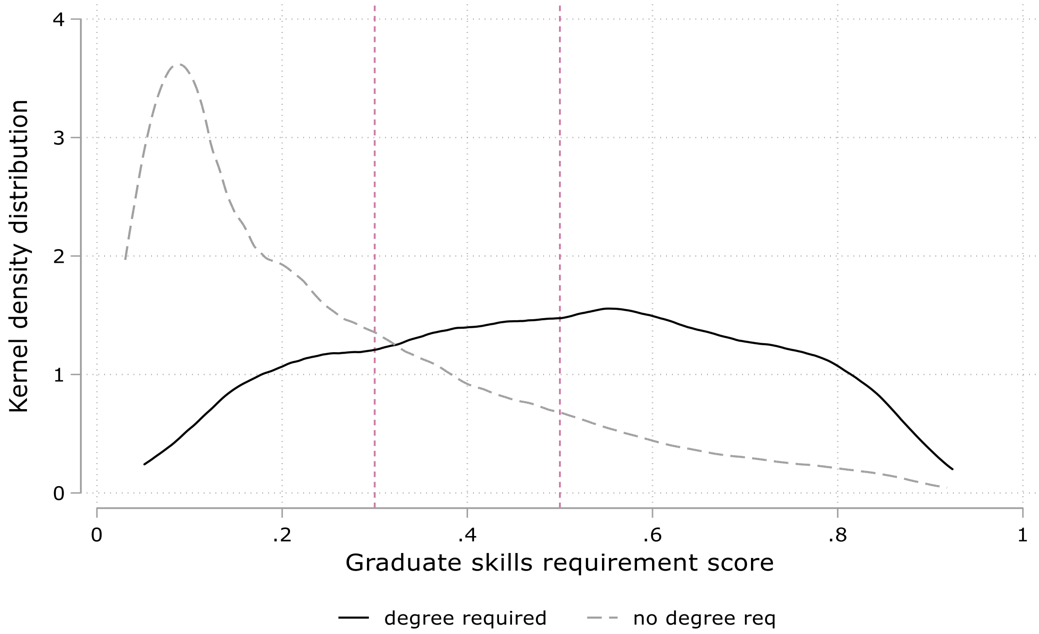


Table A1 Pay penalty by graduate job destination using gross total hourly earnings including bonus payments, 2017

	Underemployed Graduates	Matched but Underutilised Graduates	Matched graduates	p-value (UGs = MUGs)	N
	Pay penalty				
Total	-0.429*** (0.054)	-0.240*** (0.047)	(ref.)	0.002	1209
Men	-0.486*** (0.089)	-0.262*** (0.057)	(ref.)	0.020	619
Women	-0.365*** (0.064)	-0.198** (0.070)	(ref.)	0.038	590
25-34	-0.382*** (0.060)	-0.171*** (0.050)	(ref.)	0.002	503
35-65	-0.458*** (0.080)	-0.260*** (0.072)	(ref.)	0.032	706

Standard errors in parentheses. ** p < 0.01, *** p < 0.001

Table A2: Skills usage and pay d ifferentials for UGs, MUGs, and MGs with a threshold of 0.5 for task-warranted jobs.

	Underemployed Graduates	Matched but Underutilised Graduates	Matched graduates	p-value (UGs = MUGs)	N
	Skills utilisation				
Total	-0.064*** (0.014)	-0.066*** (0.011)	(ref.)	0.920	1582
Men	-0.065*** (0.020)	-0.064*** (0.015)	(ref.)	0.964	822
Women	-0.063** (0.020)	-0.070*** (0.015)	(ref.)	0.716	760
25-34	-0.045* (0.021)	-0.073*** (0.016)	(ref.)	0.153	617
35-65	-0.077*** (0.018)	-0.059*** (0.014)	(ref.)	0.376	965
	Pay penalty				
Total	-0.403*** (0.054)	-0.142*** (0.036)	(ref.)	0.000	1209
Men	-0.435*** (0.090)	-0.141** (0.045)	(ref.)	0.001	619
Women	-0.359*** (0.063)	-0.136* (0.055)	(ref.)	0.001	590
25-34	-0.374*** (0.059)	-0.129*** (0.038)	(ref.)	0.000	503
35-65	-0.422*** (0.080)	-0.143** (0.053)	(ref.)	0.001	706

Weighted OLS regression of skills utilization and log real gross hourly pay in 2017 on indicators for underemployment (non-graduate job) and underutilization (task-unwarranted graduate job) and control variables for employed graduates aged 25–65 years. Control variables comprise 5-year age-groups, sex, indicator for the presence of dependent children under 16 in the household, cohabitation status, and housing tenure. Robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$