UNIVERSIDADE DE BRASÍLIA
Faculdade de Economia, Administração e Contabilidade e Gestão Pública
Departamento de Economia
Programa de Pós-Graduação em Economia

Anaely da Silva Machado

Essays on economics of education: Higher education accountability and major-job match returns

Brasília
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Orientador: Rafael Terra de Menezes
Coorientadora: Maria Eduarda Tannuri-Pianto

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Aos amigos que sempre me apoiaram e motivaram ao longo dessa jornada.

Resumo

Esta tese possui dois artigos independentes em economia da educação superior. O primeiro artigo estima o impacto do processo de avaliação sobre a oferta e a qualidade do ensino superior brasileiro. Exploramos um experimento natural que consiste na adoção de um sistema de avaliação para os cursos de graduação no Brasil - conhecido como SINAES - implementado pelo Ministério da Educação em 2004. A regra de atribuição de notas permite aplicar o método de regressão descontínua. Nós testamos a sensibilidade dos cursos ao reforço negativo, como, por exemplo, punições no caso em que uma nota mínima não é alcançada. Também testamos se os administradores dos cursos buscam aumentar a nota com o intuito de promover o curso e atrair estudantes. Nossos resultados mostram que os administradores respondem ao risco de punição alcançando resultados melhores na próxima avaliação, mas não podemos afirmar se buscam notas maiores com o intuito de fazer propaganda e aumentar o número de matrículas. O segundo artigo avalia a aderência dos cursos de graduação às ocupações e seu efeito sobre o mercado de trabalho. Primeiro, associamos cada área de estudo às ocupações diretamente relacionadas. Em seguida, utilizamos um modelo pré-treinado de processamento de linguagem natural (PNL) sobre a descrição de atividades das ocupações na Classificação Brasileira de Ocupações (CBO), permitindo mapear a distância entre cada par de ocupações. Combinando estes dois passos, nós contabilizamos a similaridades entre a principal ocupação associada a cada área de estudo e as demais ocupações como nosso indicador de aderência entre o curso e a ocupação. Nós utilizamos este indicador para estimar o efeito da aderência do curso à ocupação sobre os retornos no mercado de trabalho para um grupo de trabalhadores que graduaram entre 2004 e 2006 no Brasil. Os resultados indicam que quanto maior a aderência do curso à ocupação, maior o salário e menor a probabilidade de deixar o emprego. Também exploramos efeitos heterogêneos: as estimativas mostram retornos salariais maiores para mulheres, trabalhadores em ocupações que requerem o nível superior, empregados do setor privado e graduados em áreas como Direito, Educação e letras, e Produção e engenharia. A inclusão da variável de controle para a similaridades entre a experiência de trabalho anterior e a ocupação atual não altera as principais conclusões do trabalho e apresenta evidências sobre o retorno positivo da adequação da experiência de trabalho anterior ao trabalho atual.

Palavras-chave: Educação superior, avaliação, mercado de trabalho, ocupação, processamento de linguagem natural (NLP)

Abstract

This thesis contains two independent essays on economics of higher education. The first one estimates the impact of accountability scores on Brazilian higher education outcomes. We explore a natural experiment: the introduction of an accountability system for Brazilian undergraduate programs named SINAES that was implemented by the Ministry of Education in 2004. The design of the evaluation system enables us to implement a regression discontinuity strategy. We test whether program quality is sensitive to negative reinforcement, such as punishments imposed when a minimum threshold is not attained. We also test whether program administrators seek higher evaluation scores as a form of advertisement to attract prospective students. Our results show that program administrators respond to the threat of punishment by improving program quality in the next evaluation cycle, but we cannot determine whether administrators seek higher grades in order to advertise their programs and increase enrollments or to improve the quality and prestige of their programs. The second essay estimates the match between occupations and college majors and its effects on labor market returns. Our major-job match index combines the direct association of each field of study to its closest occupations, and the similarity index between each pair of occupations based on the application of a pre-trained natural language processing (NLP) model to the occupation task description. We estimate the effects of major-job match on labor market returns up to 2018 for a cohort of Brazilian graduates who completed an undergraduate program between 2004 and 2006. The results suggest that the greater the major-job match, the higher the wage and the smaller the turnover. We also explore heterogeneous effects: the estimates show higher wage returns to major-job match for women, workers in occupations that require the college degree, private sector employees and graduates in fields such as Law, Education, Portuguese and foreign languages, and Production and engineering. Controlling for on-the-job learning does not significantly change our main results but adds evidence on the positive returns to matching the previous work experience to the current job.

Keywords: Higher education, accountability, labor market, occupation, natural language processing (NLP)

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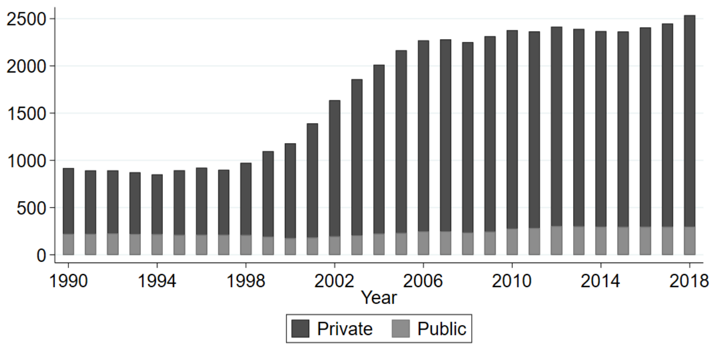
Chapter 1

Introduction

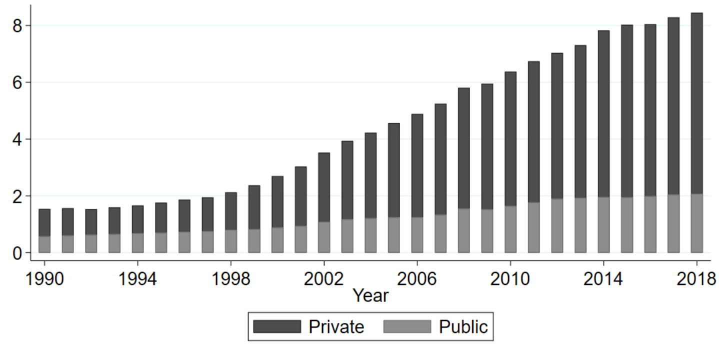
The relevance of higher education in socioeconomic development has gained attention in Brazil, especially since the late 1990s. For example, the Brazilian government established the National Plan for Education (PNE) which claimed the expansion and the access to higher education as a goal for the public policy[1]. Therefore, the increasing number of students completing the high school, changes in regulations that facilitated the entry of new institutions into the higher education market, and public policies that promoted higher education contributed to the expressive expansion of undergraduate programs in Brazil (Rezende (2010); OECD (2018)). Figure 1.1 shows that the number of higher education institutions (HEIs) tripled since the 1990s, which was led by the expansion in the number of private institutions. Enrollments increased from 1.5 million in 1990 to almost 8.5 millions in 2018 (see figure 1.2).



Source: Anísio Teixeira National Institute for Educational Studies and Research (INEP).

Figure 1.1: Number of higher education institutions in Brazil

[1]See Law No 10172 from January 9th, 2001 and Law No 13005 from June 26, 2014.



Source: INEP.

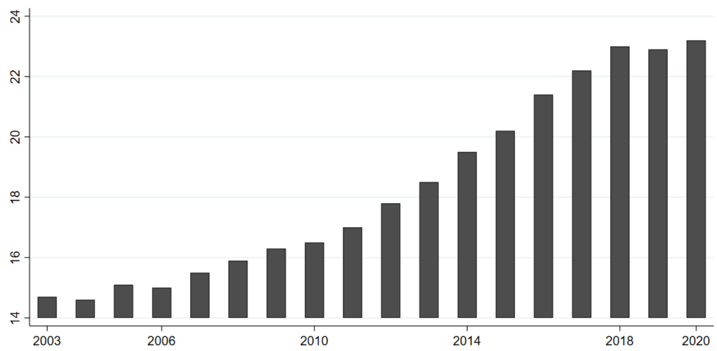
Figure 1.2: Number of enrollments in undergraduate programs in Brazil (in millions)

Moreover, the Brazilian federal government has had an important role not only in expanding the number of slots in public universities, but also in financing tuition in private institutions. The federal authorities created the Student Loan Fund (Fies), an alternative source of credit for students to obtain educational loans and pay for their studies in private undergraduate programs, and the University for All Program (ProUni), which provides full scholarships for students in private HEIs[2]. Together, Fies and ProUni account for 22% of private enrollments[3] and are regarded as important contributors to the increase in higher education enrollments among private institutions (Corbucci et al. (2016)).

On the other hand, the proportion of higher educated workforce also increased over this time (see figure 1.3): the share of workers who completed an undergraduate program increased from 15% in 2003 to 24% in 2020, according to the data for the formal labor market in Brazil. To sum up, the Brazilian higher education has evolved significantly over the last years which contributed to the increase in the level of education of the workforce.

[2]See Law No 10260 from July 12, 2001, and Law no 11096 from January 13, 2005.

[3]According to the Higher Education Census provided by INEP – the main federal authority for education evaluation in Brazil.



Source: MTE.

Figure 1.3: Proportion of formal workers who completed an undergraduate program (in %)

In this context, the government has also invested in the System of Higher Education Evaluation (SINAES) as a mechanism to promote the quality of undergraduate programs and regulate their offer. Despite the efforts to maintain a complex accountability system such as the SINAES, the research has put little attention on its effectiveness. Besides, the quality system does not take into account the graduates' trajectories to evaluate issues such as the gap between the skills developed during higher education and the ones required by the labor market. This way, we identify two relevant questions not yet explored in Brazil: (1) does the accountability system impact the quality and offer of undergraduate programs?; (2) does matching the college major to the job affect earnings??

To answer the first question, we evaluate the SINAES, which was implemented by the Ministry of Education in 2004. The system design enables us to implement a regression discontinuity design (RDD) to evaluate whether programs respond to the grades they receive. In particular, we evaluate the administrators' response to low grades associated to clear punishments, such as the reduction in financing and closure threat. Besides, we also test whether administrators seek higher scores as a form of advertisement. This way, our research represents the first attempt to evaluate the impact of accountability on higher education using a RDD approach, adding to the previous research on education accountability, such as Rockoff and Turner (2010), Rezende (2010), Deming and Figlio (2016) and Canaan and Mouganie (2018). Our results show that program administrators respond to the threat of punishment (when they receive a low grade) by improving the program quality in the next evaluation cycle, but we cannot determine whether administrators seek to achieve the highest grades.

We explore the second question by combining the unique panel data of graduates who completed their undergraduate programs between 2004 and 2006, their job trajectories in formal labor market up to 2018 and a novel strategy to compute the match level between majors and occupations. This way, we add to the research about the returns to horizontal match (for example, see Robst (2007), Nordin et al. (2010) and Reis (2018)) by exploring a large panel data for graduates in Brazil and proposing a match index that relies on a natural language processing (NLP) approach. Based on a panel data analysis with individual fixed effects, our results corroborate the main findings of the literature: the greater the major-job match, the higher the wage and the smaller the turnover. We also shed light on the relevance of matching the previous experience to the current job. Moreover, this second paper illustrates the potential of applying NLP tools to optimize social research when it requires the analysis of non-structured text description such as the Brazilian occupation classification.

Higher education is meant to provide workers with skills and knowledge to perform occupation tasks, according to the chosen major. This way, the program quality and the match between majors and jobs are important issues regarding to the efficacy of the higher education system. We believe exploring this topic contributes to the public policy that aims to promote the Brazilian higher education. On one hand, we present evidences about the efficacy of the SINAES in improving quality and regulating the offer, which signalizes whether the government can improve the accountability system. On the other hand, our major-job match index allows us to measure the transferability of skills from college to occupations and its wage premium.

This document is structured as follows. We explore the first question in chapter 2: we describe the empirical strategy and the application of the RDD approach, discuss the hypothesizes we test and present the results separately by public and private institutions. Chapter 3 describes the returns to major-job match, details our empirical strategy and displays the main estimates. Chapter 4 presents a brief discussion of our main conclusions.

References

Canaan, S. and P. Mouganie (2018). Returns to education quality for low-skilled students: evidence from a discontinuity. *Journal of Labor Economics 36*(2), 395–436.

Corbucci, P. R., L. C. Kubota, and A. P. B. Meira (2016). Evolução da educação superior privadano Brasil: da reforma universitário de 1968 à década de 2010. *Radar: tecnologia, produção e comércio exterior* (46), 7–12.

Deming, D. J. and D. Figlio (2016). Accountability in us education: applying lessons from K-12 experience to higher education. *Journal of Economic Perspectives 30*(3), 33–56.

Nordin, M., I. Persson, and D.-O. Rooth (2010). Education–occupation mismatch: is there an income penalty? *Economics of education review 29*(6), 1047–1059.

OECD (2018). *Rethinking Quality Assurance for Higher Education in Brazil, Reviews of National Policies for Education*. Paris: OECD Publishing.

Reis, M. (2018). Measuring the mismatch between field of study and occupation using a task-based approach. *Journal for labour market research 52*(1), 1–15.

Rezende, M. (2010). The effects of accountability on higher education. *Economics of Education Review 29*(5), 842–856.

Robst, J. (2007). Education and job match: the relatedness of college major and work. *Economics of Education Review 26*(4), 397–407.

Rockoff, J. and L. J. Turner (2010). Short-run impacts of accountability on school quality. *American Economic Journal: Economic Policy 2*(4), 119–47.

Chapter 2

Higher education responses to accountability

ABSTRACT

This paper estimates the impact of accountability scores on Brazilian higher education outcomes. We explore a natural experiment: the introduction of an accountability system for Brazilian undergraduate programs named SINAES that was implemented by the Ministry of Education in 2004. The design of the evaluation system enables us to implement a regression discontinuity strategy. We test whether program quality is sensitive to negative reinforcement, such as punishments imposed when a minimum threshold is not attained. We also test whether program administrators seek higher evaluation scores as a form of advertisement to attract prospective students. Our results show that program administrators respond to the threat of punishment by improving program quality in the next evaluation cycle, but we cannot determine whether administrators seek higher grades in order to advertise their programs and increase enrollments or to improve the quality and prestige of their programs.

JEL Classification: H75, I21, I23, I28
Keywords: Regression Discontinuity, Accountability, Higher Education, Impact Evaluation

2.1 Introduction

Accountability systems aim to improve education quality. Such systems evaluate institutions on the basis of student performance on standardized tests and other instruments that reflect quality in terms of infrastructure and faculty profiles. Evaluation results can be used to inform people about institutional quality and to support regulatory initiatives. Nevertheless, accountability systems are most common in basic education, though such systems may certainly be introduced at any level or in any type of education, such as higher education, when governments want to promote quality and guarantee the rational use of public funds. Moreover, candidates for higher education programs can be better informed when making decisions based on publicly disclosed grades and choose programs in which students perform the best, setting positive incentives for undergraduate programs to always strive for improvement. On the other hand, negative incentives such as punishments imposed on the administrators of low-scoring programs can also encourage institutions to improve educational quality.

While plausible, the reaction of higher education institutions (HEIs) to the introduction of accountability incentives remains largely an empirically unexplored subject. This paper attempts to address this question by investigating the effects of negative or (weakly) positive incentives – introduced by an accountability system – on higher education outcomes[1].

To this end, we explore a natural experiment created by the Brazilian Ministry of Education, which enacted its current higher education accountability system in 2007. Thereafter, undergraduate programs are evaluated every three years based on the results of a standardized exam, the National Exam of Student Performance (ENADE)[2], faculty profiles and student feedback. The results in each of these dimensions are used to compose a continuous index that summarizes program performance, the Preliminary Program Grade (CPC)[3], which is used to classify programs into 5 possible levels based on sharp cutoffs[4]. The Ministry of Education publicly discloses the performance grades and uses them to regulate undergraduate expansion and activity, conditioning approval to renew programs on whether minimum achievement standards have been met. That is, the programs must obtain a minimum

[1]Previously, Rezende (2010) attempted to evaluate the impact of accountability on higher education by conducting a regression analysis of observational panel data on Brazilian undergraduate programs for the 1996-2003 period. The author concluded that scores on National Program Exam (ENC – Exame Nacional de Cursos in Portuguese) increased program slots and improved faculty profiles.

[2]Exame Nacional de Desempenho dos Estudantes in Portuguese.

[3]Conceito Preliminar de Curso in Portuguese.

[4]We refer to the continuous CPC score as CPC_{score}, while we use CPC_{level} when referring to the CPC levels.

level of 3 to be recognized by the federal authorities under penalty of suspension if they fail to reach that level. Since information about the quality of higher education institutions can also contribute to students' choice over undergraduate programs, institutions can advertise their good results to attract more students and expand their programs. Hence, discontinuities originating in the CPC level assignment rule create an opportunity to evaluate the short run effects of accountability incentives on undergraduate outcomes in the years following the evaluations.

Our research is closely related to the literature on the response to accountability by various agents (school administrators, teachers, families and others). For example, previous research has examined performance improvements in low-performing schools after the receipt of their evaluations in Brazil (Camargo et al. (2018)), Mexico (De Hoyos et al. (2017)), Portugal (Nunes et al. (2015)), South Korea (Woo et al. (2015)), and the United States, specifically Chicago, New York City, Florida and Wisconsin (Neal and Schanzenbach (2010); Rockoff and Turner (2010); Rouse et al. (2013); Chiang (2009); Chakrabarti (2014); Deming et al. (2016)). The literature has also identified the impacts of accountability ratings on resource allocation and administrator behavior (Figlio and Winicki (2005); Craig et al. (2013, 2015)). In addition, accountability evaluations are related to student and teacher flows from low- to high-performing schools (Feng et al. (2018)).

In particular, the interest in the impact of accountability on higher education has gained attention in the literature. Evidence on the impact of an evaluation system on offers, faculty profiles and program attractiveness are found in Rezende (2010) and Bowman and Bastedo (2009) for HEIs in Brazil and the United States. Less explored is the effect of higher education quality on labor market outcomes (see Canaan and Mouganie (2018)).

Public disclosure of the results of evaluations and college/school rankings contribute to institutional reputations which in turn influence student behavior when choosing an institution and undergraduate program (Bowman and Bastedo (2009); Rezende (2010)). This means that the expected effects of accountability depend, at least partially, on the publicity and transparency of the results obtained by institutions and programs (Hastings and Weinstein (2008); Deming and Figlio (2016)). In addition, the literature suggests that the impact of accountability on education is related to the incentives faced by different agents according to their performance. For example, Figlio and Rouse (2006) and Rouse et al. (2013) investigated the relevance of the voucher threat and state oversight on the impacts of accountability. While the former found that the impacts are mainly driven by grading stigma, the latter concluded that the changes in instructional policies and practices were a result of accountability pressure. In summary, the literature indicates that the different accountability systems affect educational outcomes provided that they are related to explicit rewards and sanctions.

On the other hand, the literature also identifies critical issues for the effectiveness of accountability systems. For example, if educational assessments are tied to specific measures, then organizations seek to improve their performance related to those measures at the potential cost of other outcomes of interest due to their maximization behavior (Deming and Figlio (2016)). That is, the system sends a signal to society about what is most valued, and then, the administrators pursue that goal. Deciding which measures to include in an evaluation system for HEIs is even more difficult since different fields of study and organizations have different curricula and purposes (Deming and Figlio (2016)). Additionally, the long-run effectiveness of accountability systems may be limited by the strategic behavior of the agents, while institutional rankings tend to be effective only after the first publication (Deming and Figlio (2016); Bowman and Bastedo (2013))[5].

As is evident from the literature mentioned above, most previous research has focused on elementary to secondary education, most probably because of the absence of a structured accountability system for higher education in most countries or, when such a system exists, the lack of rules that would enable quasi-experimental evaluations of accountability systems for this level of education. To the best of our knowledge, this paper represents the first attempt to evaluate the impact of accountability on higher education using a regression discontinuity design (RDD) approach[6].

In particular, our empirical strategy is similar to that in previous works that have explored discontinuities in grade assignment rules to measure the impact of accountability, such as Chiang (2009), Rockoff and Turner (2010), Rouse et al. (2013), Chakrabarti (2014), Craig et al. (2015), Woo et al. (2015), Woo et al. (2015), Holbein and Ladd (2017), Canaan and Mouganie (2018), Feng et al. (2018).

Our main results suggest that undergraduate program administrators respond to negative incentives imposed by the federal authority – such as threats of

[5]Bowman and Bastedo (2013) studied the impact of higher education rankings and found that the initial rankings influenced peer assessments of reputation in subsequent surveys but that second-year rankings were not related to changes in reputation in the third year, and these results may be associated with the anchoring theory.

[6]Rezende (2010) studied the effects of accountability on Brazilian higher education based on OLS estimations. In addition, the accountability system was replaced by the current system, investigated in this paper. Despite the use of an RDD approach, Canaan and Mouganie (2018) mainly explores the labor market returns to higher education accountability for low-skilled students.

closure, supervisory commission visits or punishment via the withdrawal of recognition – by improving program accountability index values in comparison to other programs in the following evaluation cycle. Programs with evaluations that fall below the low-performance threshold, i.e., that have a CPC_{level} equal to 1 or 2 ($CPC_{score} < 1.945$), achieved better outcomes in the next evaluation cycle in terms of performance, faculty, infrastructure and quality overall. We also find evidence that programs just above the recognition threshold ($CPC_{score} \geq 1.945$) increase their program slots, receive more applications and admit more new students than programs just below the same threshold. We do not find clear patterns around the threshold that assigns $CPC_{level} = 5$ ($CPC_{score} \geq 3.945$), the maximum grade, which we expected programs could have used as an advertisement.

We also test whether accountability has heterogeneous effects on private and public HEIs. The Brazilian higher education system is composed of both private and public institutions. Public institutions are supported by public resources, students who attend public institutions do not pay fees, and faculty and staff enjoy job stability. These characteristics probably reduce the potential negative effects of a bad evaluation for public programs. On the other hand, in addition to competitive pressure from the private market, private institutions have more positive incentives to pursue quality in order to access public programs that offer scholarships and student loans.

The results suggest that even public institutions react to evaluation incentives. Since public institutions are not subject to the positive incentives of access to scholarships or student loans, we conclude that negative incentives – i.e., the threat of punishment – dominate their reaction. However, the magnitude of the reaction to low scores is greater among private institutions, which suggests that positive incentives may also affect administrator behavior, though it could also be the case that the more pronounced reaction among private institutions is the result of administrators having “skin in the game” and always trying to attract more students to keep their jobs, whereas public administrators enjoy job stability.

Finally, we conclude that the observed impacts are associated with clear punishment rules, while the achievement of higher grade levels does not significantly impact program effort nor candidate perceptions of future returns.

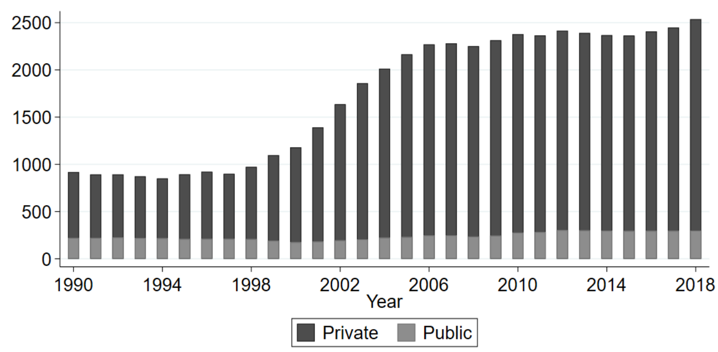
This paper is structured as follows. We describe the Brazilian higher education system and its accountability system in section 2.2. Section 2.3 describes the data and presents descriptive statistics. The empirical strategy is described in section 2.4. Section2.5 presents a discussion of the results and robustness tests, and section2.6 concludes.

2.2 The Brazilian higher education system

2.2.1 The recent expansion of the Brazilian higher education system

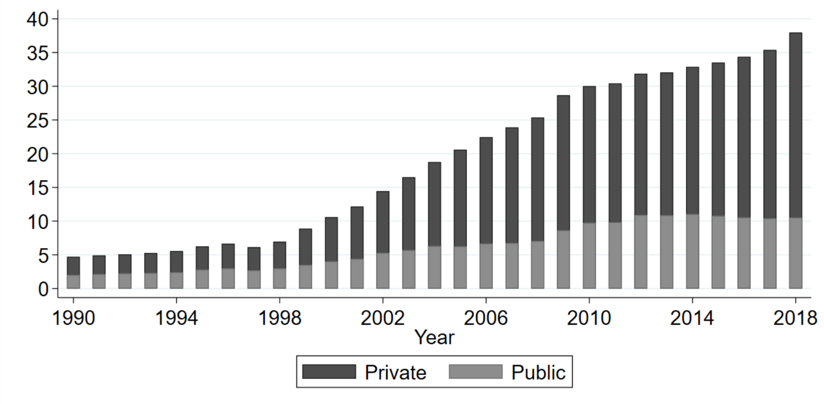
The Brazilian higher education system consists of public and private institutions. Public institutions may be fully supported by the federal government, as is the case for federal universities and federal institutes; by state governments, as is the case for state universities; and, in some cases, by municipal governments. Public institutions cannot charge tuition or fees, and faculty and staff enjoy legal job security after a three-year probationary period. In contrast, private HEIs charge tuition and fees from their students. There are various types of private institutions: publicly traded companies, private limited companies, Christian colleges and universities, think tanks, and foundations. Employees typically do not enjoy job security – although there are a few cases of institutions granting tenure to some professors.

The Brazilian higher education system has expanded significantly since the 1990s. Figure 2.1 shows that the number of HEIs tripled during that decade, which was led by the expansion in the number of private institutions. The number of undergraduate programs has evolved similarly, with the private sector representing more than 70% of the increase in undergraduate programs – see figure 2.2. Enrollments increased from 1.5 million in 1990 to almost 8.5 millions in 2018; see figure 2.3.



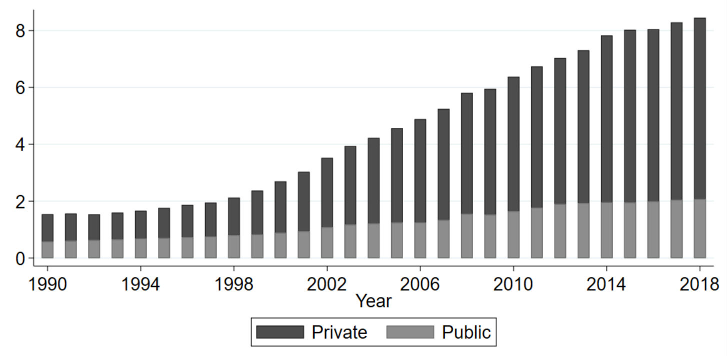
Source: Anísio Teixeira National Institute for Educational Studies and Research (INEP).

Figure 2.1: Number of higher education institutions in Brazil



Source: INEP.

Figure 2.2: Number of undergraduate programs in Brazil (in thousands)



Source: INEP.

Figure 2.3: Number of enrollments in undergraduate programs in Brazil (in millions)

The expansion of Brazilian higher education can be attributed to a few critical factors: the increasing number of students completing a high school level, changes in regulations that facilitated the entry of new institutions into the higher education market, and public policies that promoted higher education (Rezende (2010); OECD (2018)).

According to the School Census[7] reported by the Anísio Teixeira National Institute for Educational Studies and Research (INEP), [8] an agency within the Ministry of Education, the number of students graduating from high school increased from 960 thousand in 1995 to more than 2 million in 2018. During the same period, the Higher Education Census [9], also conducted by INEP, shows that the number of applications to undergraduate programs increased

[7]Censo Escolar in Portuguese. Available at `http://portal.inep.gov.br/web/guest/censo-escolar`.

[8]Instituto Nacional de Estudos e Pesquisas Educacionais "Anísio Teixeira" in Portuguese.

[9]Censo da Educação Superior in Portuguese. Available at `http://portal.inep.gov.br/web/guest/censo-da-educacao-superior`.

from 2.7 to 12.4 million[10]. Although enrollments in high schools have been decreasing in recent years in Brazil (because of demographics and improvements in school progress), there is still high demand for undergraduate programs as evidenced by the increase in applications.

A second explanation for the higher education expansion in Brazil relates to changes in the regulations established in the 1990s that facilitated the market entry of new institutions and the creation of new undergraduate programs as long as such institutions and programs underwent periodic assessment for accreditation and recognition of diplomas (Rezende (2010); OECD (2018)).

Lastly, the Brazilian federal government sought the expansion of higher education by financing tuition in private institutions and expanding the number of slots in public universities. The federal authorities created the Student Loan Fund (Fies), an alternative source of credit for students to obtain educational loans and pay for their studies in private undergraduate programs, and the University for All Program (ProUni), which provides full scholarships for students in private HEIs[11]. Together, Fies and ProUni account for 22% of private enrollments and are regarded as important contributors to the increase in higher education enrollments among private institutions (Corbucci et al. (2016)).

In 2014, the federal government enacted the National Plan for Education (PNE)[12] for the period between 2014 and 2024. That plan set specific goals for increasing enrollment in public higher education institutions, as well as for improving the quality of education and access to higher education among socioeconomically disadvantaged students (OECD (2018)), thus reinforcing the role of the state in setting the conditions for the development of higher education.

2.2.2 The accountability system for Brazilian undergraduate programs

In the last two decades, the Brazilian government and Brazilian society have discussed the relevance of an accountability system for assessing, monitoring and assuring the quality of HEIs in face of the intended expansion of undergraduate programs and enrollments (Inep (2009); OECD (2018)). In 2004, the National System of Higher Education Evaluation (SINAES)[13] was

[10]Numbers for on-site undergraduate programs.

[11]See Law No 10260 from July 12, 2001, and Law No 11096 from January 13, 2005.

[12]See Law No 13005 from June 26, 2014.

[13]Sistema Nacional de Avaliação do Ensino Superior in Portuguese.

established[14]. This system guides the Ministry of Education in its decisions about the accreditation of institutions and the authorization for and recognition of undergraduate programs[15]. SINAES evaluates all private and federal public institutions, accounting for 91% of total enrollments in Brazilian undergraduate programs[16], and is administered by INEP.

SINAES sets rules and procedures for monitoring and evaluating undergraduate programs in order to act on results indicating low-performance programs. Accordingly, every three years, INEP calculates a CPC value for each undergraduate program.[17]. The CPC reflects the overall "quality of the program"; it is a composite index that summarizes (a) student performance, (b) teaching staff profiles and (c) feedback from students about the program. The CPC formula is given in equation 2.1.

$$\begin{aligned} CPC_{score} = {} & 0.2 \cdot ENADE_c + 0.35 \cdot IDD_c + 0.075 \cdot NM_c + 0.15 \cdot ND_c \\ & + 0.075 \cdot NR_c + 0.075 \cdot NO_c + 0.05 \cdot NF_c + 0.025 \cdot NA_c \end{aligned} \tag{2.1}$$

The ENADE index evaluates learning quality and reflects student results on the ENADE, a standardized exam taken by students in their senior year covering the core disciplines of each program. ENADE results feed into the ENADE Index, which consists of the mean grade achieved by students in each discipline. ENADE results also feed into the Index for the Difference between Observed and Expected Performance (IDD),[18] which measures the value added by the higher education programs by comparing the grades achieved by students on the ENADE with their grades from the National High School Exam (ENEM)[19]. Together, the ENADE and IDD indexes account for more than half of the total weight in the CPC_{score} .

The quality of the faculty is evaluated by the proportion of its members with a master's degree (NM), the proportion with a PhD (ND), and the proportion of full or part-time faculty (NR).

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[14] Previous efforts to evaluate higher education include the Institutional Evaluation Program for Brazilian Universities (Paiub – Programa de Avaliação Institucional das Universidades Brasileiras in Portuguese), a voluntary evaluation for universities introduced in 1993, and the ENC, a standardized exam for undergraduate students in effect between 1996 and 2003. Graduate programs, in turn, have been evaluated by the General Coordination for the Improvement of Higher Education Personnel (CAPES) since 1976.

[15] See Law 10861 from April 14, 2004.

[16] State- or municipality-controlled institutions can voluntarily participate in SINAES, as they are subject to local legislation and regulations regarding education.

[17] See Regulatory Ordinance no 560 from July 9th, 2019. See also Technical note n.58 from 2020 for the CPC methodology.

[18] Indicador da Diferença entre os Desempenhos Observado e Esperado in Portuguese.

[19] Exame Nacional do Ensino Médio in Portuguese. ENEM is a national exam that evaluates the quality of high school education. Its results are also used as an entrance exam for the main universities – public or private – and as a criterion for receiving scholarships and loans.

Lastly, students complete questionnaires before taking the ENADE test wherein they provide feedback about the undergraduate program they attended. The student responses are used to produce indexes for teaching and learning (NO), infrastructure (NF) and academic and professional opportunities (NA).

Each of the indexes that make up the CPC are standardized and rescaled to range between 0 and 5. Weights sum to one and are distributed according to equation 2.1. These index values are calculated for each program every three years, following the ENADE cycle, which determines the fields evaluated each year[20].

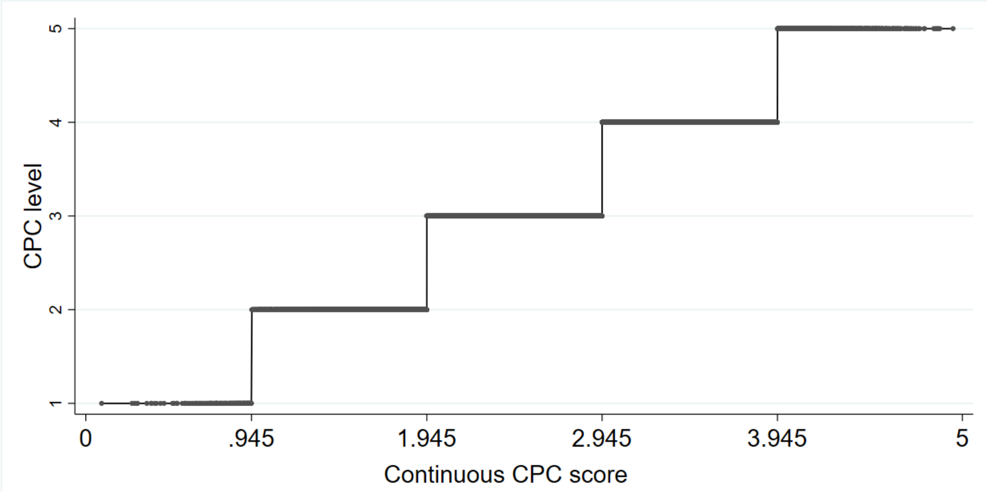
The CPC also influences the HEI general quality index, named the General Index of Programs (IGC)[21]. Coupled with graduate program scores[22], CPC scores are used to calculate the IGC, which is calculated as the mean of the graduate and CPC program scores weighted by the number of students enrolled in each program and degree level. INEP updates the IGC every year with the results of the current evaluation cycle.

Based on the CPC score – which is continuous and ranges from 0 to 5 –, the programs are classified into quality levels (i.e., CPC levels) – which are discrete and range from 1 to 5. We use the notation CPC_{score} and CPC_{level} to refer to the continuous score and the level, respectively. Programs with a CPC score below the threshold of $CPC_{score} < 0.945$ are classified as having a CPC_{level} of 1. A CPC_{score} equal to or above 0.945 but less than 1.945 results in a CPC_{level} of 2. The CPC_{level} is equal to 3 when the CPC_{score} is equal to or above 1.945 but less than 2.945. Level 4 is attained whenever CPC_{score} is equal to or above 2.945 but less than 3.945. Finally, programs with a CPC_{level} of 5 are assigned to the "excellence programs" category, i.e., the category of those programs whose CPC_{score} is equal to or greater than 3.945. Figure 2.4 shows the empirical relation between CPC_{score} and CPC_{level} (as determined by the rules described above), which makes evident the existence of sharp discontinuities in program level designations.

[20]See Regulatory Ordinance no 40 from December 12, 2007.

[21]Índice Geral de Cursos in Portuguese.

[22]Every four years, master and doctorate programs in different fields are evaluated by CAPES. See Regulatory Ordinance n. 59 from March 21, 2017.



Source: SINAES Tables (INEP). Authors' elaboration.

Figure 2.4: Empirical relation between CPC_{level} and CPC_{score}

Note: The CPC_{score} is used to classify programs into 5 possible levels. The figure illustrates the rule that determines the CPC_{level}, which makes evident the existence of sharp discontinuities in program level designations with multiple thresholds.

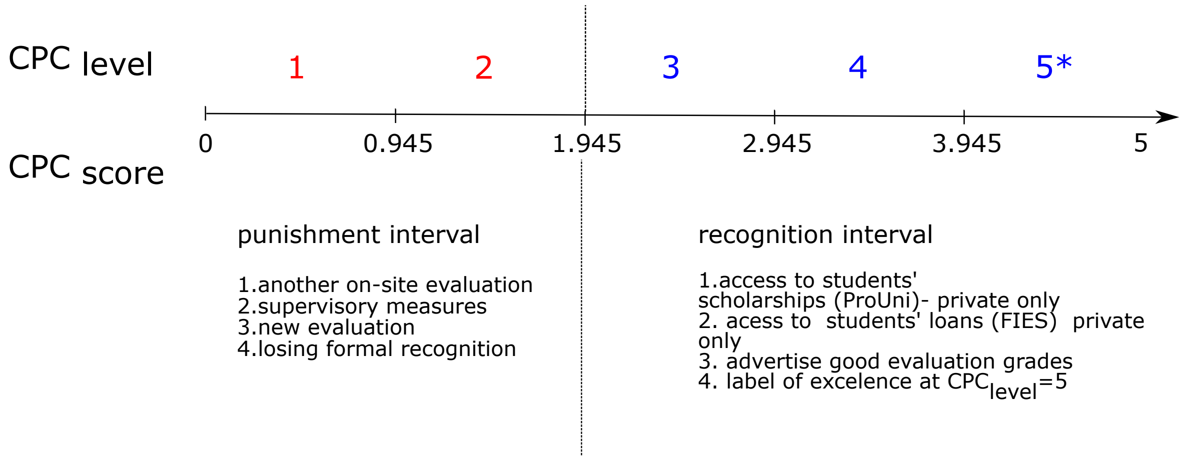
Table 2.1 shows how programs transition from the CPC level achieved in year t0 to the level achieved in the next evaluation period, t+3, i.e., in the following evaluation. Between 2007 and 2018, 18.5% of programs transitioned to a lower score in their next evaluation and 26.8% climbed to a higher level, while 54.7% remained at the same level in their subsequent evaluation.

Table 2.1: Rating transition in CPC_{level}

CPC_{level} in t	CPC_{level} in t+3					
	1	2	3	4	5	Total
1	0.02%	0.12%	0.14%	0.04%	0.00%	0.32%
2	0.15%	3.53%	9.26%	2.14%	0.08%	15.14%
3	0.09%	5.58%	34.84%	13.73%	0.42%	54.66%
4	0.02%	0.58%	10.25%	15.94%	0.90%	27.70%
5	0.00%	0.01%	0.29%	1.48%	0.40%	2.18%
Total	0.27%	9.83%	54.78%	33.32%	1.80%	100.00%

Source: SINAES Tables (INEP). Authors' elaboration.

The SINAES results determine the accreditation process for HEIs and their undergraduate programs as well as their access to publicly funded scholarships and student loans. Figure 2.5 summarizes the potential bonuses and penalties associated with each quality level.



Source: The authors.

Figure 2.5: Quality levels and corresponding bonuses and penalties

Programs that receive a CPC_{level} of 3 or above have their recognition renewed automatically. Programs with an unsatisfactory CPC_{level}, i.e., those that are classified as level 1 or 2, are subject to an additional on-site evaluation by an external reviewing commission[23]. This second evaluation involves a questionnaire – completed by the external commission – about the faculty (30% weight), the infrastructure (30%) and teaching and learning policies and practices (40%), resulting in a new index named the Program Index (CC)[24], with a CC of 3 or above being the criterion for the renewal of program recognition (OECD (2018)). In the event those programs still fail to achieve a satisfactory assessment (3 or above), the number of program slots must be reduced and the institution must sign a compromise protocol with the federal government in order to establish goals for improving quality. If the program still does not improve its evaluation scores, its formal recognition may be suspended or canceled and any diplomas issued will not be valid.

An unsatisfactory CPC also limits the participation of the institutions and programs in publicly funded programs for higher education. For example, the current legislation excludes programs evaluated at CPC levels 1 or 2 from accessing Fies, a federal government fund that provides student loans, or ProUni, a federal program that grants scholarships for disadvantaged and minority students.[25]

These accountability results are informative for society, people interested in

[23]Neglect to fulfil that obligation may result in penalties such as the temporary suspension of new enrollments, the revocation of the HEI's authorization to operate, suspension of program recognition and, for public institutions, warnings or the suspension of the person in charge of the evaluation process within the institution.

[24]Conceito de Curso in Portuguese.

[25]See Laws n. 10.260 from July 2001 and n. 13.530 from December 2017 regarding the FIES regulations. See Law n. 11.096 from January 2005 and Normative Ordinance n. 22 from November 2012 regarding the ProUni regulations.

applying to higher education and undergraduate students. They also enable HEIs to seek to improve their programs and conform them to the quality standards needed to continue functioning.

In addition, HEIs can also advertise their evaluation results to attract more students[26]. If the expected economic return of obtaining a CPC_{level} of 5 is sufficiently high, i.e., the revenue increase surpasses the costs (including opportunity costs), institutions will invest in the pursuit of that evaluation level – and will not invest if the costs exceed expected revenues.

2.2.3 Potential effects of the Brazilian higher education accountability system

As described above, the Brazilian higher education accountability system assigns quality levels to each undergraduate program based on an assignment rule that generates discontinuities. Based on this rule, we test the impacts of falling just above each cutoff relative to falling just below the same cutoff. Since each cutoff is associated with different mechanisms that would affect agents' behavior (see figure 2.5 in the previous section), we also expect to find different impacts depending on the cutoff analyzed.

First, since the cutoff that assigns programs to $CPC_{level} = 2$ does not imply any incentives or penalties that differ from those imposed on programs that receive a $CPC_{level} = 1$, falling just above or just below this cutoff may have no impact on administrator behavior. Similarly, because both of these levels are associated with the same risk of having diplomas invalidates, students and families would potentially not prefer programs with a $CPC_{level} = 2$ over those with a $CPC_{level} = 1$. This means that we do not expect the accountability system to have strong effects around the cutoff $CPC_{score} = 0.945$.

Second, the cutoff that determines whether a program is assigned to $CPC_{level} = 3$ is strongly associated with the sanctions and benefits of having a recognized program, which means that this cutoff potentially affects the behavior of both members of society and program administrators. For those programs to the left of the cutoff ($CPC_{score} < 1.945$), we expect administrators to react to their low performance by investing in the resources needed to obtain a better result in the next evaluation. This may be achieved by improving the infrastructure of the institution, hiring more professors or changing pedagogical strategies, for example. On the other hand, when applying to HEIs, students and families may prefer programs that score at least the minimum level needed to have their diplomas formally recognized by the federal gov-

[26]Figure 2.11 in Appendix A illustrates how institutions use their results for advertisement.

ernment. That is, we would expect an increase in offers and applications for programs that are to the right of this cutoff ($CPC_{score} \geqslant 1.945$) relative to programs that are to the left.

Finally, achieving a higher level of quality ($CPC_{level} = 4$ or $CPC_{level} = 5$) does not imply any additional bonuses nor does it guarantee more resources for the institution. However, achieving a higher quality grade ($CPC_{level} = 5$) can be a signal to society of the high performance of the programs and thus can be used as a form of positive marketing to attract more (and better) students[27]. Based on this line of reasoning, we predict that the administrators of those programs that receive a $CPC_{score} < 3.945$ increase effort in order to seek the highest quality rating.

In summary, we expect accountability grades to have stronger effects on programs around the cutoff that determines the minimum quality level needed to be recognized ($CPC_{level} = 3$) and for programs around the cutoff for $CPC_{level} = 5$, which is a signal of the high performance of such programs.

2.3 The data

We obtain our data from INEP – the main federal authority for education evaluation in Brazil. The first dataset consists of the quality index files, which contain annual assessment results for undergraduate programs from 2007 to 2018. The aforementioned files list the CPC scores and levels for each field of study and institution[28]. Because assessment results are aggregated by field of study and institution, we use microdata from the ENADE to identify each undergraduate program within these fields of study and institutions. Therefore, we organize the data so that our unit of observation is the program.

The accountability result tables also present the undergraduate programs' performance in each component of the CPC: faculty characteristics, mean student performance and student feedback about the program. Regarding the faculty profiles[29], we observe the percentage of faculty with a PhD, the percentage with a master's degree, and the percentage with full-time appointments (dedicating 40 hours or more per week to the program with which

[27]We would also expect a potential increase in tuitions for programs that received the highest quality rating. Unfortunately, there is no publicly available data on program tuition to test this hypothesis.

[28]Until 2015, evaluations were conducted at the field and institution level, so if an institution had two or more programs in the same field, all programs within that field received the same CPC score. From 2015 onwards, evaluations have been conducted for each program separately.

[29]Public data from the Higher Education Census do not contain information about faculty profiles for each program. This information is only available in files with the SINAES results.

they are associated). Combining data on faculty and enrollments from the Higher Education Census (described below), we also estimate the ratio of students to faculty members[30]. Student performance is captured by two indexes, one of which is the mean score achieved by students on the ENADE and the other consists of the mean value added by the program (obtained by comparing the ENADE and ENEM results), named the IDD. Feedback from students is summarized in three indexes, which also range from 0 to 5. One index is for infrastructure, another is for learning and teaching, and the final index is about perceptions of professional and academic opportunities[31].

We also analyze the institution's overall evaluation grade, given by the IGC (the general grade assigned to each HEI) to take into account the quality of the institutions and the effect of their reputation on their programs' reactions to the disclosure of their evaluation grades.

The second dataset is from the Higher Education Census for the years 2007 to 2018. The microdata on programs and students in this dataset provide information on the number of students enrolled, the number of slots and applications in the selection processes, the number of new students and the dropout rate[32]. The data also include a variable that indicates the status of the program (i.e., whether the program is still open). All data is organized at the program level.

We discard observations from online undergraduate programs[33], as the accountability system for Brazilian higher education was developed primarily for evaluating on-site programs and does not take into account the specificities of online education OECD (2018).

We paired information on the SINAES evaluation from year t with information from year t+3 in the SINAES tables for each undergraduate program. In addition, we analyzed variables from the Census for t+1, t+2, and t+3.

Table 2.2 presents a summary of the characteristics of undergraduate programs by CPC_{level} between 2007 and 2018. We see that the number of programs classified as CPC level 1 or 2 has decreased since 2009, whereas the number of programs with a CPC level of 3, 4 or 5 has increased significantly over the same period.

[30] The number of faculty members in each undergraduate program was not published for the years 2012, 2013 and 2018. Therefore, those years are excluded in regressions over variables that depend on this information (specifically, the number of faculty and the number of students per faculty member).

[31] Available from 2013 onwards.

[32] We calculate the dropout rate as the percentage of students whose situation is characterized as “inactive enrollment”, “canceled enrollment” or “transferred to another program in the same HEI”. We assume that each of these situations represents a temporary or permanent interruption of the program, which negatively affects the total number students who complete the program.

[33] Educação à Distância (EaD) in Portuguese.

Although public HEIs are fewer in number, they tend to be relatively more likely to be classified at having a CPC level of 4 or 5. In particular, within the highest level, public programs are almost as common as private programs.

Universities are responsible for most of the programs classified into the higher levels. Table 2.2 also shows that the distribution of areas of study is similar over different CPC levels. Finally, as expected, the best-performing programs are concentrated among HEIs with the highest IGC scores.

Table 2.2: Characteristics of undergraduate programs by CPC_{level}

	CPC_{level}				
	1	2	3	4	5
Number of programs					
2007-2009	120	3,720	6,355	2,091	243
2010-2012	67	2,254	8,197	4,360	377
2013-2015	43	1,989	10,210	5,418	307
2016-2018	85	1,973	11,547	7,787	443
Total	230	7,963	24,762	11,869	927
Distribution by type of administration (%)					
Private	74.92	82.20	77.09	61.72	50.88
Public	25.08	17.80	22.91	38.28	49.12
Distribution by type of academic organization (%)					
University	29.70	33.41	44.72	62.15	69.13
University Center	7.92	13.06	15.25	14.68	10.63
College	61.72	52.66	37.71	20.80	18.84
Federal Institute	0.66	0.87	2.33	2.37	1.39
Distribution by field of study (%)					
Agriculture and veterinary	3.96	2.19	2.17	3.76	4.92
Social sciences, business and law	29.04	38.76	37.14	30.82	26.71
Natural sciences, mathematics and ICTs	10.56	10.67	9.55	10.85	12.47
Education	20.79	18.70	21.06	23.35	22.67
Engineering, manufaturing and construction	13.53	11.39	11.11	10.76	12.55
Humanities and arts	6.93	2.42	2.72	3.25	5.87
Health and welfare	12.54	13.39	14.31	15.43	13.06
Services	2.64	2.49	1.93	1.78	1.76
Distribution by HEI quality (%)					
IGC=1	11.36	0.06	0.00	0.00	0.00
IGC=2	46.52	31.78	3.74	0.17	0.00
IGC=3	37.73	62.07	78.52	39.13	15.06
IGC=4	4.03	5.62	16.52	53.57	63.62
IGC=5	0.37	0.48	1.21	7.14	21.33

Source: SINAES Tables and Higher Education Census (INEP). Authors' elaboration.

Table 2.3 presents a summary of the response variables used in the following analysis by CPC_{level}. The quality indexes in t+3 increase with CPC_{level}. The same behavior is noticed among faculty attributes (faculty size, faculty with an MA, faculty with a PhD, and full-time faculty) and offer variables (slots, applications, new students and enrollments). On the other hand, the higher the quality level of the program, the fewer students per faculty member. The dropout rate does not vary by quality level. Finally, the probability of a program closing in the years following an evaluation is higher among the programs that performed the worst.

Table 2.3: Program response variables by CPC_{level}

	CPC_{level}				
	1	2	3	4	5
Program quality in t+3					
ENADE	1.78	1.98	2.30	2.93	3.60
Infrastructure	2.99	3.28	3.23	3.20	3.38
Teaching and learning	2.81	2.96	3.04	2.99	3.00
Opportunity	2.68	2.81	2.97	3.15	3.41
IDD	1.95	2.23	2.41	2.72	3.10
CPC	2.04	2.34	2.61	3.06	3.50
Program faculty profile in t+3					
Students/Faculty	10.40	10.51	10.27	8.18	6.04
Faculty	28.68	31.15	35.65	50.89	68.21
MA	19.09	23.27	29.78	46.57	63.39
PhD	10.96	11.97	16.82	33.04	47.27
Full-time	21.28	23.84	29.47	47.24	65.47
Program status and flow indicators in t+1, t+2 and t+3					
Slots in t+1	100.21	145.77	172.85	161.59	120.38
Slots in t+2	91.01	140.02	178.82	166.52	126.16
Slots in t+3	89.52	137.91	186.56	171.84	127.40
Applications in t+1	168.00	257.26	398.87	585.18	519.93
Applications in t+2	163.15	247.60	420.20	590.53	526.48
Applications in t+3	179.69	253.99	428.73	607.16	586.73
New students in t+1	50.29	73.13	87.42	84.47	71.54
New students in t+2	42.06	61.92	85.20	83.80	72.00
New students in t+3	37.89	61.22	80.92	79.78	71.73
Total enrollment in t+1	159.35	231.56	284.47	266.85	225.23
Total enrollment in t+2	145.69	217.22	276.61	266.11	228.35
Total enrollment in t+3	135.56	203.25	266.21	261.53	232.58
Dropout in t+1	37.73%	55.29%	48.58%	49.78%	39.05%
Dropout in t+2	37.86%	57.20%	59.32%	57.12%	49.99%
Dropout in t+3	50.59%	60.91%	59.37%	52.63%	40.21%
Activity status in t+1	89.47%	95.26%	97.58%	97.48%	96.86%
Activity status in t+2	81.18%	91.95%	95.81%	96.19%	96.59%
Activity status in t+3	74.53%	88.96%	94.04%	94.67%	95.03%

Source: SINAES Tables and Higher Education Census (INEP). Authors' elaboration.

Notes: Quality indexes are continuous variables and range from 0 to 5. Students per faculty member is the ratio of students to faculty members in the program. Faculty, MA, PhD and Full-time refer to the number of faculty members, the percentage of faculty with a master degree, the percentage of faculty with a PhD, and the percentage of faculty with full-time appointments (dedicating 40 hours or more per week to the program with which they are associated), respectively. Dropout is the ratio of students who leave the program to the total enrollment. Activity status indicates whether the programs are still open in the following years.

2.4 Empirical strategy

The empirical analysis used in this paper is similar to that used in previous studies that have applied an RDD to identify the impact of accountability grades on education issues (Chiang (2009); Rockoff and Turner (2010); Rouse et al. (2013); Chakrabarti (2014); Craig et al. (2015); Woo et al. (2015); Holbein and Ladd (2017); Feng et al. (2018)). In particular, our estimation strategy is quite similar to that of Rockoff and Turner (2010), which explored the heterogeneous effects of different performance levels on school outcomes. In the same way, we explore the discontinuities in CPC levels arising from the continuous grades used to determine the levels in order to compare the performance in subsequent years of undergraduate programs that received different grades. The main assumption behind this strategy is that when comparing programs that fall on either side of the grade cutoff, the assignment of a high or a low level to each program is as good as randomly determined.

We examine the impact of the grades received by each program evaluated in the period 2007-2015 on program performance in the following three years. Because the probability of treatment (i.e., being above a specific level) changes from 0 to 1 at each cutoff, we have a sharp RDD. We estimate the reduced-form regression specification described by equation 3.1[34].

$$Y_{jt+3} = \alpha + \lambda_L \mathbf{CPC}_{jt}^L + \beta \boldsymbol{f}(\mathbf{P}_{jt}) + \gamma \mathbf{D}_{jt} + \varepsilon_{jt}, \tag{2.2}$$

where Y_{jt+3} is the variable of interest for program j in year t, $\mathbf{CPC}_{jt}^L$ is a vector of dummies indicating whether a program is above CPC_{level} (L) based on the CPC_{score} that it achieved in $t = 0$ relative to the cutoffs described previously (CPC_{level}=2 when CPC_{score}≥0.945, CPC_{level}=3 when CPC_{score}≥1.945, CPC_{level}=4 when CPC_{score}≥2.945, and $CPC_{level} = 5$ when CPC_{score}≥3.945), $\mathbf{P}_{jt}$ is a vector of continuous indexes used to define the CPC_{level} (i.e., CPC_{score}, ENADE, IDD, infrastructure, teaching and learning, and faculty characteristics), $\mathbf{D}_{jt}$ is a vector of program characteristics control variables (the number of programs within the same field of study[35] in the same institution and dummies for type of administration (public or private), the year of evaluation, state, field of study, type of academic organization, and the IGC level of the institu-

[34]Because the assignment of general higher education quality ratings (the IGC_{level}) follows rules similar to those for CPC_{level} assignments, we adapt equation 3.1 to evaluate the impact of the IGC on the aggregated outcomes of HEIs. These results are presented in Appendix E.

[35]Until 2015, programs were evaluated in groups within the same area and institution, and so these programs could behave differently from programs that are evaluated individually.

tion), and ε_{jt} is an idiosyncratic error term. We add a quartic polynomial in $\mathbf{P}_{jt}$.

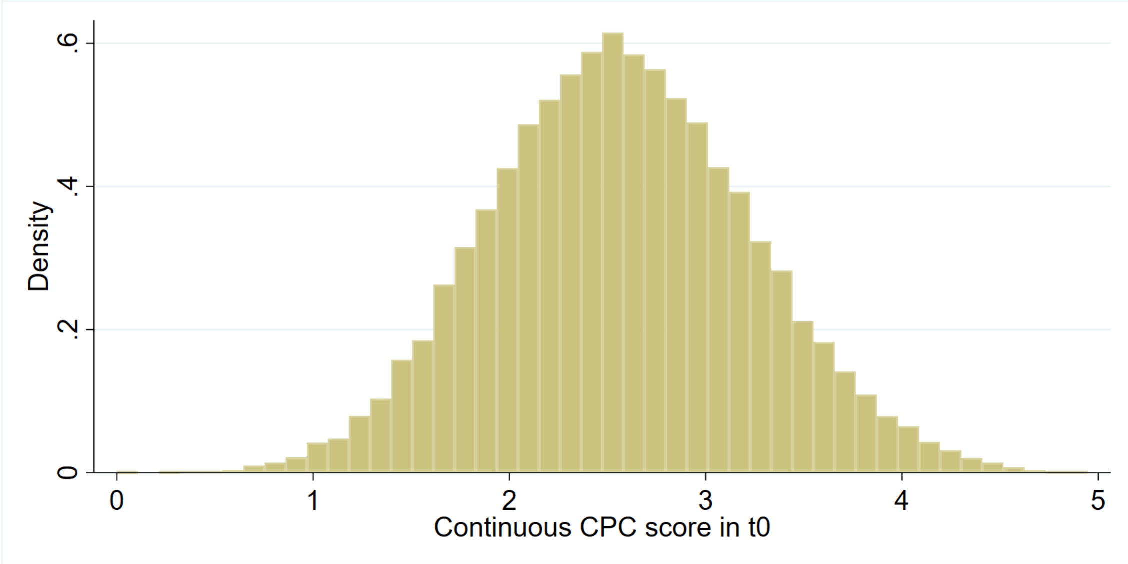
We categorize the variables of interest into three major groups: quality indexes, offer variables, and faculty characteristics{The SINAES measures of student performance (the ENADE and IDD) are not comparable over time, because they are not based on Item Response Theory or similar methodologies that make comparisons over time more credible (OECD (2018)). As our estimates are not based on variation over time, this fact does not affect our results. For the quality indexes, we weight the regressions with the number of graduating students taking the ENADE because those indexes are based on answers given by this group of students on the feedback questionnaire. For the offer variables and faculty characteristics, the regressions are weighted by the total number of students enrolled in the year of evaluation since these variables are based on data for all students in the program (not only final year students).

We conduct a few robustness tests. We "falsify" our estimates by using the same equations but with dependent variables from the previous periods. Robustness requires that predetermined characteristics exhibit no discontinuities at the thresholds that define the CPC levels (Lee and Lemieux (2010); Cattaneo et al. (2019)).

In addition, we examined modifications to $\mathbf{P}_{jt}$, varying the order of the polynomial; i.e., we tested quadratic and quartic polynomials (these results are presented in the appendix C). We also obtained cutoff-specific estimates from local polynomial estimation and robust bias-corrected inference procedures from Cattaneo et al., 2020 (results are presented in appendix D).

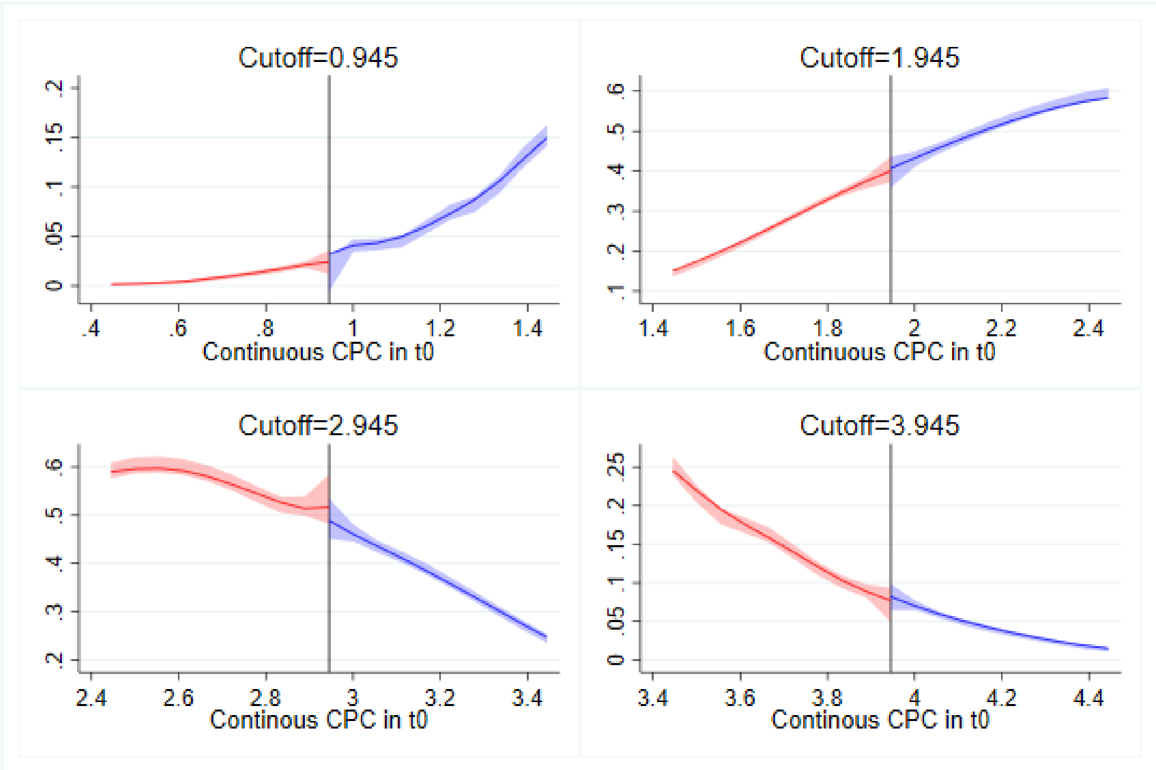
Although the accountability system for higher education in Brazil is supposed to be an exogenous system of evaluation, the manipulation of CPC levels around each CPC_{score} threshold could be a risk for our RDD specification if programs or institutions can perfectly determine the outcomes of their evaluation process. To be sure that programs do not perfectly determine their outcomes, we also test for threshold manipulation by plotting the histogram of the continuous CPC scores and testing the density around each cutoff based on a nonparametric density estimator, applying the method proposed by Cattaneo et al. (2020).

Figure 2.6 presents a histogram of the CPC_{score} with no signs of manipulation. Figure 2.7 implements manipulation tests for CPC_{score} at each CPC_{level} threshold. The figure does not suggest that there is manipulation around any of the thresholds. This is a necessary condition for conducting a credible sharp RDD analysis.



Source: SINAES Tables (INEP). Authors' elaboration.

Figure 2.6: Histogram of the CPC_{score}



Source: SINAES Tables (INEP). Authors' elaboration.

Figure 2.7: Density around thresholds of level assignments

Notes: The graphs plot the test of difference of densities around the thresholds according to the method of McCrary (2008).

2.5 Results

2.5.1 Program quality

First, we present a graphical analysis of our estimation strategy. We plot the linear results of a locally weighted Fan regression of the quality indexes against the CPC_{score} of each undergraduate program according to the method proposed by Fan et al. (1995). We estimate the local regressions separately for each group of programs that received the same CPC_{level}, including a quartic polynomial as a control. Jumps at the thresholds indicate that the outcomes are sensitive to CPC_{level} assignment.

Figure 2.8 presents graphs of the quality indicators and composite indexes measured 3 years after the evaluation, i.e., in the next evaluation cycle. Because these indicators feed into the final CPC, we expect a positive relationship between each indicator and the previous CPC_{score}. We identify a jump around threshold 1.945 (which separates CPC levels 2 and 3) for the ENADE and IDD scores, Infrastructure, Teaching and Learning, Opportunity, and CPC indexes. In these cases, the programs next to and below the threshold achieved higher outcomes in the next SINAES evaluation. We also identify a potential discontinuity around threshold 3.945 in the Opportunity index, suggesting that students identify more professional and academic opportunities in programs that received the highest score ($CPC_{level} = 5$). Around the other thresholds, jumps are less visible, indicating potentially lower impacts on the incentives for undergraduate programs related to the next evaluation among programs with a CPC level of 4 or 5.

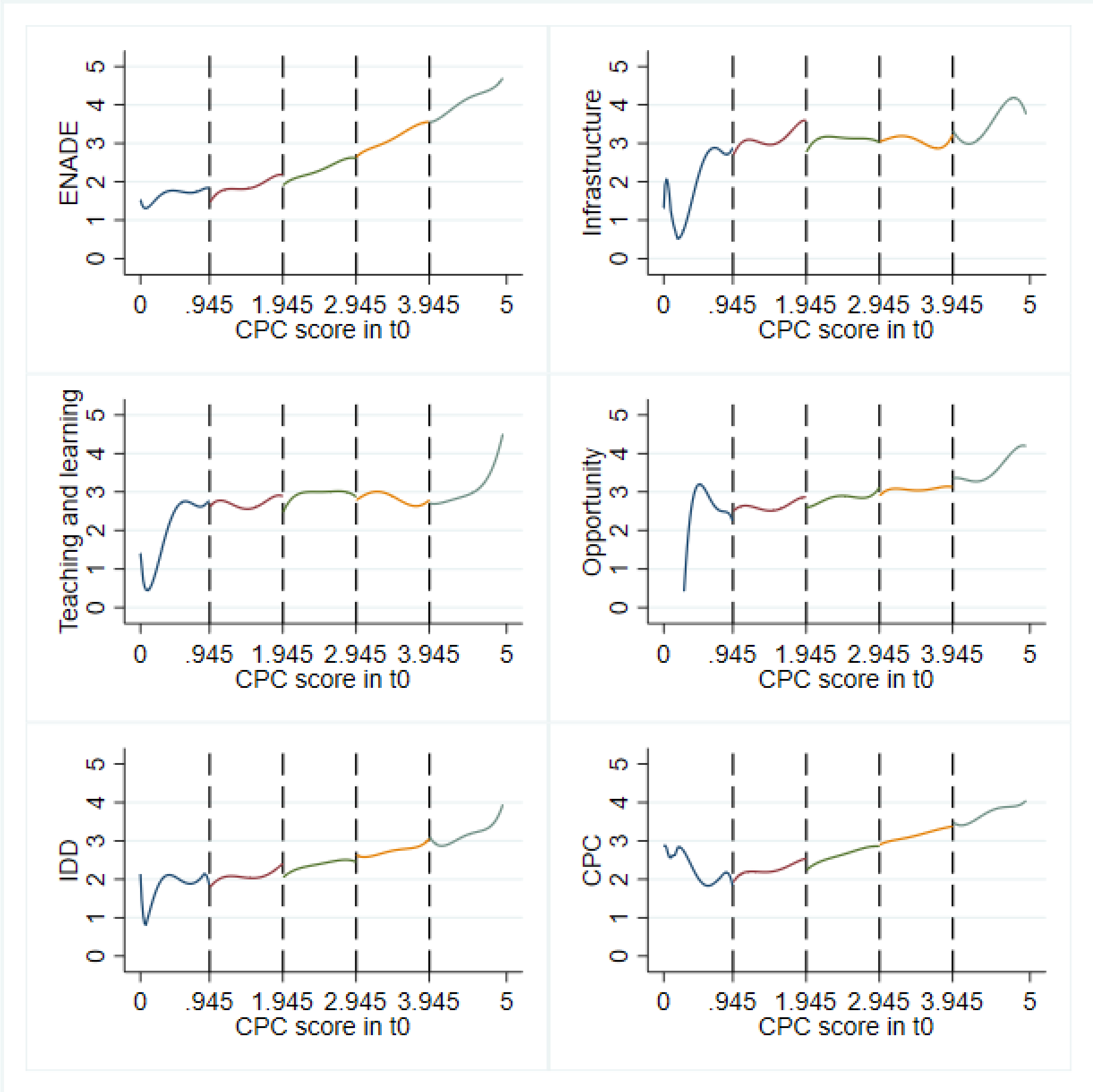


Figure 2.8: Program quality in t+3, by initial CPC_{score}

Notes: Quality indexes are continuous variables and range from 0 to 5. The graphs plot the linear results of a locally weighted Fan regression of the quality indexes against the CPC_{score} of each undergraduate program (Fan et al. (1995)). The local regressions are estimated separately for each group of programs that received the same CPC_{level}, and include a quartic polynomial as a control. Jumps at the thresholds indicate that the outcomes are sensitive to CPC_{level} assignment.

Table 2.4 shows the sharp RDD results with a quartic polynomial function in CPC_{score}. The results confirm the visible differences in figure 2.8. Being classified into $CPC_{level} = 2$ in year t increases the corresponding quality indexes in the next evaluation cycle (t+3). Thus, we obtain negative and statistically significant estimates at the CPC_{score} threshold of 1.945. The most likely explanation is that programs below the Ministry of Education recognition level overreact to the threat of punishment. Falling below level 3 triggers additional evaluations and supervisory processes that require improvements in several outcomes under penalty of suspension or closure should the program fail to fulfill its commitments. Level 2 programs have advantages around threshold 1.945 in terms of the indicators measured in t+3, such as ENADE (scores are higher by 0.195 points), Infrastructure (0.362 points higher), Teaching and learning (0.174 points higher), Opportunity (0.182 points higher), IDD (0.148 points higher) and the composite index CPC_{score} (0.158 points higher).

Alternatively, these results may reflect the program administrators' fears not only of the regulatory agency but also of bad "propaganda" that could reduce student demand for slots in the program.

At other thresholds, the evidence is inconsistent. In particular, the results for the Opportunity index at $CPC_{score} = 3.945$ are insignificant even after accounting for the potential discontinuity for this variable at this threshold visible in figure 2.8. Only at $CPC_{score} = 3.945$ do we see statistically significant differences for the ENADE and IDD, equal to 0.18 and 0.099, respectively, in favor of programs just below the threshold (for private institutions only). Nonetheless, these results are not robust to the robustness tests performed – see tables 2.5 and C.1 in the appendix.

We also run separate regressions by type of administration – public or private – to assess the potential heterogeneity in the impacts. We find stronger impacts for private HEIs, with differences still concentrated on $CPC_{score} = 1.945$ for both groups. Such differences in the responses to accountability between private and public institutions suggest that program administrators and faculty react differently to different incentive schemes, a result that is similar to the findings of Camargo et al. (2018) for secondary education in Brazil. Because teachers and managers enjoy job security in Brazilian public institutions and do not receive bonuses or salary increases for good performance, they do not face the same market incentives as their peers in private colleges. Furthermore, along with the consolidation of SINAES, the government has been expanding public institutions despite their performance results, which also reduces the incentives for public HEI managers to improve quality. For example, while the private programs classified into $CPC_{level} = 1$ or $CPC_{level} = 2$ reduced by 5% their slots in three years, the public programs classified into the same levels increased their slots by 3%, according to Higher Education Census (INEP).

Table 2.4: The impact of accountability on program quality

	(1)	(2)	(3)	(4)	(5)	(6)
	ENADE	Infrastructure	Teaching and learning	Opportunity	IDD	CPC
All sample						
CPC_{level}=2	-0.173	0.036	0.110	-0.043	-0.122	0.027
	(0.164)	(0.218)	(0.201)	(0.274)	(0.261)	(0.101)
CPC_{level}=3	-0.195***	-0.362***	-0.174***	-0.182***	-0.148***	-0.158***
	(0.064)	(0.084)	(0.045)	(0.054)	(0.038)	(0.018)
CPC_{level}=4	-0.017	0.042	0.006	0.082	0.032	0.011
	(0.026)	(0.061)	(0.074)	(0.055)	(0.022)	(0.015)
CPC_{level}=5	-0.180*	0.059	0.086	0.099	-0.099**	-0.039
	(0.094)	(0.110)	(0.089)	(0.091)	(0.043)	(0.050)
n	34,405	35,052	35,052	29,640	33,637	33,437
Programs in private institutions						
CPC_{level}=2	-0.285**	0.068	0.187	0.197	-0.181	-0.016
	(0.124)	(0.225)	(0.215)	(0.289)	(0.235)	(0.143)
CPC_{level}=3	-0.189***	-0.354***	-0.167***	-0.195***	-0.161***	-0.166***
	(0.067)	(0.076)	(0.049)	(0.065)	(0.045)	(0.023)
CPC_{level}=4	-0.006	0.030	0.010	0.138	0.051**	0.025
	(0.032)	(0.085)	(0.106)	(0.097)	(0.023)	(0.019)
CPC_{level}=5	-0.162**	0.133	0.128	0.215*	-0.254***	-0.077
	(0.065)	(0.125)	(0.122)	(0.124)	(0.071)	(0.058)
n	24,231	24,780	24,780	21,373	23,586	23,603
Programs in public institutions						
CPC_{level}=2	-0.058	-0.195	-0.202	-0.636**	0.032	0.032
	(0.378)	(0.447)	(0.396)	(0.240)	(0.403)	(0.219)
CPC_{level}=3	-0.140	-0.245**	-0.247***	-0.100*	-0.103*	-0.085*
	(0.118)	(0.101)	(0.055)	(0.055)	(0.056)	(0.042)
CPC_{level}=4	-0.010	0.087*	0.001	-0.014	-0.021	-0.004
	(0.034)	(0.043)	(0.021)	(0.046)	(0.036)	(0.014)
CPC_{level}=5	-0.229**	-0.025	0.077	0.016	-0.050	-0.062
	(0.093)	(0.114)	(0.085)	(0.119)	(0.085)	(0.048)
n	10,174	10,272	10,272	8,267	10,051	9,834

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes: Each coefficient is interpreted as the difference in performance between the programs to the left of the cutoff and the programs to the right of the same cutoff. Quality indexes are continuous measures and range from 0 to 5. The regressions are weighted by the number of senior students taking the ENADE exam. All specifications include a vector of program characteristics control variables (the number of programs within the same field of study in the same HEI and dummies for type of administration (public or private), the year of evaluation, state, field of study, type of academic organization, and the IGC level of the institution). Regressions also include a quartic polynomial on continuous indexes used to define the CPC_{level} (i.e., CPC_{score}, ENADE, IDD, infrastructure, teaching and learning, and faculty characteristics). Robust standard errors –in parentheses – are clustered at the state level.

Proper analysis of causal effects requires that the previous results be subjected to robustness tests. One type of robustness test is a falsification test. We conduct falsification tests by regressing the quality outcomes from the pre-treatment period on the same covariates as in our models in table 2.4. To claim causality, the estimates must not be in the same direction as the main estimates or have similar magnitudes. Table 2.5 shows that there are no pre-treatment jumps around threshold $CPC_{score} = 1.945$ except for the ENADE indicator, and even in this case, the direction is opposite that of the estimates in table 2.4. Thus, our results suggest that the estimates in table 2.4 are plausibly causal. Table C.1 in the appendix also reports estimates with different polynomial functions (cubic and quadratic) as controls. Only the differences at $CPC_{score} = 3.945$ ($CPC_{level} = 5$) are no longer statistically significant. Other estimates with different polynomials remain similar around threshold $CPC_{score} = 1.945$. We perform further robustness tests in section 2.5.4, wherein we estimate local regressions within specific bandwidths to confirm our results.

Finally, to exclude the possibility that the exams were manipulated, i.e., that the accountability system was gamed, we conduct an additional test in which the ratio of the number of students taking the ENADE to the total program enrollment is used as the dependent variable. Despite the fact that institutions might have incentives to manipulate the number of students participating in the ENADE, we do not find evidence of manipulation, as shown in table B.1 in the appendix.

Table 2.5: The impact of accountability scores on pre-treatment program quality

	(1)	(2)	(3)	(4)	(5)
	ENADE	Infrastructure	Teaching and learning	IDD	CPC
CPC_{level}=2	0.267	-0.370	-0.117	0.238	0.154
	(0.170)	(0.405)	(0.181)	(0.286)	(0.104)
CPC_{level}=3	0.093**	-0.071	-0.036	0.017	-0.002
	(0.042)	(0.043)	(0.038)	(0.083)	(0.057)
CPC_{level}=4	0.053	-0.008	-0.041	0.100	0.017
	(0.059)	(0.026)	(0.038)	(0.076)	(0.045)
CPC_{level}=5	-0.162	0.046	0.041	-0.253*	-0.147
	(0.100)	(0.096)	(0.110)	(0.147)	(0.088)
n	22,852	25,063	25,063	21,619	22,010

*** p<0.01, ** p<0.05, * p<0.1
Notes: Each coefficient is interpreted as the difference in performance between the programs to the left of the cutoff and the programs to the right of the same cutoff. Quality indexes are continuous measures ranging from 0 to 5 and refer to the pre-treatment measurement (i.e in t-3). The regressions are weighted by the number of senior students taking the ENADE exam. All specifications include a vector of program characteristics control variables (the number of programs within the same field of study in the same HEI and dummies for type of administration (public or private), the year of evaluation, state, field of study, type of academic organization, and the IGC level of the institution). Regressions also include a quartic polynomial on continuous indexes used to define the CPC_{level} (i.e., CPC_{score}, ENADE, IDD, infrastructure, teaching and learning, and faculty characteristics). Robust standard errors –in parentheses – are clustered at the state level.

2.5.2 Program status and flow indicators

Figure 2.9 displays graphs of slots, applications and new students (measured as the sum over three years, i.e., one evaluation cycle). The figure also shows total enrollments, the dropout rate and activity status (i.e., whether the programs are still open), which refer to the last year of the following evaluation cycle. Slots, applications, new students and enrollments are in logarithms, while the dropout rate and activity status are measured in percentages. In general, the supply side indicators increase until $CPC_{score} = 2.945$. For slots, new students, enrollment and the dropout rate, the indicators increase up to $CPC_{score} = 2.945$, and for applications, up to $CPC_{score} = 3.945$). There are small but visible jumps around thresholds $CPC_{score} = 0.945$ and $CPC_{score} = 1.945$ for slots, applications, new students and enrollment. In these cases, higher CPC_{level} assignments are associated with a greater number of slots, applications, and new students and higher enrollment. At $CPC_{score} = 3.945$ and $CPC_{score} = 4.945$, higher CPC_{level} assignments lead to a decrease in program slots, applications, new students, enrollment and the dropout rate.

Nevertheless, regressions around each of the thresholds show no statistical significance, which render these results less reliable.

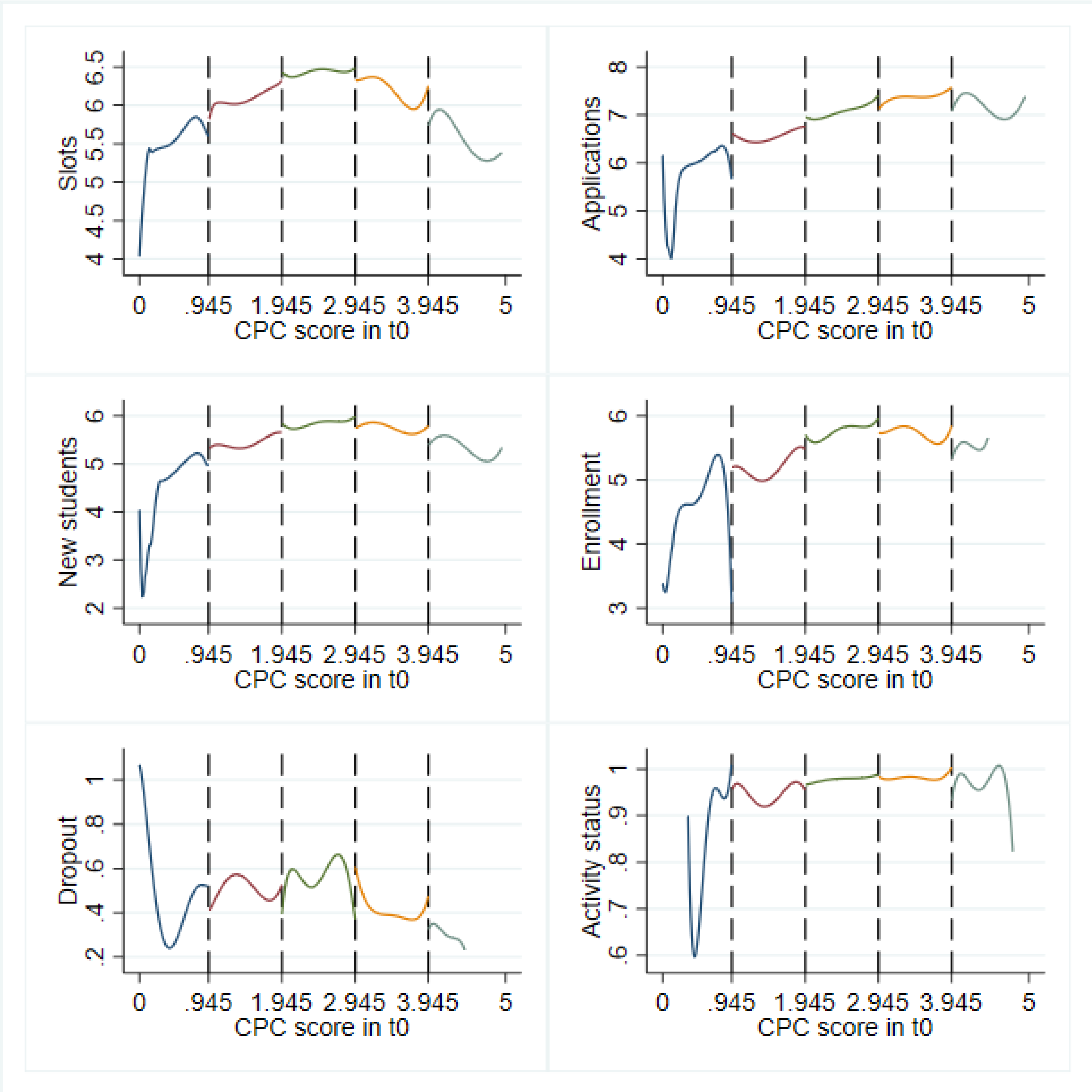


Figure 2.9: Program status and flow indicators in t+3, by initial CPC_{score}

Notes: Slots, applications and new students are the sum of the variables for the period from t+1 to t+3. Enrollments, dropout and activity status are measured in t+3. Outcome variables such as slots, applications, new students and enrollments are in logarithm form. Dropout is the ratio of students who leave the program to the total enrollment. Activity status indicates whether programs are still working in the following years. The regressions are weighted by the total number of students enrolled in the year of evaluation. Dropout is the ratio of students who leave the program to the total enrollment. Activity status indicates whether courses are still open in t+3. The graphs plot the linear results of a locally weighted Fan regression of the quality indexes against the CPC_{score} of each undergraduate program (Fan et al. (1995)). The local regressions are estimated separately for each group of programs that received the same CPC_{level}, and include a quartic polynomial as a control. Jumps at the thresholds indicate that the outcomes are sensitive to CPC_{level} assignment.

Table 2.6 partially confirms the results presented in figure 2.9. At threshold $CPC_{score} = 1.945$, the number of slots increases by 13.4% and the number of applications and new students increase by 12.5% and 10.3%, respectively, at recognized institutions. As expected, these results are driven by private institutions, while we do not find evidence that public institutions increase the number of program openings, new students or applications because of the inflexibility of state-led institutions.

The falsification test presented in table 2.7 – in which the pre-treatment outcomes are regressed on the same covariates as in table 2.6 – shows that the statistically significant results around threshold $CPC_{score} = 1.945$ in table 2.6 are not statistically different from zero when using pre-treatment outcomes. This result reinforces the plausibility that the estimates in table 2.6 are causal.

Finally, the results in table 2.6 suggest that legal recognition by the federal regulator increases the number of program slots, applications and new students. Demand-related explanations are the most likely, as applications increase with recognition. This recognition effect may also reflect positive reinforcement, as recognition increases student access to scholarships and loans.

Table 2.6: The impact of accountability on program status and flow indicators

	(1)	(2)	(3)	(4)	(5)	(6)
	Slots	Applications	New students	Total enrollment	Dropout	Activity
All sample						
CPC_{level}	0.106	0.124	0.173	0.122	-0.060	0.010
	(0.133)	(0.240)	(0.174)	(0.149)	(0.131)	(0.035)
CPC_{level}=3	0.134***	0.125***	0.103**	0.049	0.021	0.004
	(0.041)	(0.041)	(0.039)	(0.043)	(0.072)	(0.005)
CPC_{level}=4	-0.008	-0.024	-0.025	-0.044*	0.027	0.006*
	(0.032)	(0.039)	(0.028)	(0.023)	(0.086)	(0.003)
CPC_{level}=5	0.014	-0.053	-0.016	-0.013	-0.012	0.018
	(0.043)	(0.086)	(0.053)	(0.058)	(0.083)	(0.013)
n	37,861	37,484	37,277	38,819	37,115	32,978
Programs in private institutions						
CPC_{level}=2	0.078	0.133	0.325*	0.230	-0.085	0.005
	(0.129)	(0.267)	(0.160)	(0.145)	(0.211)	(0.043)
CPC_{level}=3	0.182***	0.167***	0.139***	0.078	0.030	0.004
	(0.050)	(0.052)	(0.046)	(0.050)	(0.083)	(0.006)
CPC_{level}=4	-0.005	-0.050	-0.017	-0.045	0.055	0.003
	(0.044)	(0.040)	(0.043)	(0.035)	(0.120)	(0.004)
CPC_{level}=5	-0.084	-0.159*	-0.083	-0.052	0.105	0.019
	(0.086)	(0.080)	(0.092)	(0.087)	(0.065)	(0.018)
n	27,216	26,892	26,675	27,727	26,352	24,091
Programs in public institutions						
CPC_{level}=2	0.229	0.082	-0.003	0.019	-0.195*	0.000
	(0.188)	(0.273)	(0.240)	(0.162)	(0.111)	(0.055)
CPC_{level}=3	-0.066	0.027	-0.056	-0.069	-0.029	0.003
	(0.072)	(0.050)	(0.077)	(0.052)	(0.052)	(0.010)
CPC_{level}=4	-0.042	0.004	-0.033	-0.015	-0.022	0.009
	(0.040)	(0.079)	(0.038)	(0.027)	(0.029)	(0.006)
CPC_{level}=5	0.102*	0.067	0.055	-0.008	-0.114	0.013
	(0.055)	(0.082)	(0.077)	(0.075)	(0.121)	(0.014)
n	10,645	10,592	10,602	11,092	10,763	8,887

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes: Each coefficient is interpreted as the difference in performance between the programs to the left of the cutoff and the programs to the right of the same cutoff. Columns (1)-(3) refer to the sum of new slots, applications and new students over the period t+1 to t+3. Columns (4)-(6) refer to enrollment, the dropout rate and the activity status in t+3. Outcome variables such as new slots, applications, new students and enrollment are in logarithm form. Dropout is the ratio of students who leave the program to the total enrollment. Activity status indicates whether programs are still working in the following years. The regressions are weighted by the total number of students enrolled in the year of evaluation. All specifications include a vector of program characteristics control variables (the number of programs within the same field of study in the same HEI and dummies for type of administration (public or private), the year of evaluation, state, field of study, type of academic organization, and the IGC level of the institution). Regressions also include a quartic polynomial on continuous indexes used to define the CPC_{level} (i.e., CPC_{score}, ENADE, IDD, infrastructure, teaching and learning, and faculty characteristics). Robust standard errors –in parentheses – are clustered at the state level.

Table 2.7: The impact of accountability scores on pre-treatment program status and flow indicators

	(7)	(8)	(9)	(10)	(11)	(12)
	Slots	Applications	New students	Total enrollment	Dropout	Activity
CPC_{level}=2	0.056	0.075	0.144	0.094	-0.063**	0.006
	(0.134)	(0.237)	(0.170)	(0.158)	(0.030)	(0.016)
CPC_{level}=3	0.039	0.014	0.047	0.042	0.014	0.001
	(0.041)	(0.041)	(0.044)	(0.038)	(0.009)	(0.002)
CPC_{level}=4	0.013	-0.033	-0.001	-0.040	0.002	-0.000
	(0.025)	(0.031)	(0.026)	(0.025)	(0.008)	(0.001)
CPC_{level}=5	-0.006	-0.118	0.017	0.045	-0.008	0.002
	(0.050)	(0.070)	(0.074)	(0.066)	(0.025)	(0.002)
n	37,845	37,517	37,616	39,425	39,425	17,798

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes: Each coefficient is interpreted as the difference in performance between the programs to the left of the cutoff and the programs to the right of the same cutoff. Offer variables refer to measures in t0 (pre-treatment measurement). Outcome variables such as new slots, applications, new students and enrollment are in logarithm form. Dropout is the ratio of students who leave the program to the total enrollment. Activity status indicates whether programs are still working in the following years. The regressions are weighted by the total number of students enrolled in the year of evaluation. All specifications include a vector of program characteristics control variables (the number of programs within the same field of study in the same HEI and dummies for type of administration (public or private), the year of evaluation, state, field of study, type of academic organization, and the IGC level of the institution). Regressions also include a quartic polynomial on continuous indexes used to define the CPC_{level} (i.e., CPC_{score}, ENADE, IDD, infrastructure, teaching and learning, and faculty characteristics). Robust standard errors –in parentheses – are clustered at the state level.

2.5.3 Program faculty

Faculty profiles can also change in response to evaluation scores. Figure 2.10 presents graphs for faculty profiles 3 years after the evaluation. For the number of students per faculty member, we identify an almost flat relation with CPC, with no clear jumps around thresholds. Except for faculty with an MA, which is negatively related to CPC_{score}, the other faculty indicators are positively related to CPC. In general, we do not find straightforward jumps around the thresholds. There are small visible jumps around $CPC_{score} = 3.945$, with more faculty with a PhD and fewer with an MA in programs evaluated at CPC level 5.

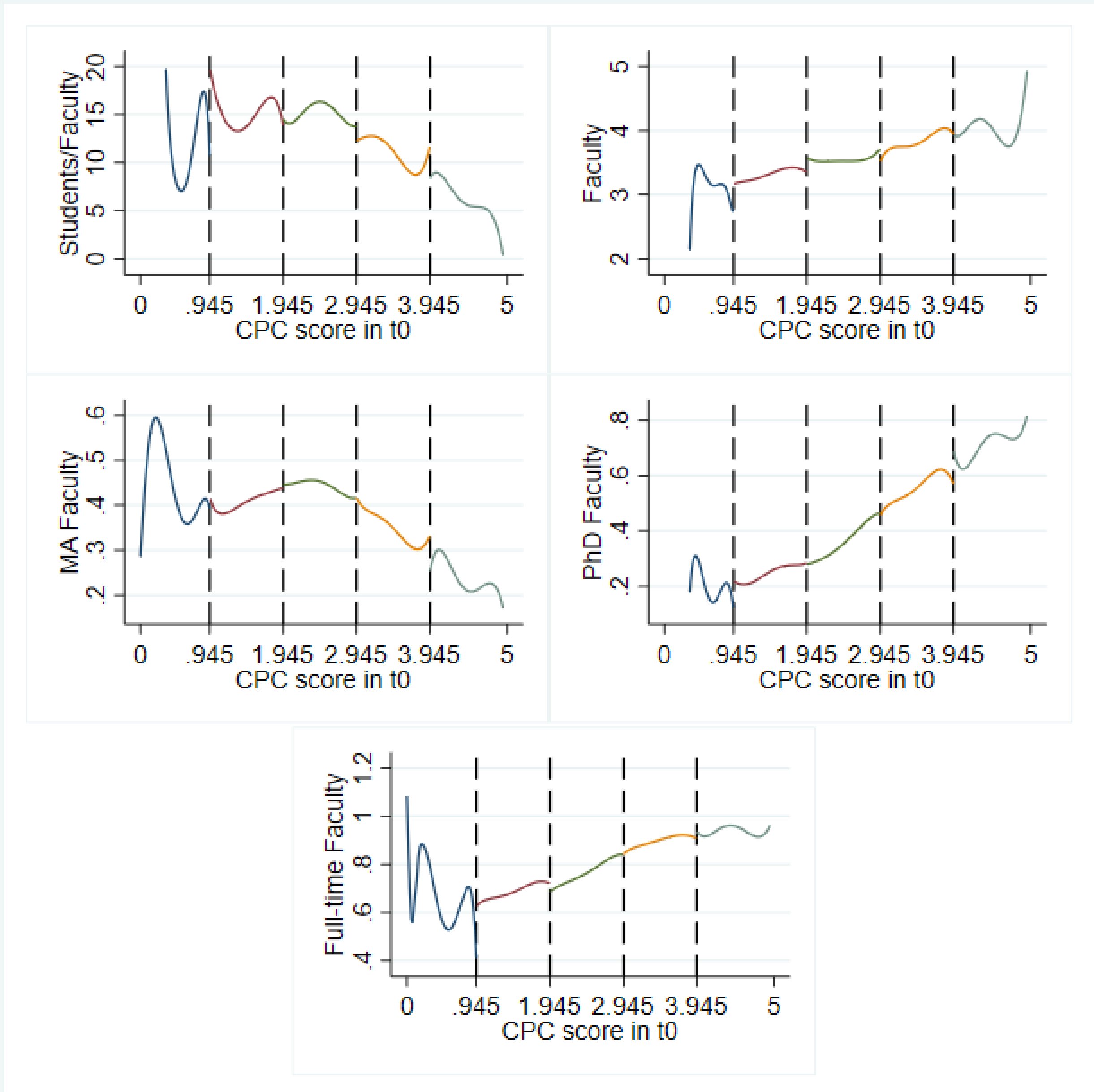


Figure 2.10: Program faculty profile in t+3, by initial CPC_{score}

Notes:Faculty variables are measured in t+3. Students/faculty is the ratio between the number of students and the number of professors associated with the program. Faculty is the number of faculty members and is in logarithm form. MA, PhD and Full-time refer respectively to the percentage of faculty members with a master degree, percentage of faculty members with a doctoral degree, and percentage of faculty members in a full-time working contract. The graphs plot the linear results of a locally weighted Fan regression of the quality indexes against the CPC_{score} of each undergraduate program (Fan et al. (1995)). The local regressions are estimated separately for each group of programs that received the same CPC_{level}, and include a quartic polynomial as a control. Jumps at the thresholds indicate that the outcomes are sensitive to CPC_{level} assignment.

The results in table 2.8 indicate significant impacts around threshold $CPC_{score} = 1.945$ for PhD and full-time faculty, as shown in columns (4) and (5). In contrast, we do not find any significant impact on the number of students per faculty member, faculty size or the percentage of faculty with an MA degree.

Our results suggest that programs that fall below the recognition threshold, i.e., $CPC_{score} = 1.945$, overreact to their evaluation by hiring more PhD and full-time faculty. Programs under the supervision of the regulatory authority, i.e., with a CPC_{score} just below 1.945, increase the percentage of professors with a PhD by 2.7 percentage points and the percentage with full-time contracts by 3.5 percentage points by the next evaluation.

In addition, table 2.8 suggests that only private institutions react to low scores. Around CPC_{score}=1.945, we also find that private institutions below the threshold increase the number of faculty members by 9.6%. In general, public institutions do not react to evaluations by changing faculty inputs, as the hiring process depends on public funding and such positions include job security, which prevents administrators from adjusting these inputs.

To evaluate the robustness of these findings, we also estimate the same regression over variables measured in the last three years in columns 1 through 6 of table 2.9 . Around $CPC_{score} = 1.945$, we do not find any significant estimates, which leads us to conclude that there are no previous discontinuities around that threshold.

These results confirm those we find for other outcomes. Undergraduate programs overreact to bad evaluations. Perhaps because they have imperfect control over their outcomes, program administrators adopt several measures to improve their indicators and be re-classified in the next evaluation cycle. We do not find evidence of a “score effect”, wherein better-evaluated programs invest in the improvement of their indicators to maintain and, whenever possible, increase their scores.

Table 2.8: The impact of accountability on program faculty profile

	Students/ faculty	Faculty	MA	PhD	Full-time
All sample					
CPC_{level}=2	6.042	-0.192	-0.033	0.000	-0.010
	(6.305)	(0.138)	(0.034)	(0.047)	(0.050)
CPC_{level}=3	0.478	0.053	0.004	-0.027***	-0.035***
	(0.477)	(0.036)	(0.008)	(0.006)	(0.005)
CPC_{level}=4	-0.397	0.012	0.005	-0.014*	0.003
	(0.506)	(0.034)	(0.006)	(0.008)	(0.008)
CPC_{level}=5	0.508	0.030	-0.011	0.019	0.012
	(0.532)	(0.064)	(0.018)	(0.017)	(0.009)
n	25,043	25,117	34,804	34,804	34,804
Programs in private institutions					
CPC_{level}=2	-0.419	-0.015	-0.067*	-0.027	-0.011
	(3.081)	(0.125)	(0.033)	(0.057)	(0.060)
CPC_{level}=3	0.426	0.096***	0.005	-0.038***	-0.042***
	(0.630)	(0.034)	(0.007)	(0.008)	(0.007)
CPC_{level}=4	-0.128	0.021	0.001	-0.011	0.006
	(0.653)	(0.036)	(0.006)	(0.007)	(0.009)
CPC_{level}=5	0.406	0.054	-0.025*	0.027*	0.024
	(1.092)	(0.054)	(0.014)	(0.014)	(0.017)
n	16,710	16,749	24,638	24,638	24,638
Programs in public institutions					
CPC_{level}=2	23.552	-0.543**	0.035	0.027	-0.061
	(18.551)	(0.220)	(0.043)	(0.029)	(0.060)
CPC_{level}=3	-0.701	-0.109	0.011	0.015	-0.006
	(1.136)	(0.073)	(0.020)	(0.009)	(0.008)
CPC_{level}=4	-1.165	0.012	0.002	-0.006	0.003
	(0.924)	(0.055)	(0.006)	(0.008)	(0.004)
CPC_{level}=5	0.524	0.009	0.013	-0.002	-0.002
	(0.445)	(0.057)	(0.012)	(0.014)	(0.004)
n	8,333	8,368	10,166	10,166	10,166

*** p<0.01, ** p<0.05, * p<0.1

Notes: Each coefficient is interpreted as the difference in performance between the programs to the left of the cutoff and the programs to the right of the same cutoff. Faculty variables are measured in t+3. Students/faculty is the ratio between the number of students and the number of professors associated with the program. Faculty is the number of faculty members and is in logarithm form. MA, PhD and Full-time refer respectively to the percentage of faculty members with a master degree, percentage of faculty members with a doctoral degree, and percentage of faculty members in a full-time working contract. Regressions are weighted by the number of enrollments in the year of evaluation. All specifications include a vector of program characteristics control variables (the number of programs within the same field of study in the same HEI and dummies for type of administration (public or private), the year of evaluation, state, field of study, type of academic organization, and the IGC level of the institution). Regressions also include a quartic polynomial on continuous indexes used to define the CPC_{level} (i.e., CPC_{score}, ENADE, IDD, infrastructure, teaching and learning, and faculty characteristics). Robust standard errors –in parentheses – are clustered at the state level.

Table 2.9: The impact of accountability scores on pre-treatment program faculty profile

	(1)	(2)	(3)	(4)	(5)
	Students/ faculty	Faculty	MA	PhD	Full-time
CPC_{level}=2	3.097	0.153	-0.018	-0.004	0.039
	(2.247)	(0.228)	(0.067)	(0.024)	(0.074)
CPC_{level}=3	0.877	0.043	-0.011	0.012	0.000
	(0.589)	(0.041)	(0.010)	(0.008)	(0.013)
CPC_{level}=4	-0.256	-0.002	-0.006	-0.015***	-0.009
	(0.475)	(0.030)	(0.004)	(0.004)	(0.009)
CPC_{level}=5	4.012	-0.090	-0.047***	-0.024**	-0.023*
	(2.858)	(0.063)	(0.015)	(0.012)	(0.013)
n	19,740	19,858	23,229	25,373	25,373

*** $p<0.01$, ** $p<0.05$, * $p<0.1$
Notes: Each coefficient is interpreted as the difference in performance between the programs to the left of the cutoff and the programs to the right of the same cutoff. Faculty variables refer to the pre-treatement measurement (i.e in t-3). Students/faculty is the ratio between the number of students and the number of professors associated with the program. Faculty is the number of faculty members and is in logarithm form. MA, PhD and Full-time refer respectively to the percentage of faculty members with a master degree, percentage of faculty members with a doctoral degree, and percentage of faculty members in a full-time working contract. Regressions are weighted by the number of enrollments in the year of evaluation. All specifications include a vector of program characteristics control variables (the number of programs within the same field of study in the same HEI and dummies for type of administration (public or private), the year of evaluation, state, field of study, type of academic organization, and the IGC level of the institution). Regressions also include a quartic polynomial on continuous indexes used to define the CPC_{level} (i.e., CPC_{score}, ENADE, IDD, infrastructure, teaching and learning, and faculty characteristics). Robust standard errors –in parentheses – are clustered at the state level.

2.5.4 Local regressions

This section presents robustness tests of the previous estimates around the threshold $CPC_{score} = 1.945$. We estimate local linear regressions of equation 3.1 with bandwidths $h \leq 1$, $h \leq 0.5$ and $h \leq 0.25$ over the same set of outcomes analyzed in the previous sections. Local regressions within small enough bandwidths reduce bias from selection on unobservables. Table 2.10 shows estimates for the quality outputs, which include the following indicators and indexes: 1) ENADE, 2) Infrastructure, 3) Teaching and learning, 4) Opportunity, 5) IDD and 6) CPC_{score}. As we reduce the bandwidth, we notice that the magnitudes, signs, and statistical significance of the results remain similar. In fact, compared to the previous results, the estimates from the regression with the smallest bandwidth, $h \leq 0.25$, seem to be greater in magnitude. Thus, our results corroborate and reinforce our previous conclusions. Undergraduate programs evaluated below the recognition level overreact in order to improve their performance on the ENADE and IDD indexes, as well as to improve their program infrastructure, teaching and learning, and opportunity indicators and attain recognition during the next evaluation cycle. We do not report the results for the other thresholds, as none of them are statistically significant here or in the previous sections.

Table 2.10: Local regressions of the impact of accountability on program quality

	(1)	(2)	(3)	(4)	(5)	(6)
	ENADE	Infrastructure	Teaching and learning	Opportunity	IDD	CPC
Unlimited distance to cutoff						
CPC_{level}=3	-0.189***	-0.363***	-0.177***	-0.143***	-0.180***	-0.157***
	(0.064)	(0.085)	(0.045)	(0.037)	(0.059)	(0.019)
n	34,405	35,052	35,052	33,637	29,640	33,437
Distance≤1						
CPC_{level}=3	-0.181**	-0.439***	-0.267***	-0.199***	-0.268***	-0.181***
	(0.087)	(0.096)	(0.042)	(0.071)	(0.065)	(0.047)
n	23,524	24,015	24,015	22,894	19,911	22,731
Distance≤0.5						
CPC_{level}=3	-0.190*	-0.427***	-0.357***	-0.265*	-0.207**	-0.254***
	(0.099)	(0.089)	(0.083)	(0.138)	(0.083)	(0.089)
n	12,153	12,416	12,416	11,742	9,849	11,649
Distance≤0.25						
CPC_{level}=3	-0.154**	-0.472***	-0.353***	-0.173**	-0.192**	-0.224***
	(0.065)	(0.064)	(0.084)	(0.083)	(0.085)	(0.054)
n	6,063	6,215	6,215	5,834	4,821	5,786

*** p<0.01, ** p<0.05, * p<0.1
Notes: Each coefficient is interpreted as the difference in performance between the programs to the left of the cutoff and the programs to the right of the same cutoff. Quality indicators are continuous and range from 0 to 5. The regressions are weighted by the number of senior students taking the ENADE exam. All specifications include a vector of program characteristics control variables (the number of programs within the same field of study in the same HEI and dummies for type of administration (public or private), the year of evaluation, state, field of study, type of academic organization, and the IGC level of the institution). Regressions also include a quartic polynomial on continuous indexes used to define the CPC_{level} (i.e., CPC_{score}, ENADE, IDD, infrastructure, teaching and learning, and faculty characteristics). Robust standard errors –in parentheses – are clustered at the state level.

Table 2.11 presents estimates of the level changes that occur at the threshold $CPC_{score} = 1.945$ in the number of slots, applications, and new students and in enrollment and the dropout rate. Within the smallest bandwidth of $h \leq 0.25$, estimates are very similar to the parametric estimates, except that the standard errors are larger and only the number of new students remains statistically significant, though only at the 10% level. Nevertheless, altogether, the results confirm the parametric estimates and suggest that the obtaining recognition, i.e., $CPC_{level} = 3$ or higher, results in an increase in the number of slots, applications and new students.

Table 2.11: Local regressions of the impact of accountability on program status and flow indicators

	(1)	(2)	(3)	(4)	(5)	(6)
	Slots	Applications	New students	Total enrollment	Dropout	Closure situation
Unlimited distance to cutoff						
CPC_{level}=3	0.132***	0.124***	0.101**	0.047	0.022	0.003
	(0.041)	(0.042)	(0.040)	(0.043)	(0.070)	(0.005)
n	37,861	37,484	37,277	38,819	37,115	32,978
Distance≤1						
CPC_{level}=3	0.104**	0.126**	0.086*	0.021	0.029	0.015*
	(0.048)	(0.046)	(0.042)	(0.046)	(0.092)	(0.008)
n	26,266	25,951	25,765	26,917	25,613	22,455
Distance≤0.5						
CPC_{level}=3	0.096	0.096*	0.102	0.084	-0.027	-0.001
	(0.066)	(0.054)	(0.076)	(0.070)	(0.065)	(0.008)
n	13,825	13,628	13,518	14,194	13,396	11,357
Distance≤0.25						
CPC_{level}=3	0.106	0.126*	0.106	0.077	-0.023	-0.004
	(0.083)	(0.070)	(0.086)	(0.083)	(0.061)	(0.012)
n	6,975	6,882	6,800	7,159	6,733	5,617

*** p<0.01, ** p<0.05, * p<0.1

Notes: Each coefficient is interpreted as the difference in performance between the programs to the left of the cutoff and the programs to the right of the same cutoff. Columns (1)-(3) refer to the sum of new slots, applications and new students over the period t+1 to t+3. Columns (4)-(6) refer to enrollment, the dropout rate and the activity status in t+3. Outcome variables such as new slots, applications, new students and enrollment are in logarithm form. Dropout is the ratio of students who leave the program to the total enrollment. Activity status indicates whether programs are still working in the following years. The regressions are weighted by the total number of students enrolled in the year of evaluation. All specifications include a vector of program characteristics control variables (the number of programs within the same field of study in the same HEI and dummies for type of administration (public or private), the year of evaluation, state, field of study, type of academic organization, and the IGC level of the institution). Regressions also include a quartic polynomial on continuous indexes used to define the CPC_{level} (i.e., CPC_{score}, ENADE, IDD, infrastructure, teaching and learning, and faculty characteristics). Robust standard errors –in parentheses – are clustered at the state level.

Finally, table 2.12 presents estimates of the level changes in the number of students per faculty member, the number of faculty members, the number of faculty members with an MA degree, the number with a PhD, and the number that are full-time at threshold $CPC_{score} = 1.945$. Within the smallest bandwidth, $h \leq 0.25$, the estimates are very similar to those from the parametric regressions, but the standard errors are larger and none of the estimates are statistically significant.

Table 2.12: Local regressions of the impact of accountability on program faculty profile

	(1)	(2)	(3)	(4)	(5)
	Students/ faculty	Faculty	MA	PhD	Full-time
Unlimited distance to cutoff					
CPC=3	0.390	0.055	0.005	-0.027***	-0.035***
	(0.481)	(0.036)	(0.008)	(0.005)	(0.005)
n	25,043	25,117	34,804	34,804	34,804
Distance≤1					
CPC_{level}=3	-0.827	0.096	0.003	-0.018	-0.027***
	(0.957)	(0.068)	(0.009)	(0.013)	(0.008)
n	16,922	16,972	23,833	23,833	23,833
Distance≤0.5					
CPC_{level}=3	-0.013	0.128	0.006	-0.014	-0.019
	(0.918)	(0.098)	(0.011)	(0.018)	(0.012)
n	8,711	8,741	12,311	12,311	12,311
Distance≤0.25					
CPC_{level}=3	0.146	0.115	0.015	-0.020	-0.017
	(1.429)	(0.120)	(0.016)	(0.023)	(0.015)
n	4,345	4,361	6,168	6,168	6,168

*** p<0.01, ** p<0.05, * p<0.1
Notes: Each coefficient is interpreted as the difference in performance between the programs to the left of the cutoff and the programs to the right of the same cutoff. Faculty variables are measured in t+3. Students/faculty is the ratio between the number of students and the number of professors associated with the program. Faculty is the number of faculty members and is in logarithm form. MA, PhD and Full-time refer respectively to the percentage of faculty members with a master degree, percentage of faculty members with a doctoral degree, and percentage of faculty members in a full-time working contract. Regressions are weighted by the number of enrollments in the year of evaluation. All specifications include a vector of program characteristics control variables (the number of programs within the same field of study in the same HEI and dummies for type of administration (public or private), the year of evaluation, state, field of study, type of academic organization, and the IGC level of the institution). Regressions also include a quartic polynomial on continuous indexes used to define the CPC_{level} (i.e., CPC_{score}, ENADE, IDD, infrastructure, teaching and learning, and faculty characteristics). Robust standard errors –in parentheses – are clustered at the state level.

Local estimates corroborate the main parametric estimates obtained in the previous sections. Results for the quality outcomes, as measured by the ENADE, IDD, CPC, Infrastructure, Teaching and learning, and Opportunity indexes, seem to be robust to falsification, specification and bandwidth tests. Outcomes related to offers and faculty seem to be robust to falsification and specification tests, but the standard errors are quite large within small bandwidths and we cannot reject the null hypothesis of no effect, although the magnitudes and sign remain stable.

2.5.5 Heterogeneous effects by field of study

In the previous estimations, we examined the heterogeneity in the effects by the type of administration. In addition, we also expect to find heterogeneous effects by field of study. To this extent, we estimate equation 3.1 for each subgroup of programs within each field of study. In this section, we mainly explore the results for the quality (measured by the CPC score in t+3) and offer (measured by the number of new slots in the three years following each evaluation)[36] outcomes.

The table 2.13 reports the impact of accountability on CPC scores in t+3 by area. The results confirm the pattern found in the previous estimations: the impact mainly occurs around the cutoff for $CPC_{level} = 3$ and for programs in private institutions. Additionally, at the threshold $CPC_{score} = 1.945$, the CPC index increases for programs in Social sciences, business and law, Health, and Education that are just under the cutoff in t+3 relative to the CPC index for programs in the same areas that are just above the same cutoff. This result is found only in regressions in which the sample is restricted to programs in private institutions.

Table 2.14 displays the impact of accountability on the number of new slots in the following three years after each evaluation by area. In the estimations over the full sample, the impact around threshold $CPC_{score} = 1.945$ is positive and programs that received a $CPC_{level} = 3$ (i.e., that are above this cutoff) increase the number of slots in Engineering and related fields, the Social sciences, business and law, and Health by 13.2% (p-value$<$0.1), 16.0% (p-value$<$0.05) and 20.1% (p-value$<$0.05), respectively. Again, similar results are observed for the estimations by area over the sample of programs in private institutions.

In both tables, the results for programs within the Sciences, math and computation and Other areas do not demonstrate a consistent pattern around the thresholds. Specifically, there is no significant impact of accountability on the number of new slots for theses programs in the estimations that use the full sample or those restricted to private institutions (see table 2.14).

[36] For simplicity, we do not report regression results for all variables by area, but these results can be obtained upon request to the authors.

Table 2.13: The impact of accountability on CPC score in t+3, by field of study

	(1)	(2)	(3)	(4)	(5)	(6)
	Engineering and related	Social sciences, business and law	Health	Education	Sciences, math and computation	Others
All sample						
CPC=2	0.177	-0.038	0.881**	0.043	-0.411*	-0.540
	(0.392)	(0.263)	(0.392)	(0.265)	(0.210)	(0.402)
CPC=3	-0.055	-0.199***	-0.156***	-0.165***	-0.012	0.000
	(0.034)	(0.032)	(0.051)	(0.039)	(0.038)	(0.076)
CPC=4	-0.003	0.017	0.025	0.011	0.036	-0.083
	(0.037)	(0.021)	(0.042)	(0.022)	(0.036)	(0.051)
CPC=5	0.045	-0.067	0.084	-0.117**	-0.186**	0.155
	(0.110)	(0.072)	(0.084)	(0.049)	(0.084)	(0.174)
n	3,953	11,766	3,833	7,878	3,946	2,052
Programs in private institutions						
CPC=2	0.368	0.003	0.374	-0.196	-0.777***	-0.928**
	(0.361)	(0.282)	(0.426)	(0.576)	(0.262)	(0.392)
CPC=3	-0.035	-0.192***	-0.125**	-0.215**	0.010	-0.104
	(0.041)	(0.041)	(0.059)	(0.101)	(0.053)	(0.119)
CPC=4	0.014	0.025	0.055	-0.011	-0.024	0.078
	(0.038)	(0.021)	(0.048)	(0.050)	(0.043)	(0.074)
CPC=5	-0.106	-0.074	0.254**	-0.351**	-0.118	0.237
	(0.243)	(0.078)	(0.096)	(0.146)	(0.140)	(0.172)
n	2,552	9,966	3,049	4,203	2,651	1,179
Programs in public institutions						
CPC=2	-0.378	-0.381	1.095***	0.005	-0.767**	-0.733*
	(0.538)	(0.503)	(0.378)	(0.321)	(0.332)	(0.394)
CPC=3	-0.217**	-0.145	-0.048	-0.038	-0.009	0.082
	(0.088)	(0.102)	(0.081)	(0.061)	(0.108)	(0.138)
CPC=4	-0.021	0.011	-0.158**	0.048	0.122**	-0.185**
	(0.055)	(0.036)	(0.065)	(0.033)	(0.046)	(0.072)
CPC=5	0.068	-0.202	0.045	-0.069	-0.136	0.107
	(0.098)	(0.119)	(0.113)	(0.101)	(0.097)	(0.164)
n	1,401	1,800	784	3,675	1,295	873

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes: Each coefficient is interpreted as the difference in performance between the programs to the left of the cutoff and the programs to the right of the same cutoff. The CPC in t+3 is continuous and range from 0 to 5. The regressions are weighted by the number of senior students taking the ENADE exam. All specifications include a vector of program characteristics control variables (the number of programs within the same field of study in the same HEI and dummies for type of administration (public or private), the year of evaluation, state, field of study, type of academic organization, and the IGC level of the institution). Regressions also include a quartic polynomial on continuous indexes used to define the CPC_{level} (i.e., CPC_{score}, ENADE, IDD, infrastructure, teaching and learning, and faculty characteristics). Robust standard errors –in parentheses – are clustered at the state level.

Table 2.14: The impact of accountability on the total number of slots, by field of study

	(1)	(2)	(3)	(4)	(5)	(6)
	Engineering and related	Social sciences, business and law	Health	Education	Sciences, math and computation	Others
All sample						
CPC=2	0.239	-0.320	-0.389	0.377**	0.506	0.058
	(0.185)	(0.236)	(0.412)	(0.179)	(0.302)	(0.499)
CPC=3	0.132*	0.160**	0.201**	-0.012	0.022	0.099
	(0.074)	(0.072)	(0.084)	(0.103)	(0.074)	(0.101)
CPC=4	-0.012	-0.077	0.132**	0.074	-0.029	-0.000
	(0.066)	(0.062)	(0.057)	(0.066)	(0.069)	(0.070)
CPC=5	0.091	-0.068	-0.014	0.180	-0.005	0.131
	(0.096)	(0.075)	(0.069)	(0.141)	(0.114)	(0.118)
n	4,374	13,048	4,228	9,197	4,510	2,504
Only private institutions						
CPC=2	0.442**	-0.440*	-0.549	0.503	0.186	0.239
	(0.166)	(0.255)	(0.448)	(0.533)	(0.333)	(0.729)
CPC=3	0.166**	0.201**	0.215*	0.007	0.023	0.064
	(0.072)	(0.081)	(0.105)	(0.087)	(0.068)	(0.084)
CPC=4	-0.021	-0.077	0.189**	0.226***	-0.070	0.053
	(0.077)	(0.071)	(0.073)	(0.042)	(0.082)	(0.082)
CPC=5	0.233	-0.087	0.095	0.279***	-0.098	-0.524
	(0.199)	(0.128)	(0.155)	(0.045)	(0.222)	(0.346)
n	2,821	11,144	3,391	5,172	3,159	1,529
Only public insitutions						
CPC=2	-2.298***	-0.230	-0.294	0.304	1.005**	0.700
	(0.554)	(0.591)	(0.381)	(0.207)	(0.415)	(0.609)
CPC=3	-0.204	-0.077	0.069	-0.060	-0.008	-0.069
	(0.167)	(0.076)	(0.189)	(0.142)	(0.131)	(0.147)
CPC=4	-0.103	-0.020	0.050	-0.071	-0.084	0.016
	(0.082)	(0.070)	(0.077)	(0.088)	(0.081)	(0.081)
CPC=5	0.118	-0.028	-0.025	0.186	0.180*	0.234*
	(0.099)	(0.117)	(0.131)	(0.177)	(0.094)	(0.114)
n	1,553	1,904	837	4,025	1,351	975

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes: Each coefficient is interpreted as the difference in performance between the programs to the left of the cutoff and the programs to the right of the same cutoff. The dependent variable is the sum of new slots over the period t+1 to t+3 and is measured in logarithm form. The regressions are weighted by the total number of students enrolled in the year of evaluation. All specifications include a vector of program characteristics control variables (the number of programs within the same field of study in the same HEI and dummies for type of administration (public or private), the year of evaluation, state, field of study, type of academic organization, and the IGC level of the institution). Regressions also include a quartic polynomial on continuous indexes used to define the CPC_{level} (i.e., CPC_{score}, ENADE, IDD, infrastructure, teaching and learning, and faculty characteristics). Robust standard errors –in parentheses – are clustered at the state level.

2.6 Conclusions

Higher education accountability is meant to provide information about the quality of undergraduate programs and to support public regulation of HEIs. Our results suggest that SINAES impacts Brazilian HEIs in the years following the publication of results, mainly for HEIs around the cutoff that determines the minimum level required for federal approval of the program. The programs that receive a low score ($CPC_{score} < 1.945$) in a certain period achieve higher quality indexes in terms of student performance, infrastructure, faculty and quality overall in the next evaluation cycle. As a result, those programs also obtain a higher CPC_{score} 3 years after the evaluation than those programs that are just above the threshold ($CPC_{score} \geq 1.945$). On the other hand, programs just above this threshold increase the number of slots available, receive more applications and admit more new students than programs just below the same threshold. These results suggest that program administrators respond to the threat of punishment related to this threshold.

Even though we expected administrators to use their results as an advertisement when programs achieved higher scores (i.e., CPC_{level}=4 or 5), we do not find consistent impacts from reaching this level on either program effort or candidate perceptions of future returns.

In addition to identifying impacts mainly around $CPC_{score} = 1.945$, our main results are stronger for private HEIs, which we argue are related to the competitive pressure and positive incentives (such as access to public programs that offer scholarships and student loans) that private institutions face.

Although we discuss the potential mechanisms that explain administrators' behavioral changes, questions related to how society at large reacts to evaluation results remain unanswered. For example, how do candidates for higher education use accountability scores to decide which program to attend? Why do students still decide to attend programs with low scores? On the other hand, do employers take into account the quality of undergraduate programs when selecting prospective employees? More research is needed to answer these and other questions regarding how different agents respond to higher education accountability and to contribute to our understanding of the effects of this evaluation policy.

References

Bowman, N. A. and M. N. Bastedo (2009). Getting on the front page: organizational reputation, status signals, and the impact of US News and World Report on student decisions. *Research in Higher Education 50*(5), 415–436.

Bowman, N. A. and M. N. Bastedo (2013). Anchoring effects in world university rankings: exploring biases in reputation scores. In *Higher Education in the Global Age*, pp. 271–287. Routledge.

Camargo, B., R. Camelo, S. Firpo, and V. Ponczek (2018). Information, market incentives, and student performance evidence from a regression discontinuity design in Brazil. *Journal of Human Resources 53*(2), 414–444.

Canaan, S. and P. Mouganie (2018). Returns to education quality for low-skilled students: evidence from a discontinuity. *Journal of Labor Economics 36*(2), 395–436.

Cattaneo, M. D., N. Idrobo, and R. Titiunik (2019). *A practical introduction to regression discontinuity designs: foundations*. Cambridge University Press.

Cattaneo, M. D., M. Jansson, and X. Ma (2020). Simple local polynomial density estimators. *Journal of the American Statistical Association 115*(531), 1449–1455.

Cattaneo, M. D., R. Titiunik, and G. Vazquez-Bare (2020). Analysis of regression-discontinuity designs with multiple cutoffs or multiple scores. *The Stata Journal 20*(4), 866–891.

Chakrabarti, R. (2014). Incentives and responses under No Child Left Behind: credible threats and the role of competition. *Journal of Public Economics 110*, 124–146.

Chiang, H. (2009). How accountability pressure on failing schools affects student achievement. *Journal of Public Economics 93*(9-10), 1045–1057.

Corbucci, P. R., L. C. Kubota, and A. P. B. Meira (2016). Evolução da educação superior privadano Brasil: da reforma universitário de 1968 à década de 2010. *Radar: tecnologia, produção e comércio exterior* (46), 7–12.

Craig, S. G., S. A. Imberman, and A. Perdue (2013). Does it pay to get an A? School resource allocations in response to accountability ratings. *Journal of urban Economics 73*(1), 30–42.

Craig, S. G., S. A. Imberman, and A. Perdue (2015). Do administrators respond to their accountability ratings? The response of school budgets to accountability grades. *Economics of Education Review 49*, 55–68.

De Hoyos, R., V. A. Garcia-Moreno, and H. A. Patrinos (2017). The impact of an accountability intervention with diagnostic feedback: evidence from Mexico. *Economics of Education Review 58*, 123–140.

Deming, D. J., S. Cohodes, J. Jennings, and C. Jencks (2016). School accountability, postsecondary attainment, and earnings. *Review of Economics and Statistics 98*(5), 848–862.

Deming, D. J. and D. Figlio (2016). Accountability in us education: applying lessons from K-12 experience to higher education. *Journal of Economic Perspectives 30*(3), 33–56.

Fan, J., N. E. Heckman, and M. P. Wand (1995). Local polynomial kernel regression for generalized linear models and quasi-likelihood functions. *Journal of the American Statistical Association 90*(429), 141–150.

Feng, L., D. Figlio, and T. Sass (2018). School accountability and teacher mobility. *Journal of Urban Economics 103*, 1–17.

Figlio, D. N. and C. E. Rouse (2006). Do accountability and voucher threats improve low-performing schools? *Journal of Public Economics 90*(1-2), 239–255.

Figlio, D. N. and J. Winicki (2005). Food for thought: the effects of school accountability plans on school nutrition. *Journal of public Economics 89*(2-3), 381–394.

Hastings, J. S. and J. M. Weinstein (2008). Information, school choice, and academic achievement: evidence from two experiments. *The Quarterly journal of economics 123*(4), 1373–1414.

Holbein, J. B. and H. F. Ladd (2017). Accountability pressure: regression discontinuity estimates of how No Child Left Behind influenced student behavior. *Economics of Education Review 58*, 55–67.

Inep (2009). *Sistema Nacional de Avaliação da Educação Superior: da concepção à regulamentação* (5 ed.). Brasilia: Instituto Nacional de Estudos e Pesquisas Educacionais Anísio Teixeira.

Lee, D. S. and T. Lemieux (2010). Regression discontinuity designs in economics. *Journal of economic literature 48*(2), 281–355.

McCrary, J. (2008). Manipulation of the running variable in the regression discontinuity design: a density test. *Journal of econometrics 142*(2), 698–714.

Mizala, A. and M. Urquiola (2013). School markets: the impact of information approximating schools' effectiveness. *Journal of Development Economics 103*, 313–335.

Neal, D. and D. W. Schanzenbach (2010). Left behind by design:pproficiency counts and test-based accountability. *The Review of Economics and Statistics 92*(2), 263–283.

Nunes, L. C., A. B. Reis, and C. Seabra (2015). The publication of school rankings: a step toward increased accountability? *Economics of Education Review 49*, 15–23.

OECD (2018). *Rethinking Quality Assurance for Higher Education in Brazil, Reviews of National Policies for Education*. Paris: OECD Publishing.

Rezende, M. (2010). The effects of accountability on higher education. *Economics of Education Review 29*(5), 842–856.

Rockoff, J. and L. J. Turner (2010). Short-run impacts of accountability on school quality. *American Economic Journal: Economic Policy 2*(4), 119–47.

Rouse, C. E., J. Hannaway, D. Goldhaber, and D. Figlio (2013). Feeling the Florida heat? How low-performing schools respond to voucher and accountability pressure. *American Economic Journal: Economic Policy 5*(2), 251–81.

Woo, S., S. Lee, and K. Kim (2015). Carrot and stick? Impact of a low-stakes school accountability program on student achievement. *Economics Letters 137*, 195–199.

Appendices

A The use of the higher education accountability results as advertisement

Figure 2.11: Example of the CPC level used as positive advertising

Note: The name on the building's facade should be IESB, the name of the institution, but managers replace the letter "S" with the number 5 to advertise their performance in the evaluation.

B Robustness check on the number of students taking the ENADE exam

Table B.1: Accountability and the number of students taking the ENADE

	(1)	(2)
	t=0	t=3
CPC_{level}=2	0.015	-0.028
	(0.012)	(0.028)
CPC_{level}=3	-0.004	-0.003
	(0.003)	(0.003)
CPC_{level}=4	-0.001	0.001
	(0.002)	(0.002)
CPC_{level}=5	-0.002	-0.010
	(0.004)	(0.008)
n	29,087	29,087

*** $p<0.01$, ** $p<0.05$, * $p<0.1$
Notes: The dependent variable is the the ratio of the number of students taking the ENADE to the total program enrollment. Each coefficient is interpreted as the difference in performance between the programs to the left of the cutoff and the programs to the right of the same cutoff. Regressions are weighted by total enrollments. All specifications include a vector of program characteristics control variables (the number of programs within the same field of study in the same HEI and dummies for type of administration (public or private), the year of evaluation, state, field of study, type of academic organization, and the IGC level of the institution). Regressions also include a quartic polynomial on continuous indexes used to define the CPC_{level} (i.e., CPC_{score}, ENADE, IDD, infrastructure, teaching and learning, and faculty characteristics). Robust standard errors –in parentheses – are clustered at the state level.

C Robustness check varying the polynomial order

Table C.1: The impact of accountability on program quality varying the order of the polynomial

	(1)	(2)	(3)	(4)	(5)	(6)
	ENADE	Infrastructure	Teaching and learning	Opportunity	IDD	CPC
Cubic polynomial						
CPC_{level}=2	-0.263	-0.258	-0.201	-0.288	-0.216	-0.163
	(0.175)	(0.203)	(0.214)	(0.287)	(0.212)	(0.110)
CPC_{level}=3	-0.188***	-0.324***	-0.134**	-0.154***	-0.139***	-0.143***
	(0.063)	(0.079)	(0.052)	(0.055)	(0.040)	(0.017)
CPC_{level}=4	-0.036	0.014	-0.019	0.060	0.019	-0.013
	(0.029)	(0.057)	(0.065)	(0.054)	(0.027)	(0.027)
CPC_{level}=5	-0.110	0.167	0.183*	0.196**	-0.048	0.054
	(0.098)	(0.129)	(0.106)	(0.073)	(0.078)	(0.058)
n	34,405	35,052	35,052	29,640	33,637	33,437
Quadratic polynomial						
CPC_{level}=2	-0.125	-0.199	-0.270*	-0.348**	-0.060	-0.117
	(0.134)	(0.177)	(0.152)	(0.157)	(0.191)	(0.080)
CPC_{level}=3	-0.181**	-0.326***	-0.138**	-0.169**	-0.128***	-0.144***
	(0.067)	(0.086)	(0.057)	(0.066)	(0.034)	(0.019)
CPC_{level}=4	-0.052	0.012	-0.016	0.073	0.001	-0.017
	(0.032)	(0.046)	(0.051)	(0.045)	(0.024)	(0.031)
CPC_{level}=5	-0.021	0.185	0.151	0.135*	0.056	0.080
	(0.071)	(0.115)	(0.119)	(0.078)	(0.100)	(0.051)
n	34,405	35,052	35,052	29,640	33,637	33,437

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes: Each coefficient is interpreted as the difference in performance between the programs to the left of the cutoff and the programs to the right of the same cutoff. Quality indicators are continuous and range from 0 to 5. The regressions are weighted by the number of senior students taking the ENADE exam. All specifications include a vector of program characteristics control variables (the number of programs within the same field of study in the same HEI and dummies for type of administration (public or private), the year of evaluation, state, field of study, type of academic organization, and the IGC level of the institution). Regressions also include a quartic polynomial on continuous indexes used to define the CPC_{level} (i.e., CPC_{score}, ENADE, IDD, infrastructure, teaching and learning, and faculty characteristics). Robust standard errors –in parentheses – are clustered at the state level.

Table C.2: The impact of accountability on program status and flow indicators varying the order of the polynomial

	(1)	(2)	(3)	(4)	(5)	(6)
	Slots	Applications	New students	Enrollment	Dropout	Acitivity status
Cubic polynomial						
CPC=2	0.102	0.056	0.057	0.013	-0.043	0.025
	(0.116)	(0.195)	(0.144)	(0.124)	(0.162)	(0.032)
CPC=3	0.129***	0.132***	0.113***	0.057	0.020	0.002
	(0.036)	(0.039)	(0.034)	(0.037)	(0.073)	(0.004)
CPC=4	-0.007	-0.034	-0.038	-0.058**	0.030	0.007*
	(0.031)	(0.041)	(0.029)	(0.026)	(0.080)	(0.004)
CPC=5	0.025	-0.003	0.047	0.056	-0.026	0.011
	(0.038)	(0.085)	(0.053)	(0.066)	(0.087)	(0.010)
n	37,861	37,484	37,277	38,819	37,115	32,978
Quadratic polynomial						
CPC=2	-0.056	-0.084	-0.113	-0.071	0.002	0.019
	(0.098)	(0.161)	(0.181)	(0.154)	(0.162)	(0.032)
CPC=3	0.132***	0.131***	0.114***	0.058	0.021	0.002
	(0.039)	(0.037)	(0.037)	(0.039)	(0.075)	(0.004)
CPC=4	-0.006	-0.027	-0.034	-0.056**	0.026	0.007**
	(0.029)	(0.035)	(0.024)	(0.021)	(0.075)	(0.003)
CPC=5	-0.001	-0.044	0.008	0.038	0.011	0.008
	(0.058)	(0.070)	(0.041)	(0.052)	(0.062)	(0.008)
n	37,861	37,484	37,277	38,819	37,115	32,978

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes: Each coefficient is interpreted as the difference in performance between the programs to the left of the cutoff and the programs to the right of the same cutoff. Columns (1)-(3) refer to the sum of new slots, applications and new students over the period t+1 to t+3. Columns (4)-(6) refer to enrollment, the dropout rate and the activity status in t+3. Outcome variables such as new slots, applications, new students and enrollment are in logarithm form. Dropout is the ratio of students who leave the program to the total enrollment. Activity status indicates whether programs are still working in the following years. The regressions are weighted by the total number of students enrolled in the year of evaluation. All specifications include a vector of program characteristics control variables (the number of programs within the same field of study in the same HEI and dummies for type of administration (public or private), the year of evaluation, state, field of study, type of academic organization, and the IGC level of the institution). Regressions also include a quartic polynomial on continuous indexes used to define the CPC_{level} (i.e., CPC_{score}, ENADE, IDD, infrastructure, teaching and learning, and faculty characteristics). Robust standard errors –in parentheses – are clustered at the state level.

Table C.3: The impact of accountability on program faculty profile varying the order of the polynomial

	(1)	(2)	(3)	(4)	(5)
	Students by Faculty	Faculty	MA	PhD	Full-time
Cubic polynomial					
CPC=2	3.306	-0.076	-0.015	-0.029	-0.027
	(5.137)	(0.128)	(0.025)	(0.046)	(0.056)
CPC=3	0.811	0.037	0.003	-0.024***	-0.033***
	(0.490)	(0.033)	(0.008)	(0.006)	(0.006)
CPC=4	-0.686	0.020	0.006	-0.017**	0.001
	(0.526)	(0.035)	(0.006)	(0.008)	(0.008)
CPC=5	1.364*	0.017	-0.018	0.032	0.018*
	(0.664)	(0.068)	(0.021)	(0.019)	(0.010)
n	25,043	25,117	34,804	34,804	34,804
Quadratic polynomial					
CPC=2	1.223	-0.001	-0.039*	-0.005	-0.053
	(3.477)	(0.121)	(0.019)	(0.037)	(0.067)
CPC=3	0.709	0.041	0.005	-0.026***	-0.034***
	(0.478)	(0.034)	(0.007)	(0.005)	(0.005)
CPC=4	-0.430	0.004	0.004	-0.015*	0.003
	(0.458)	(0.031)	(0.007)	(0.008)	(0.008)
CPC=5	0.097	0.083*	-0.016	0.030**	0.007
	(1.105)	(0.046)	(0.012)	(0.012)	(0.010)
n	25,043	25,117	34,804	34,804	34,804

*** $p<0.01$, ** $p<0.05$, * $p<0.1$
Notes: Each coefficient is interpreted as the difference in performance between the programs to the left of the cutoff and the programs to the right of the same cutoff. Faculty variables are measured in t+3. Students/faculty is the ratio between the number of students and the number of professors associated with the program. Faculty is the number of faculty members and is in logarithm form. MA, PhD and Full-time refer respectively to the percentage of faculty members with a master degree, percentage of faculty members with a doctoral degree, and percentage of faculty members in a full-time working contract. Regressions are weighted by the number of enrollments in the year of evaluation. All specifications include a vector of program characteristics control variables (the number of programs within the same field of study in the same HEI and dummies for type of administration (public or private), the year of evaluation, state, field of study, type of academic organization, and the IGC level of the institution). Regressions also include a quartic polynomial on continuous indexes used to define the CPC_{level} (i.e., CPC_{score}, ENADE, IDD, infrastructure, teaching and learning, and faculty characteristics). Robust standard errors –in parentheses – are clustered at the state level.

D Robustness check applying the method of Cattaneo et al. (2020)

Table D.1: The impact of accountability on program quality applying the method of Cattaneo et al. (2020)

	(1)	(2)	(3)	(4)	(5)	(6)
	ENADE	Infrastructure	Teaching and learning	Opportunity	IDD	CPC
CPC=2	0.994	0.675	0.327	-5.460***	0.185	-0.285
	(0.627)	(0.966)	(0.666)	(1.362)	(0.948)	(0.616)
CPC=3	-0.145**	-0.170**	-0.222**	-0.233**	-0.102	-0.168***
	(0.064)	(0.076)	(0.095)	(0.105)	(0.073)	(0.055)
CPC=4	-0.006	-0.037	0.004	-0.040	-0.062	-0.038
	(0.058)	(0.066)	(0.060)	(0.088)	(0.080)	(0.041)
CPC=5	-0.267	0.368**	0.241	0.180	-0.121	-0.080
	(0.173)	(0.153)	(0.215)	(0.249)	(0.291)	(0.122)

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes: Each coefficient is interpreted as the difference in performance between the programs to the left of the cutoff and the programs to the right of the same cutoff. Quality indicators are continuous and range from 0 to 5. All specifications include a vector of program characteristics control variables (the number of programs within the same field of study in the same HEI and dummies for type of administration (public or private), the year of evaluation, state, field of study, type of academic organization, and the IGC level of the institution). Regressions also include a quartic polynomial on continuous indexes used to define the CPC_{level} (i.e., CPC_{score}, ENADE, IDD, infrastructure, teaching and learning, and faculty characteristics). The table shows cutoff-specific treatment effects based on local polynomial estimation and robust bias-corrected inference procedures, following Cattaneo et al. (2020). Robust standard errors –in parentheses – are clustered at the state level.

Table D.2: The impact of accountability on program status and flow indicators applying the method of Cattaneo et al. (2020)

	(1)	(2)	(3)	(4)	(5)	(6)
	Slots	Applications	New students	Enrollments	Dropout	Closure situation
CPC=2	0.419	0.782**	1.602***	1.745***	-0.371	0.629***
	(0.282)	(0.356)	(0.539)	(0.572)	(0.305)	(0.219)
CPC=3	0.112	0.119	-0.097	-0.143	0.081	0.025
	(0.085)	(0.146)	(0.144)	(0.121)	(0.195)	(0.024)
CPC=4	-0.100*	-0.142*	-0.110*	-0.089	-0.009	-0.002
	(0.060)	(0.082)	(0.058)	(0.079)	(0.184)	(0.015)
CPC=5	-0.209*	-0.429**	-0.184	-0.274**	0.232	-0.052
	(0.115)	(0.177)	(0.192)	(0.139)	(0.319)	(0.062)

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes: Each coefficient is interpreted as the difference in performance between the programs to the left of the cutoff and the programs to the right of the same cutoff. Columns (1)-(3) refer to the sum of new slots, applications and new students over the period t+1 to t+3. Columns (4)-(6) refer to enrollment, the dropout rate and the activity status in t+3. Outcome variables such as new slots, applications, new students and enrollment are in logarithm form. Dropout is the ratio of students who leave the program to the total enrollment. Activity status indicates whether programs are still working in the following years. All specifications include a vector of program characteristics control variables (the number of programs within the same field of study in the same HEI and dummies for type of administration (public or private), the year of evaluation, state, field of study, type of academic organization, and the IGC level of the institution). Regressions also include a quartic polynomial on continuous indexes used to define the CPC_{level} (i.e., CPC_{score}, ENADE, IDD, infrastructure, teaching and learning, and faculty characteristics). The table shows cutoff-specific treatment effects based on local polynomial estimation and robust bias-corrected inference procedures, following Cattaneo et al. (2020). Robust standard errors –in parentheses – are clustered at the state level.

Table D.3: The impact of accountability on program faculty profile applying the method of Cattaneo et al. (2020)

	(1)	(2)	(3)	(4)	(5)
	Students by Faculty	Faculty	MA	PhD	Full-time
CPC=2	22.148***	0.293	0.578**	-0.654	0.587
	(4.703)	(0.267)	(0.287)	(0.564)	(0.376)
CPC=3	-9.067	0.008	-0.143	0.033	0.010
	(8.408)	(0.465)	(0.513)	(0.093)	(0.068)
CPC=4	1.080	-0.071	-0.083	-0.092	-0.046
	(0.858)	(0.063)	(0.064)	(0.072)	(0.061)
CPC=5	-1.794	0.030	-0.002	0.113	-0.000
	(1.507)	(0.158)	(0.160)	(0.194)	(0.158)

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes: Each coefficient is interpreted as the difference in performance between the programs to the left of the cutoff and the programs to the right of the same cutoff. Faculty variables are measured in t+3. Students/faculty is the ratio between the number of students and the number of professors associated with the program. Faculty is the number of faculty members and is in logarithm form. MA, PhD and Full-time refer respectively to the percentage of faculty members with a master degree, percentage of faculty members with a doctoral degree, and percentage of faculty members in a full-time working contract. All specifications include a vector of program characteristics control variables (the number of programs within the same field of study in the same HEI and dummies for type of administration (public or private), the year of evaluation, state, field of study, type of academic organization, and the IGC level of the institution). Regressions also include a quartic polynomial on continuous indexes used to define the CPC_{level} (i.e., CPC_{score}, ENADE, IDD, infrastructure, teaching and learning, and faculty characteristics). The table shows cutoff-specific treatment effects based on local polynomial estimation and robust bias-corrected inference procedures, following Cattaneo et al. (2020). Robust standard errors –in parentheses – are clustered at the state level.

E Institution quality

This section adapts equation 3.1 to estimate the impacts of the higher education institution evaluation on institutional outcomes. As mentioned before, the quality of the institution is summarized in the IGC score, which follows the same rule as CPC for classifying courses from levels 1 to 5. The IGC level is updated every year based on the results of the courses evaluated in the same year and the results from courses evaluated over the last 2 years.

Thus, we run the following reduced-form regression specification:

$$Y_{jt+3} = \alpha + \lambda_L \mathbf{IGC}^L_{jt} + \beta \boldsymbol{f}(\mathbf{Q}_{jt}) + \gamma \mathbf{C}_{jt} + \varepsilon_{jt} \tag{2.3}$$

where Y_{jt+3} is the dependent variable for higher education institution j in year t such as the following IGC_{score}, ENADE score, MA and PhD grades –as evaluated by Capes –; $\mathbf{IGC}_{jt}^{L}$ is a dummy indicating whether an institution is at IGC level L or below that based on IGC score achieved in $t = 0$. $\mathbf{Q}_{jt}$ is a quartic polynomial on the IGC score. $\mathbf{C}_{jt}$ is a vector of covariates for institutional characteristics, such as the number of courses, a dummy for type of administration (whether public or private), dummies for years of evaluation, and state dummies; and ε_{jt} is the idiosyncratic error term.

Tables E.1, E.3 and E.2 display the results for equation 3.2. It is evident that there are no clear impacts of IGC level on either outcome. This indicates that accountability has stronger impacts at the course level, which is expected since it is somewhat rare to find an entire Higher Education Institution that is below the minimum threshold of recognition.

Table E.1: Impacts of HEI score on instituion quality

	(1)	(2)	(3)	(4)
	IGC	ENADE	Master	Doctorate
IGC_{level}=2	0.008	0.033	0.096*	0.176
	(0.132)	(0.130)	(0.054)	(0.122)
IGC_{level}=3	-0.020	-0.029**	-0.025	0.018
	(0.012)	(0.011)	(0.046)	(0.043)
IGC_{level}=4	-0.001	0.002	0.037*	0.044
	(0.015)	(0.016)	(0.019)	(0.044)
IGC_{level}=5	0.006	0.038	-0.031	0.062
	(0.024)	(0.049)	(0.023)	(0.046)
n	15,526	15,548	15,627	15,627

*** p<0.01, ** p<0.05, * p<0.1

Notes: Each coefficient is interpreted as the difference in performance between the HEIs to the left of the cutoff and the HEIs to the right of the same cutoff. Quality indexes are continuous measures and range from 0 to 5. The regressions are weighted by the number of senior students taking the ENADE exam. All specifications include a vector of control variables for HEI characteristics (dummies for type of administration (public or private), the year of evaluation, state, type of academic organization, and the IGC level of the institution). Regressions also include a quartic polynomial on IGC_{score} with interactions with IGC_{level}. Robust standard errors –in parentheses – are clustered at the state level.

Table E.2: Impacts of HEI score on flow indicators

	(1)	(2)	(3)	(4)	(5)
	slots	Applications	New students	Total enrollment	Dropout
IGC_{level} =2	0.670*	0.628	0.463	0.825*	-0.308**
	(0.338)	(0.537)	(0.331)	(0.419)	(0.126)
IGC_{level}=3	0.021	0.315*	0.141	0.205	-0.074
	(0.084)	(0.166)	(0.150)	(0.130)	(0.081)
IGC_{level}=4	0.342*	0.209*	0.131	0.194	0.040
	(0.199)	(0.102)	(0.098)	(0.133)	(0.028)
IGC_{level}=5	0.420*	0.587	0.146	0.671*	0.054
	(0.241)	(0.360)	(0.287)	(0.351)	(0.066)
n	15,381	15,220	15,610	15,085	15,610

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes: Each coefficient is interpreted as the difference in performance between the HEIs to the left of the cutoff and the HEIs to the right of the same cutoff. Columns (1)-(3) refer to the sum of new slots, applications and new students over the period t+1 to t+3. Columns (4)-(6) refer to enrollment, the dropout rate and the activity status in t+3. Outcome variables such as new slots, applications, new students and enrollment are in logarithm form. Dropout is the ratio of students who leave the program to the total enrollment. Activity status indicates whether programs are still working in the following years. The regressions are weighted by the total number of students enrolled in the year of evaluation. All specifications include a vector of control variables for HEI characteristics (dummies for type of administration (public or private), the year of evaluation, state, type of academic organization, and the IGC level of the institution). Regressions also include a quartic polynomial on IGC_{score} with interactions with IGC_{level}. Robust standard errors –in parentheses – are clustered at the state level.

Table E.3: Impacts of HEI score on instituion faculty profile

	(1)	(2)	(3)	(4)	(5)
	Students/ faculty	Faculty	MA	PhD	Full-time
IGC_{level}=2	15.702	0.236	-0.051	-0.088*	-0.276**
	(13.756)	(0.242)	(0.055)	(0.050)	(0.101)
IGC_{level}=3	-0.316	0.039	-0.022**	0.009	0.033
	(2.142)	(0.056)	(0.010)	(0.013)	(0.021)
IGC_{level}=4	3.667**	0.071	0.001	-0.020	0.008
	(1.545)	(0.052)	(0.015)	(0.022)	(0.040)
IGC_{level}=5	-1.035	-0.027	0.013	-0.010	0.044
	(2.275)	(0.109)	(0.015)	(0.020)	(0.047)
n	15,615	15,615	15,615	15,615	15,615

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes:Each coefficient is interpreted as the difference in performance between the HEIs to the left of the cutoff and the HEIs to the right of the same cutoff. Faculty variables are measured in t+3. Students/faculty is the ratio between the number of students and the number of professors associated with the HEI. Faculty is the number of faculty members and is in logarithm form. MA, PhD and Full-time refer respectively to the percentage of faculty members with a master degree, percentage of faculty members with a doctoral degree, and percentage of faculty members in a full-time working contract. Regressions are weighted by the number of enrollments in the year of evaluation. All specifications include a vector of control variables for HEI characteristics (dummies for type of administration (public or private), the year of evaluation, state, type of academic organization, and the IGC level of the institution). Regressions also include a quartic polynomial on IGC_{score} with interactions with IGC_{level}. Robust standard errors –in parentheses – are clustered at the state level.

Chapter 3

Returns to major-job match

ABSTRACT

This paper estimates the similarity between occupations and college majors and its effects on labor market returns. Our major-job match index combines the direct association of each field of study to its closest occupations, and the similarity index between each pair of occupations based on the application of a pre-trained natural language processing (NLP) model to the occupation task description. We estimate the effects of major-job match on labor market returns up to 2018 for a cohort of Brazilian graduates who completed an undergraduate program between 2004 and 2006. The results suggest that the greater the major-job match, the higher the wage and the smaller the turnover. We also explore heterogeneous effects: the estimates show higher wage returns to major-job match for women, workers who also match the level of education, private sector employees and graduates in fields such as Law, Education, Portuguese and foreign languages, and Production and engineering. Controlling for on-the-job learning does not change significantly our main results, but adds evidence on the positive returns to matching the previous work experience to the current job.

JEL Classification: J24, J31, I26
Keywords: Horizontal Match, Higher Education, On-the-job Learning, Human Capital, NLP

3.1 Introduction

Field-of-study mismatch (or horizontal mismatch) occurs when workers are employed in occupations that are not related to their previous education – for example, when an individual majored in civil engineering during college, but works as an administrative assistant. The mismatch may result in society losses by two main mechanisms: the inefficiency in the investment to provide a set of skills that the graduates do not perform in the labor market, and the loss of productivity that results from the skill gap in the workforce ability and the occupation requirements.

This paper adds to this topic by analyzing career trajectories for workers who completed the higher education in Brazil and investigating the potential returns of major-job match. We rely on the unique panel dataset of graduates evaluated in their senior year by the National Exam of Student Performance (ENADE) in the period from 2004 to 2006 and their job trajectories in formal labor market up to 2018. We also propose a continuous measure for major-job match that combines the association of each field of study to its closest occupations (for example, the programs in Economics are associated to the occupation of economist as a perfect match) and a Natural Language Process (NLP) approach that allows us to compute the similarity between the main occupations associated to each major and the others (in the example, it is represented by the similarity between economists and other occupations, such as engineers or teachers). This way, we obtain the match index for each pair of major-occupation – in our example, the match index between Economics and engineers is represented by the similarity index between economists and engineers. Besides, based on the same NLP approach, we measure the relatedness of the previous work experience to the current job, which captures on-the-job learning and represents our proxy for job-to-job match. We believe that including a control variable for job-to-job match contributes to the robustness of our results and adds evidence on the returns to matching the previous work experience to the current job.

Our research is closely related to the literature on the effects of field-of-study match/mismatch. Previous research has mainly explored the wage penalties to the misalignment between field of study and occupations in Brazil (Reis (2018)), Europe (Iammarino and Marinelli (2015); Montt (2017)), China (Zhu (2014)), and United States (Robst (2007a,b); Yakusheva (2010); Nordin et al. (2010); Bender and Heywood (2011); Kinsler and Pavan (2015); Almasi et al. (2020); Choi and Hur (2020); Guvenen et al. (2020); Schweri et al. (2020)). In addition, less explored topics have studied the effects of horizontal match on turnover, job satisfaction and firm productivity (Kampelmann and Rycx (2012); Choi and Hur (2020); Ge et al. (2020); Guvenen et al. (2020)).

Most of the literature mentioned above have focused on the effects of post-secondary education match on labor market returns, since it uses to focus on specific skills according to the chosen field of study, while basic education tends to teach more general skills. In particular, the major-job match literature extends the research on the returns to tertiary education (Kinsler and Pavan (2015); Altonji et al. (2016)).

This topic is also relevant to the discussion on the alignment of the higher education supply with the labor market demand. For example, previous evidence already discussed the gap between the expansion of college enrollments and available jobs for Europe and Brazil (Biagi et al. (2020); Ortiz et al. (2020)). The gap between the demand and the offer of qualified workers implies in a large number of educated individuals who are unable to find a job, or have an occupation that do not match the education they received, while companies have problems in filling their vacancies (Biagi et al. (2020)).

The Brazilian case illustrates some of the challenges faced by developing countries that experienced a major expansion in higher education since the 2000s. Ortiz et al. (2020) analyzed mismatches between local labor markets and Brazilian higher education offer, and found that a high share of public universities was associated to lower mismatches, while private universities did not contribute to a better matching. This result was associated to the heterogeneous behavior in private and public institutions: private institutions use to offer low-cost majors that are already well supplied, while public universities are designed to address particular shortages of the local economy. Since private universities respond for most enrollments in Brazilian higher education, the results found in Ortiz et al. (2020) suggest a relevant regional gap between higher education enrollment and labor market demand in Brazil.

The literature on horizontal match is consistent with the human capital theory. In particular, some authors described the formal education as a form of human capital accumulation in which individuals develop different skills according to the field of study they choose (Robst (2007a); Kinsler and Pavan (2015)). In fact, the literature refers to human capital accumulation through education analogously to on-the-job learning – for example, Kinsler and Pavan (2015) described the evolution of skills according to majors, which is similar to the ability development through work experience described by Gathmann and Schönberg (2010). So, on-the-job learning and formal education are forms of human capital accumulation and, this way, provide workers with skills to perform the tasks required by occupations in the labor market. Under this framework, mismatched workers use fewer skills learned in college or accumulated in previous jobs then matched workers, which means that part of the accumulated human capital is useless to perform the job (Robst (2007a); Gathmann and Schönberg (2010)). Moreover, if college and on-the-job learning human capital are substitutes, mismatched workers would invest more in on-the-job training, which would reduce the income difference to the matched individuals from the same field of education over time (Nordin et al. (2010)).

Finally, our research follows the literature that describes occupations as a set of tasks (Gathmann and Schönberg (2010); Yamaguchi (2012); Robinson (2018); Reis (2018); Adamczyk et al. (2022)). These authors proposed to represent occupations as vectors of tasks and measured the similarity of occupations by the distance between occupations in the task complexity space. Under this framework, the more similar the occupation vectors, the more transferable the skills are from one occupation to another. We apply this concept to measure the similarity between occupations and use it to connect each major to all occupations, based on the assumption that college programs provide individuals with skills to perform all tasks related to the main occupations associated to their major (for example, we assume that the graduates are able to complete all tasks performed by economists when graduating in Economics). In particular, our research follows Adamczyk et al. (2022) in the use of NLP analysis to measure the distance among occupations to study labor market trajectories.

Empirically, the major-job match index has been computed differently according to the data availability. Most studies focused on self-reported mismatch obtained from surveys (for example, see Robst (2007a), Zhu (2014), Kinsler and Pavan (2015), Montt (2017) and Choi and Hur (2020)), while some researches explored direct measures of major-job match/mismatch by identifying occupations that are closer to the college program (see Nordin et al. (2010) and Reis (2018)). Our research adds to the literature by innovating the methodology to compute the match index that combines a direct association and a NLP approach.

To the best of our knowledge, this is the first attempt to evaluate the effects of field-of-study match on individual job trajectories in developing countries. Besides we build a rich and unique dataset that allows us to describe the graduate work trajectories for more than 10 years. Finally, our study also innovates the mismatch literature by testing the robustness of major-job match coefficients to controlling the relatedness of previous work experience to the current job.

Our results corroborate the main findings of the literature: the greater the major-job match, the higher the wage and the smaller the turnover. We also explore heterogeneous effects in wage estimations for gender, type of job, vertical mismatch status and field of study. The estimates show higher wage returns to education match for women, workers in occupations that require the college degree, private sector employees and graduates in fields such as Law, Education, Portuguese and foreign languages, and Production and engineering.

Additionally, we explore the job-to-job match index. The inclusion of this variable in our estimates does not change the main findings. Besides, the increasing in labor market experience over time do not imply in reducing the return to major-job match, at least over the first 12 years following graduation. We are also able to compare the effects of major-job match with job-to-job match: the estimates evidence the positive returns to job-to-job match, which tends to be higher then the major-job match effect.

This paper is structured as follows. In section 3.2, we present our concept of major-job and job-to-job match and its implications for labor market outcomes. We describe the data in section 3.3. The empirical strategy for accounting the match indexes is discussed in section 3.4. Section 3.5 presents the returns to major-job match, explores the role of job-to-job match in our results, and discusses the heterogeneity in estimations by demographic profiles, vertical mismatch, type of job and field of study. We also explore the effects of our match indexes on turnover in section 3.6. Finally, section 3.7 presents the main conclusions.

3.2 Conceptual framework

This section describes the conceptual framework for the major-job match and its labor market returns[1]. Under this framework, workers receive a wage that depends on the human capital accumulated throughout college and labor market experience that is transferable to the current occupation[2][3].

[1]We follow Gathmann and Schönberg (2010), which builds a conceptual approach based on the classic Roy model (see Roy (1951)) to describe the implications of skill transferability for occupational mobility.

[2]Our approach is similar to Gathmann and Schönberg (2010) and Robinson (2018), which also measured the distance between occupations. In our case, we take into account the distance between any major-occupation pair.

[3]For an in-depth discussion about the returns to major choice and major-job match, see Kinsler and Pavan (2015). They developed and estimated a structural model of major choice and labor market outcomes, wherein individuals choose the field of study in the first stage, whereas in the second stage, they choose a job that may or may not be related to the major.

3.2.1 Occupations and the task approach

Suppose there is a fixed number of tasks that are performed in the production of goods and services. Workers combine these tasks in different intensities according to the occupation requirements. In other words, some tasks may be crucial for the job, some may be just partially performed, and others can be irrelevant. Thus, occupations differ in the relative importance of each task for production as suggested by Gathmann and Schönberg (2010).

For example, if the economy requires only two kinds of tasks, e.g.,programming (t^P) and negotiation (t^N), we expect engineers and business professionals to perform each task at different intensities – while engineers need to master programming, but do not need to master negotiation, business professionals have to acquire negotiation abilities but do not need to know programming. The ability to accomplish the tasks in the labor market is part of the workers' human capital, which they accumulate throughout their lives. The productivity of workers in an occupation – and consequently their salaries – depends on the amount of ability (the accumulated human capital) they use to perform the job tasks.

3.2.2 Ability and human capital accumulation

Individuals finish the secondary education endowed with an scholastic ability to perform the tasks required by the occupation i ($\mathbf{t}_i$). The abilities required by occupations are represented by a vector of abilities to execute each task. As exemplified, if the economy requires only programming (t^P) and negotiation (t^N), then $\mathbf{t}_i = [t_{iP}, t_{iN}]$.

While in college, individuals develop abilities in each task, according to the major they choose. So, an individual who chooses the major M accumulates the ability $\mathbf{H}_i^M$. The skills accumulated in college can be described as a vector of ability in each task ($\mathbf{H}_i^M = [H_{iP}^M, H_{iN}^M]$). In this case, $\mathbf{H}_i^M$ depends directly on the major choice.

Individuals also develop ability in the labor market through passive learning-by-doing. Human capital that is accumulated through work experience resembles college human capital, such that, $\mathbf{H}_i^L = [H_{iP}^L, H_{iN}^L]$. $\mathbf{H}_i^L$ depends on the previous labor market experience.

More specifically, the total ability (T_{it}) of an individual i in time t depends on the initial endowment ($\mathbf{t}_i$), the accumulation of ability throughout the formal education ($\mathbf{H}_i^M$) and the previous experience in the labor market ($\mathbf{H}_i^L$):

$$T_{it} = \mathbf{H}_{it}^{M} + \mathbf{H}_{it}^{L} + \mathbf{t}_i \tag{3.1}$$

3.2.3 Labor market

3.2.3.1 Tasks and occupation productivity

Productivity of the individual i in the occupation o depends on the accumulated ability required to perform the occupation tasks. Suppose that the use of an ability in a specific occupation is maximum when individuals master the tasks required by the occupation. In this case, the human capital is fully transferred to the job and the maximum productivity is achieved. Alternatively, if workers accumulate part of the ability to execute the task without mastering it, the maximum productivity in the occupation is not achieved. On the other hand, if workers accumulate human capital to execute a task that is not required by their occupation, it will be useless. In summary, the accumulated ability may be partially or fully transferred to the job tasks according to the distance between the human capital accumulated by workers and the one required by occupations.

Equation 3.2 formally describes the productivity function (measured in log units):

$$\ln X_{iot}^{ML} = \rho_o^M \underbrace{[\boldsymbol{\lambda}_o^M(\mathbf{H}_{it}^M)]}_{S_{io}^M} + \rho_o^L \underbrace{[\boldsymbol{\lambda}_o^L(\mathbf{H}_{it}^L)]}_{S_{io}^L} + \underbrace{\rho_o^A \underbrace{[\boldsymbol{\lambda}_o^A(\mathbf{t}_i)]}_{S_{io}^A}}_{m_{io}} \tag{3.2}$$

where X_{iot}^{ML} consists of the task productivity of worker i, with major M and previous experience L, employed in the occupation o. $\boldsymbol{\lambda}_o^M$, $\boldsymbol{\lambda}_o^L$ and $\boldsymbol{\lambda}_o^A$ are vectors with objective measures of human capital from major, labor market experience and scholastic ability, respectively, that are combined to perform each occupation task; and ρ_o^M, ρ_o^L, ρ_o^A are the returns to each type of human capital (major pursued, work experience and scholastic ability, respectively). The terms in vectors $\boldsymbol{\lambda}_o^M$, $\boldsymbol{\lambda}_o^L$ and $\boldsymbol{\lambda}_o^A$ range from 0 to 1, indicating the proportions of previously accumulated abilities in each task that are effectively transferred to the occupation.

Because our main interest lies on the effect of the general match level between each human capital source and all occupation tasks instead of individual task match, we can simplify the notation in equation 3.2 henceforth as follows: $\boldsymbol{\lambda}_o^M(\mathbf{H}_{it}^M) = S_{io}^M$, $\boldsymbol{\lambda}_o^L(\mathbf{H}_{it}^L) = S_{io}^L$ and $\boldsymbol{\lambda}_o^A(\mathbf{H}_{it}^A) = S_{io}^A$. The terms S_{io}^M, S_{io}^L and S_{io}^A measure the amount of accumulated ability – from major, work experience and scholastic ability, respectively – that is used to perform all tasks within occupation o. Finally, the term m_{io} reflects the return to the initial scholastic ability endowment.

3.2.3.2 Wages

Wages in occupation o and time t for the individual i with major M and previous experience L in the labor market equal the productivity multiplied by the occupation-specific price, P_o. Thus, the wage determination is described by the equation 3.3:

$$\ln w_{iot}^{ML} = p_o + \rho_o^M S_{io}^M + \rho_o^L S_{io}^L + m_{io} \tag{3.3}$$

where $p_o = \ln P_o$. Equation 3.3 is straightforward to explain why workers earn more when employed in an occupation that does not perfectly match their major. To illustrate this, consider a worker who earn the major $\hat{O}$ that matches perfectly the occupation o (i.e. $\boldsymbol{\alpha}_o = [\mathbf{1}]$). Consider an alternative job in an occupation o' that does not match perfectly the individual's major (i.e., at least one term in the vector $\boldsymbol{\alpha}_{o'}$ is lower than 1). Thus, $S_{io}^M = 1$ and $S_{io'}^M < 1$. For simplicity, suppose that the worker i has no previous experience in the labor market, so $S_{io'}^L = S_{io}^L = 0$. Thus, the worker receives a smaller wage in occupation o' if:

$$(p_{o'} - p_o) + (\rho_{o'}^M S_{io'}^M - \rho_o^M) + (m_{io'} - m_{io}) < 0 \tag{3.4}$$

Equation 3.4 suggests that major-job mismatch in o', compared to a perfect major-job match in o, determines a wage penalty whenever the average price per unit of productivity in occupation o' is smaller than in o ($p_{o'} < p_o$), the return to ability accumulated from major degree M is smaller in this new occupation ($\rho_{o'}^M < \rho_o^M$) and the return to the scholastic ability is also smaller ($m_{io'} < m_{io}$). On the other hand, if one of these returns is higher in the second occupation (o') and compensates the penalty in other components, then deviating from the perfect match is advantageous for workers. So, it is possible that a worsening in the major-job match will lead to a "ceteris paribus" increase in wage as long as the abilities that are transferable to the occupation o' are more valuable in its market than the sum of all the useful abilities in o and respective prices.

If we allow on-the-job learning, the human capital accumulated through labor market experience can also be transferred between occupations and compensate or reinforce the wage penalty of deviating from a job that perfectly matches the major degree.

We describe our strategy for computing the similarity among occupations in the section 3.4 and its use as proxies for major-job and job-to-job match indexes.

3.3 The data

Our dataset combines the data about senior undergraduate students for the years 2004, 2005 and 2006 and their labor market trajectory until 2018. We describe each data source below.

3.3.1 Senior students' data

The National Institute for Educational Studies and Research (INEP)[4] – an agency within the Ministry of Education and the main institution for education statistics in Brazil – provides the data about senior undergraduate students.

In 2004, the National System of Higher Education Evaluation (SINAES)[5] established an accountability system for monitoring the quality of higher education institutions in Brazil. Along with the SINAES, INEP established the National Student Performance Exam (ENADE)[6], a standardized exam applied to senior students covering the core disciplines of each program. The undergraduate programs are evaluated every three years according to the ENADE cycle that determines the fields that are going to be evaluated each year[7], and its results feed into the ENADE Index, which consists of the average performance of students in each discipline.

We use identified data from the first cycle of the ENADE, i.e. covering the period between 2004 and 2006. The microdata covers information about senior and freshman students of each program, including student performance and socioeconomic characteristics. We discarded observations about fresh-

[4]Instituto Nacional de Estudos e Pesquisas Educacionais Anísio Teixeira in Portuguese .

[5]Sistema Nacional de Avaliação do Ensino Superior in Portuguese .

[6]Exame Nacional de Desempenho de Estudantes in Portuguese. See Law 10861 of April 14, 2004.

[7]See Regulatory Ordinance no 40, of December 12, 2007.

man students, due to the high dropout rates in Brazilian higher education[8]. Our initial sample totals 445,825 observations. We drop observations with invalid identification and senior students who attended more than one undergraduate program between 2004 and 2006. Besides that, we also remove students who did not attend the exam. Our final sample consists of 346,379 senior students in programs grouped into 84 fields of study (the Appendix A describes the fields of study evaluated per year) .

3.3.2 Formal labor market data

The Ministry of Labor (MTE) – the federal authority for employment issues in Brazil – provides the data on formal labor market in the Annual Social Information Report (RAIS)[9]. RAIS is an annual administrative record covering information of all formal workers (i.e. those who have a formal employment relationship with an employer) in all sectors of the economy (agriculture, manufacturing, construction and services). All companies are legally obliged to report its employees information. RAIS informs individual characteristics such as occupation, wage, date of admission, date of separation, sector, gender, age and race, but it does not inform the employee major. The dataset also informs employer information, including location and company size. RAIS allows us to follow the same person over time, so that we can evaluate the workers' employment trajectories in formal labor market[10].

We use data from RAIS for the period between 2003 and 2018. We combined ENADE data described in the section 3.3.1 with RAIS data by the national unique individual identification code (the CPF). Then, we identify the employment contracts for each graduate from ENADE data and whether or not they were in a formal contract.

We exclude potential incorrect registries, outliers in terms of salary and observations without the occupation code (about 10% of the observed employment contracts for the sample of graduates described previously)[11].

[8] According to INEP, the dropout rate is around 50%.

[9] Relação Anual de Informações Sociais in Portuguese.

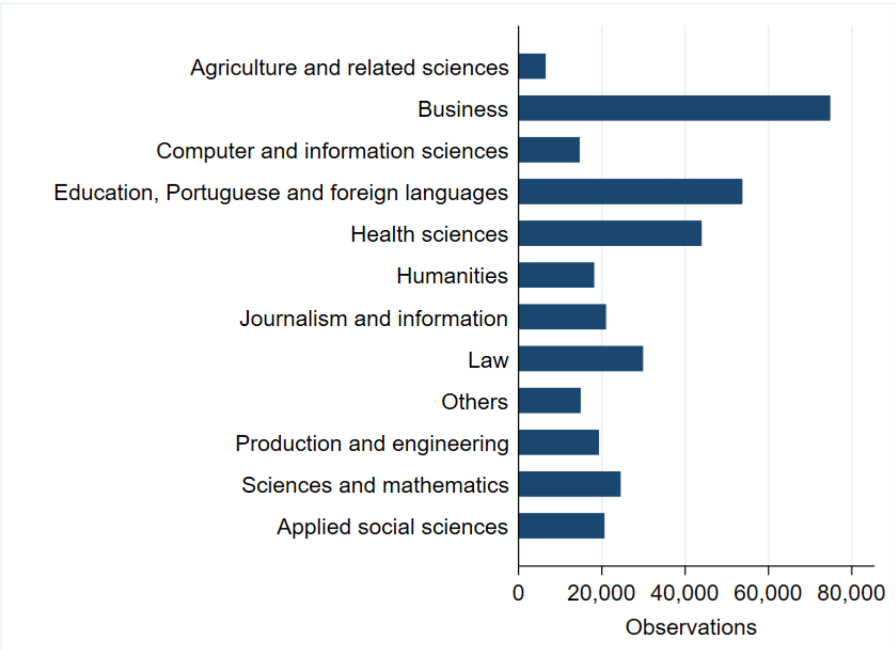
[10] As data covers only the formal employment contracts, we cannot tell whether the exit from the administrative records in RAIS means a transition to unemployment, informality or to employer statuses.

[11] These exclusions did not changed significantly our main results.

3.3.3 Descriptive statistics

Figure 3.1 shows the distribution of senior students taking the ENADE exam between 2004 and 2006 by field of study[12]. Programs within Business concentrate the highest number of senior students in our dataset (78,000 observations, representing 22% of our sample). Education, Portuguese and foreign languages and Health areas stand out with 16% and 13% of the sample, respectively.

Table 3.1 presents a summary of individual characteristics. Field specific average performance in ENADE is 39 points, while the mean grade in general knowledge is 49 points. Our sample of graduates has 28 years on average in the year of graduation, with a standard deviation of 7.3 years. Most of them started working before finishing higher education (55%). The data also indicates that most of graduates are self-declared whites (71%), and belong to families with income over 3 minimum wages (79%). About 60% of our sample are women and 57% finished the high school in a public institution. Scholarships and student loans are also representative in our sample (23% of the senior students received a scholarship and 47% had access to a student loan).



Source: INEP. Authors' elaboration.

Figure 3.1: Number of graduates by area

[12]The section D displays the categorization of detailed fields by aggregated fields of study.

Table 3.1: Senior students' characteristics

Variable	N	Mean	Std. Dev.
Field-specific grade (from 0 to 100)	346,367	39.21	16.56
General knowledge grade (from 0 to 100)	346,361	49.08	18.61
Job before graduation (proportion)	341,936	0.55	0.50
Age (years)	346,379	27.92	7.35
White (proportion)	289,275	0.71	0.45
Male (proportion)	346,379	0.40	0.49
Income up to 3 minimum wages (proportion)	287,857	0.21	0.41
Parents with a college degree (proportion)	288,325	0.23	0.42
Public school (proportion)	289,540	0.57	0.50
Scholarship (proportion)	286,706	0.23	0.42
Student loan (proportion)	287,321	0.47	0.50

Source: INEP. Authors' elaboration.

Notes: Statistics are based on students' answers to the socioeconomic questionnaire and ENADE results.

Table 3.2 reports employment characteristics of the sample by area. The results highlight different patterns in formal employability across fields: graduates from programs within Agriculture and related sciences, Law and Health sciences present a formal employment rate about 50%, while workers with a major in Business, Computer and information sciences, Humanities, Education, Portuguese and foreign languages or Sciences and mathematics present a much higher formal employability, about 70%. On the other hand, workers with major in Production and engineering, Computer and information sciences and Law receive the highest hourly wage in the sample (R$ 29.7, R$ 22.4 and R$ 22.1, respectively). The turnover is at 28% for all sample.

Figures 3.2, 3.3 and 3.4 show the employment trajectory since graduation. Formal employability rises in the first years after graduation, but decreases after eight years. This pattern reflects economic conditions that reduced the availability of formal jobs[13]. The hourly wage increases over all period, but it does at a slower pace in the last years. We also notice that the turnover increases in the first year after graduation, but decreases until the 10th year since graduation, which is an expected result as the firm cost of firing an employee increases over time in Brazil.

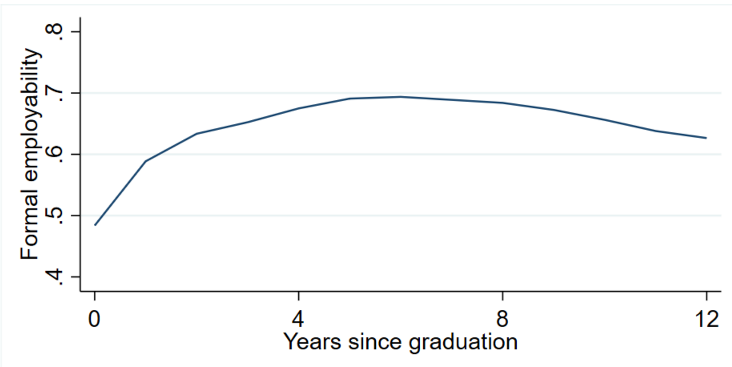
[13]Between 2014 and 2016, the Brazilian economy lost 3.5 million formal vacancies in response to the fall in GDP. Since then, the economy has registered low growth, and the formal employment did not recover the level before the crisis.

Table 3.2: Employment characteristics

Areas	Formal employability (%)	Real hourly wage (R$)	Turnover (%)
Agriculture and related sciences	49.95	16.6	33.90
Business	71.12	17.6	28.74
Computer and information sciences	73.01	22.4	28.50
Education, Portuguese and foreign languages	77.14	14.9	21.49
Health sciences	48.33	15.9	34.65
Humanities	70.78	15.7	22.94
Journalism and information	60.56	17.3	35.28
Law	49.01	22.1	23.16
Others	55.88	13.7	35.18
Production and engineering	64.66	29.7	29.26
Sciences and mathematics	71.78	16.8	24.91
Applied social sciences	58.08	18.5	31.37
Total	64.47	17.7	27.82

Source: INEP and MTE. Authors' elaboration.

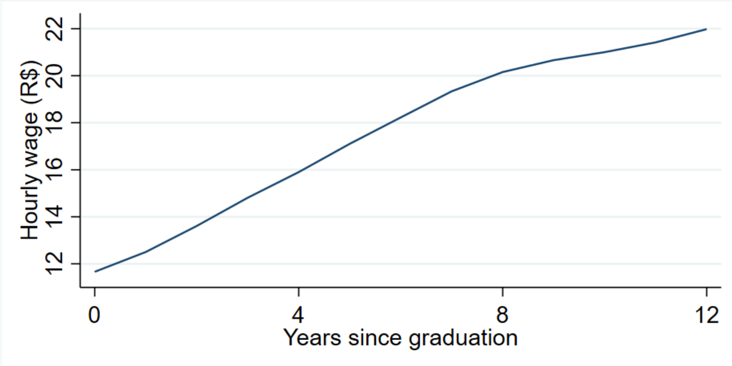
Notes: The dataset includes information from ENADE for years between 2004 and 2006 and formal employment records from RAIS up to 2018. We restrict results to observations up to 12 years following ENADE's exam in order to have the same number of periods observed for each year of evaluation. Hourly wage and turnover are calculated only for graduates in formal jobs. Real hourly wage is adjusted for inflation based on IPCA - Brazilian consumer price index. Turnover is the proportion of employees changing jobs or leaving the formal labor market in the next period.



Source: INEP and MTE. Authors' elaboration.

Figure 3.2: Formal employment by year since graduation

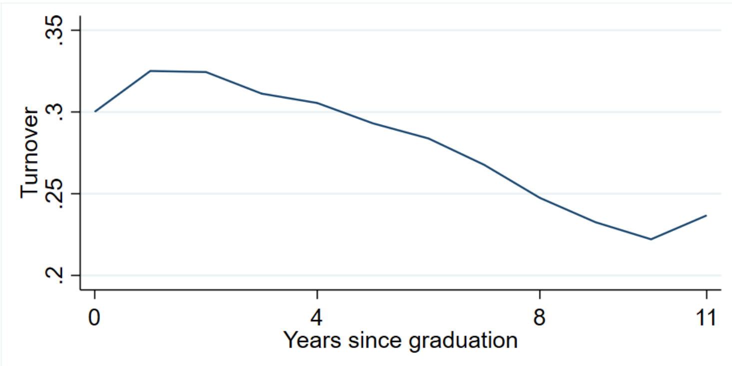
Notes: The dataset includes information from ENADE for years between 2004 and 2006 and formal employment records from RAIS up to 2018. The employment variable is the proportion of graduates in a formal job by years since graduation.



Source: INEP and MTE. Authors' elaboration.

Figure 3.3: Real hourly wage by year since graduation

Notes: The dataset includes information from ENADE for years between 2004 and 2006 and formal employment records from RAIS up to 2018. Hourly wage is adjusted for inflation based on IPCA - Brazilian consumer price index. The variable is calculated only for formally employed individuals in the year.



Source: INEP and MTE. Authors' elaboration.

Figure 3.4: Turnover by year since graduation

Notes: The Dataset includes information from ENADE for years between 2004 and 2006 and formal employment records from RAIS up to 2018. Turnover is the proportion of employees who moved to a different firm or left the formal labor market in the next period. The variable is calculated only for graduates in formal jobs.

3.4 Measuring major-job match

3.4.1 Occupation description

We rely on the Brazilian Occupation Classification (CBO)[14] – also provided by the MTE - to identify the tasks attributed to each occupation and calculate the match index (see section 3.4). CBO is based on the DACUM method

[14]Classificação Brasileira de Ocupações in Portuguese. Available at `http://www.mtecbo.gov.br`

– Developing a Curriculum -, which consists of meetings with experienced professionals to describe their jobs and duties. In a 2-day workshop, a group of 8 to 12 experts describe each occupation, which results in the occupation profile that is validated by another group. The MTE mobilized 7 thousand experts to build the 2002 edition of the CBO, that described 607 occupations at the 4-digit level (the broad occupation level) (MTE (2010)).

The current edition of the CBO describes 618 broad occupations, containing information about tasks performed by workers and general requisites such as tools and level of education[15]. Each broad occupation contains detailed occupations at the 6-digit level, amounting to 2641 different categories. Because occupations within the broad occupation level are quite similar, our definition of "occupation" refers to the broad occupation level (i.e. we refer to each category described at the 4-digit level as an individual occupation).

The occupational profile table contains the list of the activities performed by each occupation at the 6-digit level[16]. We use this information to measure the similarities among occupations. We also use the broad occupation description to obtain information about the level of education and the specific major required when these information are available. This data is disposable in the web page of the CBO, and we "scrapped" the website to tabulate the information.

3.4.2 The match indexes

One of the main challenges of our study consists of calculating the match indexes. The literature applies many different strategies to determine the major-job match according to the availability of data about the relationship between fields of study and occupations. Most studies focused on self-reported mismatch obtained from surveys that ask employees whether they work in a closely related, partially related or not related occupation to their previous training (for example, see Robst (2007a), Zhu (2014), Kinsler and Pavan (2015), Montt (2017), Choi and Hur (2020)). On the other hand, some researches explored direct measures of major-job match/mismatch by identifying occupations that are closer to the college program (see Nordin et al. (2010) and Reis (2018)). This second approach is more objective than self-reported match measures (Robst (2007a); Nordin et al. (2010); Somers et al. (2019)).

[15]The current edition is an upgrade of the 2002 CBO edition. Since then, new occupations were added to the classification. Nonetheless, the description of previously added occupations is very similar to the one in 2002.

[16]Available at `http://www.mtecbo.gov.br/cbosite/pages/downloads.jsf`.

In this paper, we combine this second approach with a natural language processing (NLP) strategy to determine the closeness between each field of study and any other occupation. Thus, we build a continuous major-job match index that varies from 0 to 1. The index is based on the following steps: (1) first, we link each field of study to at least one directly related occupation; (2) we calculate the similarity between each pair of occupations using a pre-trained NLP model; and (3) we define the closeness between each pair of major and occupation. In addition, we describe our proxy for the job-to-job match index in step (4), which relies on the similarity index from the step (2). We describe each step below.

(i) Identifying the main occupations related to each field of study

We assume that graduates learn skills and acquire knowledge to perform all activities related to the main occupations associated to their major. Thus, we link each major to at least one occupation combining information from the occupation description in the CBO, the correspondence adopted by Reis (2018) and the results from the ranking of the most frequent occupations by major in our sample[17]. The appendixB displays the final table that lists the main occupations associated to each field of study.

(ii) The similarity index between occupation pairs

The similarity index between occupations is based on the task description. As mentioned in the section 3.4.1, the occupational profile table from the CBO describes the activities performed by each occupation[18]. The table comprises 4180 aggregated activities and each occupation at the 4-digit level is described by 4 to 15 aggregated activities[19]. The activities are described with a verb and an object – for example, "to analyze data" and "to teach the students". The wide variety of descriptors for activities stems from the absence of a standardization process in CBO, i.e., we can find similar activities described in many different ways (for example, "to analyze data", "to analyze the data" or "to evaluate data"). The NLP approach is then applied to handle the wide variability in task description and objectively measure the distance among occupations.

First we clean the activities description removing stopwords and special

[17] Each field of study is associated with 212 (minimum 63 and maximum 544) different occupations on average in our sample, and these results can be obtained upon request to the authors.

[18] The occupational profile table from the CBO is organized at the 6-digit level and we group it into the 4-digit level.

[19] The table also describes 45,833 detailed activities, and each occupation is described by 5 to 181 detailed activities. We do not use the description of detailed activities in this study.

characters[20] and group them into one document by occupation[21]. Second, we use the pre-trained model BERTimbau, a Bert model trained for Brazilian Portuguese (Souza et al. (2020)), to map our documents into vectors of reals numbers – i.e. we apply a sentence embedding strategy to transform the group of work activities attributed to each occupation into a vector representation. Specifically, we use the base version of the BERTimbau model, which maps text into a vector of the size 768. Third, we compute the occupation similarity as the vector distance measured by the cosine similarity index as described in equation 3.5:

$$Similarity_{AB} = \frac{A * B}{\|A\| * \|B\|} = \frac{\sum_{A_i * B_i}}{\sqrt{\sum_i A_i^2} * \sqrt{\sum_i B_i^2}} \tag{3.5}$$

where $Similarity_{AB}$ is the similarity index for the pair of occupation vectors A and B. The index varies between 0 and 1, and the occupations are more similar the closer the index is to 1.

Applying the BERTimbau model contributes to directly identify text similarities among occupation task description. Besides, this model has the advantage of capturing the context meaning[22], since it is based on the BERT model trained by Google which is considered the state of the art among NLP models (Devlin et al., 2018).

(iii) The distance between each field of study and occupation (the major-job match index - S^M_{iot})

We assume that graduates are able to fully perform activities related to the main occupations associated to their major. By definition, it means that the similarity between the main occupations associated to each field of study equals to 1. For example, we assume that the graduates are able to complete all tasks performed by economists when graduating in Economics. So that, economist is the main occupation associated to the programs in Economics, which we define as a perfect match – i.e. S^M_{iot} equals to 1 if a worker i majored in $M = Economics$ and works as $o = economist$ in period t.

[20]We also removed activities like “to demonstrate personal skills”, since they are more generic than the activity description.

[21]In NLP approach, the documents are the distinct text objects. In our case, each occupation is described by one document that comprises all activities attributed to this occupation.

[22]This is particularly advantageous in comparison to applying the TF-IDF (term frequency-inverse document frequency) approach. It is a statistical measure that evaluates how relevant a word is to a document in a collection of documents and it is calculated by multiplying how many times a word appears in a document, and the inverse document frequency of the word across a set of documents. This way, TF-IDF does not take into account neither the similarity between words, neither the meaning of words in a context.

We also suppose that the match level between majors and jobs is represented by the similarity between the main occupations associated to each major and other occupations. So, combining steps (1) and (2) we compute the similarity for each pair of major and occupation in our dataset[23]. For majors that we impute 2 or more related occupations, we consider the highest similarity index among the occupations.

Considering the case above, we determine the similarity between Economics and each occupation as the similarity index calculated for economists and each other occupation in the CBO. So that, the major-job match index for workers who majored in Economics but work as administrators equals to 0.72 (the similarity index between economists and administrators). On the other hand, the graduates in Economics who are employed as a shoe and leather worker register an index equal to 0.20. The appendix C describes some of the highest and lowest matches in our dataset.

(iv) The proxy for job-to-job match (S^{L}_{iot})

As we highlight in the section 3.2, the experience accumulated in the labor market that is transferable to the current occupation is also relevant in the wage equation. We also use the $Similarity_{AB}$ to build a proxy for job-to-job match (S^{L}_{iot}). We calculate the index as the average of the $Similarity_{AB}$ between the current job and each of the three previous jobs. If a worker did not have a job in one of these years, then we compute a $Similarity_{AB} = 0$ for this year. Then, the index consists of the mean transferability of the tasks used in the previous formal jobs to the current job.

We also test variations in the empirical strategy by considering only one previous job, five or ten previous jobs. Using these variations instead of the proposed measure – that considers only three previous jobs - does not significantly change our main conclusions.

3.4.3 Patterns in major-job match

Table 3.3 displays the summary statistics for major-job and job-to-job match indexes by area. The major-job match is 0.67 for workers who completed the higher education between 2004 and 2006 and were employed in the formal

[23] Reis (2018) also estimated a continuous match measure based on the distance between each pair of occupations. The author first grouped the activities described in the CBO into 18 task categories. Then, he described each occupation as a vector with 18 positions that express the relevance of each of these categories in its description. The author calculated the distance between occupations as the cosine similarity between the two vectors used to describe each pair of occupations.

labor market up to 2018. Job-to-job match index equals 0.73. Nevertheless, the standard deviation index is greater for the job-to-job match than for the major-match index. The major-job match varies significantly across areas: Agriculture and related sciences have the lowest average for major-job match (0.45), while Education, Portuguese and foreign languages have the highest value for the index (0.77). Job-to-job match varies between 0.66 and 0.78 on average.

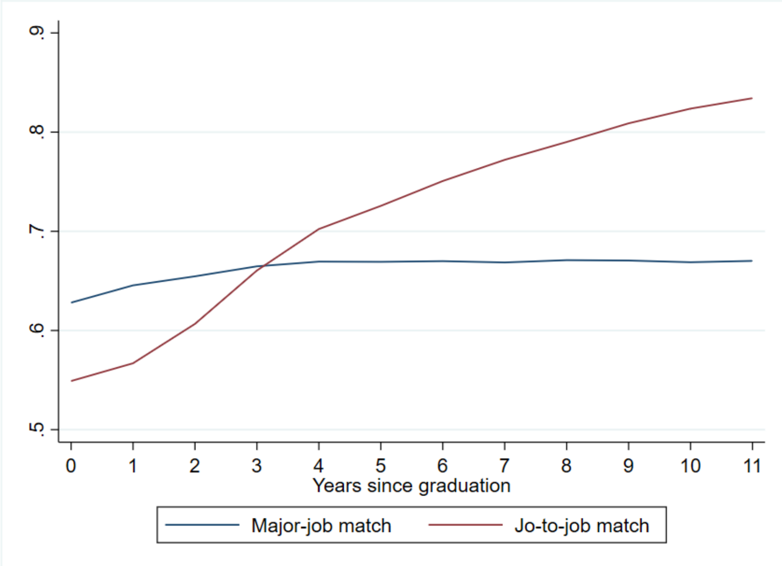
Table 3.3: Descriptive statistics of major-job match and job-to-job match by area

Areas	Match	mean	sd	min	max	N
Agriculture and related sciences	S^M_{iot}	0.45	0.18	0.00	1.00	45,807
	S^L_{iot}	0.66	0.34	0.00	1.00	
Business	S^M_{iot}	0.63	0.16	0.06	1.00	656,943
	S^L_{iot}	0.78	0.26	0.00	1.00	
Computer and information sciences	S^M_{iot}	0.75	0.19	0.08	1.00	136,884
	S^L_{iot}	0.73	0.30	0.00	1.00	
Education, Portuguese and foreign languages	S^M_{iot}	0.77	0.19	0.23	1.00	544,913
	S^L_{iot}	0.78	0.27	0.00	1.00	
Health sciences	S^M_{iot}	0.60	0.16	0.12	1.00	301,042
	S^L_{iot}	0.66	0.34	0.00	1.00	
Humanities	S^M_{iot}	0.73	0.21	0.23	1.00	166,655
	S^L_{iot}	0.74	0.30	0.00	1.00	
Journalism and information	S^M_{iot}	0.67	0.20	0.21	1.00	157,450
	S^L_{iot}	0.68	0.31	0.00	1.00	
Law	S^M_{iot}	0.54	0.20	0.10	1.00	163,990
	S^L_{iot}	0.71	0.34	0.00	1.00	
Others	S^M_{iot}	0.54	0.20	0.04	1.00	103,575
	S^L_{iot}	0.67	0.31	0.00	1.00	
Production and engineering	S^M_{iot}	0.67	0.23	0.05	1.00	148,623
	S^L_{iot}	0.69	0.32	0.00	1.00	
Sciences and mathematics	S^M_{iot}	0.73	0.20	0.19	1.00	229,074
	S^L_{iot}	0.73	0.30	0.00	1.00	
Applied social sciences	S^M_{iot}	0.60	0.19	0.15	1.00	149,402
	S^L_{iot}	0.71	0.32	0.00	1.00	
Total	S^M_{iot}	0.67	0.20	0.00	1.00	2,804,358
	S^L_{iot}	0.73	0.30	0.00	1.00	

Source: INEP and MTE. Authors' elaboration.

Notes: We use data from ENADE between 2004 and 2006 and the RAIS records up to 2018. The major-job match is an index that indicates the similarity between the job performed by workers and their major. The job-to-job match measures the similarity between the current job and the jobs performed by workers in the previous three years.

Figure 3.5 displays the match indexes by years since graduation. We observe a relative stability in major-job match, whereas job-to-job match index increases throughout the period.



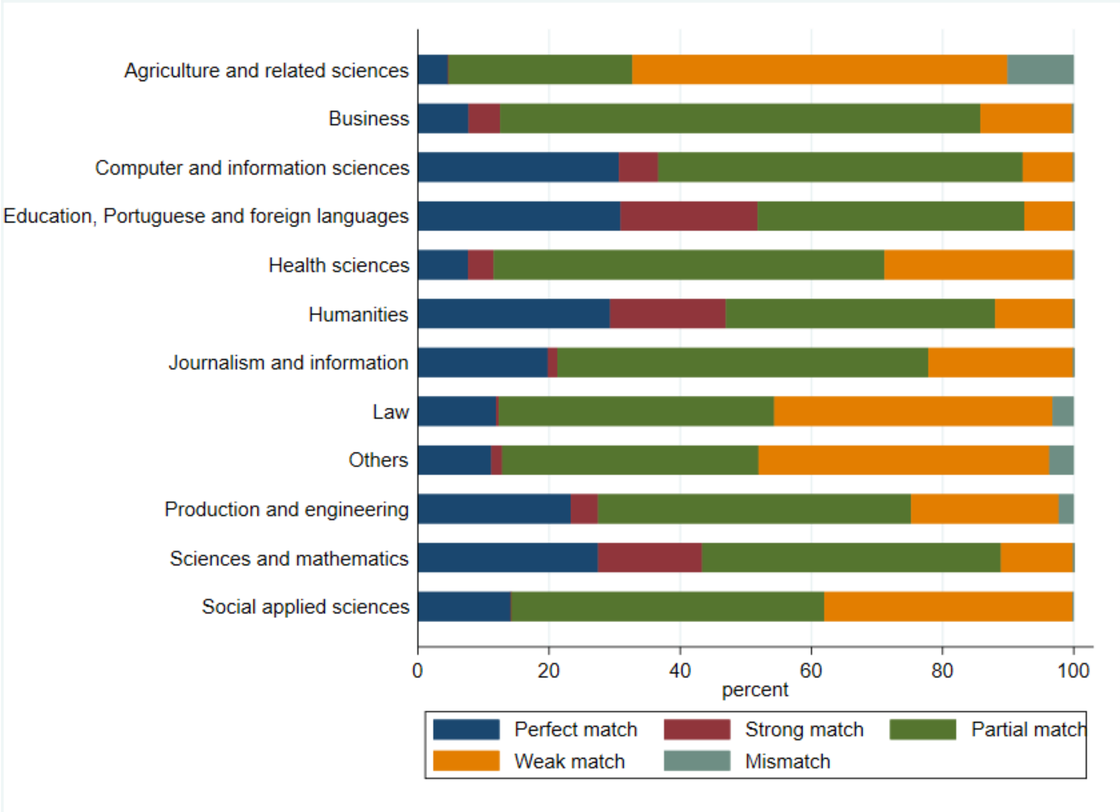
Source: INEP and MTE. Authors' elaboration.

Figure 3.5: Major-job match and job-to-job match over years since graduation

Notes: We use data from ENADE between 2004 and 2006 and the RAIS records up to 2018. The major-job match is an index that indicates the similarity between the job performed by workers and their major. The job-to-job match measures the similarity between the current job and the jobs performed by workers in the previous three years.

Figure 3.6 shows the distribution of observations by match level. The match category (in blue) includes only workers in occupations that perfectly match their major (i.e $S_{iot}^{M} = 1$); the strong match (red) includes workers with $0.75 \leq S_{iot}^{M} < 1$; the partial match (green) includes workers with $0.5 \leq S_{iot}^{M} < 0.75$; the weak match (yellow) includes workers with $0.25 \leq S_{iot}^{M} < 0.5$; and the mismatch category (grey) comprises workers with an index $S_{iot}^{M} < 0.25$. The figure highlights that few observations are classified in the "mismatch" category (less then 1% or our sample). The programs in Agriculture and related sciences register the higher mismatch compared to the other areas (10%). The observations are mainly concentrated in the weak match (53%) and partial match (19%) categories. Strong and perfect match categories respond to 9% and 18% of all sample, respectively.

On the other hand, the match patterns differ significantly by areas. For example, while Education and Portuguese and foreign languages concentrate 52% of the observations in "match" and "strong match" categories, only 5% of workers from Agriculture and related sciences are classified among those categories.



Source: INEP and MTE. Authors' elaboration.

Figure 3.6: Distribution of workers by match level

Notes: We use data from ENADE between 2004 and 2006 and the RAIS records up to 2018. The match levels indicate the similarity between the job performed by workers and their major.

3.5 Returns to major-job match

3.5.1 Empirical strategy

To estimate the contribution of major-job match to individual wage, we run the log-wage equation 3.3 from Section 3.2, with controls for individual fixed effects and job characteristics. The wage equation is then given as follows:

$$\ln w_{iot} = \rho_o^M S_{iot}^M + \rho_o^L S_{iot}^L + \beta D_{it} + y_i + e_{it} \tag{3.6}$$

where w_{iot} is the log hourly labor earnings; S_{iot}^M is the major-job match index, with return ρ_o^M (our main parameter of interest); S_{iot}^L is the job-to-job match index, with return ρ_o^L; y_i is the individual fixed effect; D is a vector of observed job characteristics (it includes variables such as the tenure in the current and in the three previous occupations and its quadratic terms; and dummies for firm state, years and occupation groups); and e_{it} is the error term.

The fixed effects estimator accounts for the individual unobserved heterogeneity. This strategy improves previous studies that are based on OLS regressions, which potentially leads to biased estimations of the returns to major-job match. In particular, the fixed effects estimator also controls for individual ability (i.e. we control time invariant fixed effects in the m_{io} term in equation 3.2). Nevertheless, the data do not allow for controlling for potential selection into occupations and formal labor market, which we acknowledge as a possible limitation of our study.

Finally, we test the sensitivity of our estimations to variations in our empirical strategy such as testing alternatives to compute the match indexes and restricting the sample considered in the estimations. We also explore heterogeneous effects in terms of gender, vertical mismatch, type of job and field of study.

3.5.2 Results

Table 3.4 shows the results for equation 3.6 estimates. The first column omits the job-to-job match term (S^L_{iot}) and the coefficient for the major-job match is 11.3%. The coefficient for S^M_{iot} remains practically the same when including S^L_{iot} in the regression (10.4%). The third column omits the occupation dummies and the coefficient for (S^M_{iot}) rises to 32.3%, while the coefficient for S^L_{iot} falls. The difference between columns (2) and (3) indicates that the omission of occupation specific dummies overestimates the effects of major-job match. The results are close to the literature estimates: for example, working in a related job was associated to a positive gain around 10% in wages in comparison to working in a not related job in Robst (2007a) and Nordin et al. (2010).

We also test the wage penalty by match levels. To this end, we add dummies of match levels and present the results in column (4) of table 3.4. The omitted group includes workers with $S^M_{iot} < 0.25$ (the mismatch level from figure 3.6). The results with theses dummies shows that the wage return to the weak match ($0.25 \leq S^M_{iot} < 0.5$) is 4.5% in comparison to the mismatch category ($S^M_{iot} < 0.25$). The return increases with levels: we compute effects of 8.6% for partial match ($0.5 \leq S^M_{iot} < 0.75$), and 10%-11% for strong and perfect matches ($S^M_{iot} \geq 0.75$). The coefficient for S^L_{iot} remains close to the one estimated in column (2), around 12%.

Table 3.4: Effects of major-job match index on wages

	(1)	(2)	(3)	(4)
Major-Job Match - S^M_{iot}	0.113***	0.104***	0.304***	
	(0.005)	(0.005)	(0.004)	
Job-Job Match - S^L_{iot}		0.124***	0.099***	0.125***
		(0.002)	(0.002)	(0.002)
Perfect Match - $S^M_{iot} = 1$				0.100***
				(0.009)
Strong Match - $0.75 \leq S^M_{iot} < 1$				0.108***
				(0.010)
Partial Match $0.5 \leq S^M_{iot} < 0.75$				0.086***
				(0.009)
Weak Match $0.25 \leq S^M_{iot} < 0.5$				0.045***
				(0.009)
Constant	3.138***	3.086***	2.625***	3.082***
	(0.027)	(0.027)	(0.024)	(0.028)
Dummies for occupation groups	Yes	Yes	No	Yes
Observations	2,651,264	2,651,264	2,673,115	2,651,264
R-squared	0.373	0.375	0.364	0.375
Unique IDs	304,225	304,225	304,617	304,225

*** p<0.01, ** p<0.05, * p<0.1.
Notes: The dependent variable is the logarithmic of the hourly wage. The match indexes are continuous and range from 0 to 1. All specifications include a vector of job characteristics (dummies for firm state, occupation groups and years), tenure in the current and the three previous jobs and its quadratic terms, and individual fixed effects. Robust standard error in parentheses.

If college and on-the-job learning human capital are substitutes, mismatched workers would invest more in on-the-job training and the return to major-job match would reduce over time (Nordin et al., 2010). To test this hypothesis, we estimate the effects of major-job match over time for inexperienced workers (graduates younger than 25 years old, who were not employed in the year of graduation) and senior workers (graduates above 35 years old, who were already employed by the time they graduated). If the hypothesis is true, we would expect a decrease in major-job match coefficient over time and higher effects for inexperienced workers than for seniors.

Figure 3.7 shows the marginal effects of major-job match by years since graduation. The effects of major-job match increases over time. Besides, the return to major-job match is negative in the first year after graduation but increases from the second year forward. The negative coefficient in the first year may reflect the career-oriented decision to accept lower paying jobs to follow a related-major career. In general, these jobs select recent graduates for trainee or similar positions as a start point for a career in the field of study.

The figure also shows that this pattern is similar for senior workers and inexperienced workers in the first 5 years after graduation. But the returns are higher for senior workers than for inexperienced ones from the sixth year after graduation onward. Overall, these estimates do not corroborate the hypothesis that the returns to major-job match in decreasing over time, at least for the first 12 years following graduation.

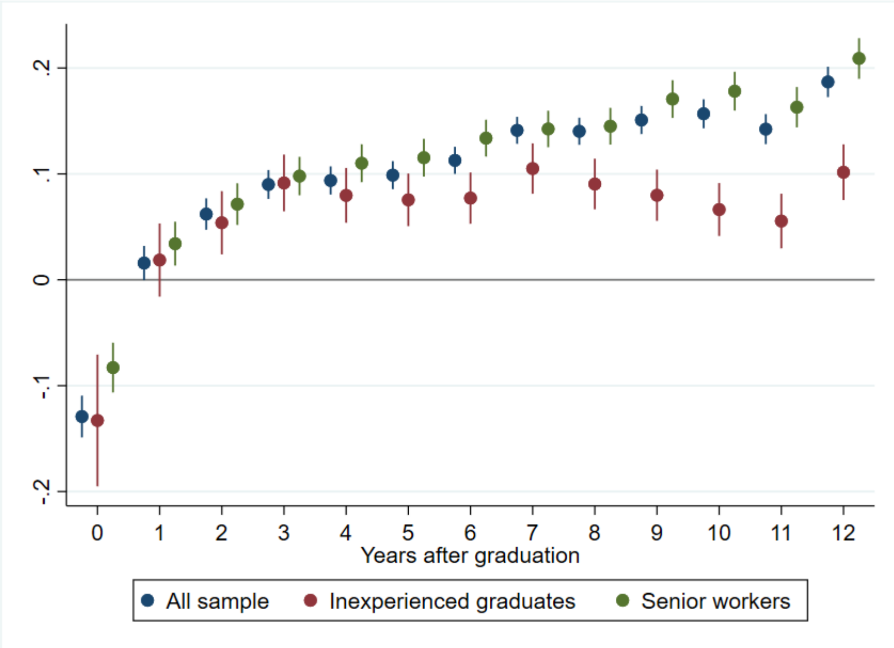


Figure 3.7: Effects of major-job match on wages by year since graduation

Notes: The figure plots the marginal effects of major-job match on wages by year since graduation. To obtain these results we include an interaction between S^{M}_{iot} and the dummies for years to the estimation. The dependent variable is the logarithmic of the hourly wage. The estimate includes a vector of job control variables (dummies for firm states, occupation groups and years), tenure in the current and the three previous jobs and its quadratic terms, and individual fixed effects. Robust standard error in parentheses.

3.5.3 Sensitivity analysis

This section explores the sensitivity of our results to variations in the empirical strategy such as testing alternative measures for the match indexes and restricting the sample considered in the estimations.

An important concern of our empirical strategy is the measurement of the match indexes. As mentioned previously, we use the base version of the BERTimbau model, which maps text into a vector of the size 768. Additionally, we also compute similarity using the large version of this model, which transforms the text into vectors of the size 1024. Column (1) of the table 3.5 shows the results using the major-job and job-to-job matches measured by the large version of BERTimbau model, which results in similar coefficients to the ones displayed in the table 3.4 (11.7% for major-job match and 15.6% for job-to-job match). We also measure the similarity among occupations using the skill description instead of the task description and applying the base version of BERTimbau model. Column (2) of table 3.4 reports the estimate using the match indexes based on the skill description and shows a slightly smaller coefficient for the match index, but still positive and statistically significant. It is worth noting that the skill description tends to be more generic, whereas task description is more specific to the occupation, so that we expect that the index based on the skill description overestimates the similarity between occupations[24]. In general, these alternative estimates of major-job and job-to-job matches corroborate the previous results in table 3.4.

Besides, if someone has an informal job that matches the current job, we are underestimating the job-to-job match. We estimate our main specification over a subsample comprising graduates observed every year after graduation in column (3) of table 3.5 and compare it with the estimate for the sample of graduates observed only 5 times or less in the same period in column (4). The results suggest that there is no significant bias in the estimates, as the coefficients are similar between individuals observed every year and those observed less often (about 10%-12%) after graduation.

[24]For example, both teachers and professional business must develop skill in communication, but they perform different tasks related to the same skill: the teacher use the communication skill to teach students, whereas business professional use it to negotiate with customers or providers.

Table 3.5: Effects of major-job match on wages - Alternative indexes

	(1) Bert-Large	(2) Bert-Base-Comp	(3) Only IDs observed every year after graduation	(3) Only IDs observed 5 times or less
S^M_{iot}	0.117***	0.070***	0.098***	0.117***
	(0.007)	(0.006)	(0.008)	(0.020)
S^L_{iot}	0.156***	0.123***	0.128***	0.065***
	(0.003)	(0.002)	(0.004)	(0.007)
Constant	3.031***	3.097***	3.117***	3.059***
	(0.039)	(0.028)	(0.045)	(0.107)
Observations	1,300,637	2,651,264	1,268,494	190,979
R-squared	0.375	0.376	0.455	0.173
Unique IDs	146,812	304,225	107,431	60,308

*** $p<0.01$, ** $p<0.05$, * $p<0.1$.
Notes: The dependent variable is the logarithmic of the hourly wage. The match indexes are continuous and range from 0 to 1. All specifications include a vector of job characteristics (dummies for firm state, occupation groups and years), tenure in the current and the three previous jobs and its quadratic terms, and individual fixed effects. Robust standard error in parentheses.

Table 3.6 varies the number of periods considered to calculate the job-to-job match index(S^L_{iot}). Because we define S^L_{iot} as the average of the similarity indexes between the current job and each of the three previous jobs, the observations between 2003 and 2005 may underestimate the previous experience since we only start observing workers from 2003 on. Thus, column (1) restricts the sample to observations from the year 2006 onwards, but the results remain similar. Columns (2), (3) and (4) report results for variations in the number of periods considered in the computation of S^L_{iot}. As we only observe workers from 2003 onwards, the specifications in columns (3) and (4) are interpreted as the accumulation of experience since graduation. Under these variations in the computation of the job-to-job match, the results remain almost the same for both the S^M_{iot} and S^L_{iot} coefficients, except for specification (3) that shows a smaller coefficient, but still positive and statistically significant, for S^L_{iot}.

Table 3.6: Effects of major-job match on wages, varying job-to-job match specification

	(1)	(2)	(3)	(4)
S_{iot}^{M}	0.105***	0.111***	0.107***	0.110***
	(0.005)	(0.005)	(0.005)	(0.005)
S_{iot}^{L}	0.123***	0.064***	0.133***	0.091***
	(0.002)	(0.001)	(0.003)	(0.005)
Constant	3.084***	3.111***	3.087***	3.103***
	(0.028)	(0.027)	(0.027)	(0.027)
Number of previous jobs considered in S_{iot}^{L}	3	1	5	10
Sample	Obs. for years>2005	All	All	All
Observations	2,571,401	2,651,267	2,651,267	2,651,267
R-squared	0.357	0.375	0.376	0.375
Unique IDs	303,016	304,225	304,225	304,225

*** p<0.01, ** p<0.05, * p<0.1.
Notes: The dependent variable is the logarithmic of the hourly wage. The match indexes are continuous and range from 0 to 1. All specifications include a vector of job characteristics (dummies for firm state, occupation groups and years), tenure in the current and the three previous jobs and its quadratic terms, and individual fixed effects. Robust standard error in parentheses.

3.5.4 Heterogeneous effects

Finally, we explore the potential heterogeneity in job match returns by gender, vertical mismatch, sector and employment contract, and field of study.

3.5.4.1 Gender

Table 3.7 presents the results by gender. The return to major-job match is 11.9% for women, whereas the coefficient is smaller (8.6%) for men. The result corroborates most findings of the literature, which indicates a larger wage penalty for mismatched women when compared to men (for example, see Robst (2007b), Nordin et al. (2010), Reis (2018), and Choi and Hur (2020)). On the other hand, the job-to-job return is higher for men (15%) compared to women (9.9%). Overall, our results indicate that matching the major is more valued for women, while matching previous experience is more valued for men.

This difference in returns to major-job and job-to-job matches can be attributed to the heterogeneity in gender reasons for accepting a job: men tend to report career-related reasons for mismatch while women are more likely to report amenity or constraint reasons for mismatch, which explains part of the difference in wage returns (Robst, 2007b). So, men are more career-oriented in terms of looking for better opportunities, payments and promotion expectations then women. On the other hand, working conditions such as hours and non-market reasons such as household duties strongly influence female decision about jobs.

Table 3.7: Effects of major-job match on wages by gender

	(1) Female	(2) Male
S_{iot}^{M}	0.119***	0.086***
	(0.007)	(0.008)
S_{iot}^{L}	0.099***	0.150***
	(0.003)	(0.003)
Constant	3.021***	3.263***
	(0.038)	(0.041)
Observations	1,634,940	1,016,324
R-squared	0.377	0.377
Unique IDs	185,230	118,995

*** p<0.01, ** p<0.05, * p<0.1.
Notes: The dependent variable is the logarithmic of the hourly wage. The match indexes are continuous and range from 0 to 1. All specifications include a vector of job characteristics (dummies for firm state, occupation groups and years), tenure in the current and the three previous jobs and its quadratic terms, and individual fixed effects. Robust standard error in parentheses.

3.5.4.2 Vertical mismatch

The return to major-job match can also be correlated to the vertical mismatch, which is the case of overeducated workers. To explore this issue, we split the sample into two groups based on the education requirements of the occupation according to the CBO description. When the occupation requires a college degree or higher, we classify workers in these occupations as “well matched”, otherwise we classify as “overeducated”. This is relevant for our estimates, as almost 50% of our sample is classified as overeducated. Workers who are well matched to their level of education are expected to transfer more college skills to the occupation.

Table 3.8 suggests that returns are higher to the major-job match for workers who are well matched in terms of level of education compared to overeducated workers. Similar results are observed for the job-to-job match coefficient. Thus, matching the education level results in higher wage premium for both major-job and job-to-job match index.

This result contrasts the findings in the literature for developed countries in

Europe. Montt (2017) explored a cross-country data and found that matching the field of study did not translate into significant wage difference for well matched workers, while matching the field contributed to high returns for overqualified workers in Europe. On the other hand, our estimates show well matched workers experience positive returns to major-job match, and have significant higher returns to major-job match then overqualified workers in Brazil. Although we cannot specify which mechanisms lead this difference, we suppose that labor market context differs significantly between Brazil and Europe in terms of returns to horizontal and vertical match: for example, it may be the case that Brazilian labor market for graduates is less saturated or college skills are less transferable among occupations, so that the returns to major tend to be higher in Brazil then in Europe for well matched workers.

Table 3.8: Effects of major-job match on wages by vertical mismatch

	(1) Well Matched	(2) Overeducated
S^M_{iot}	0.142***	0.076***
	(0.011)	(0.008)
S^L_{iot}	0.134***	0.062***
	(0.003)	(0.003)
Constant	2.588***	2.910***
	(0.033)	(0.040)
Observations	1,327,548	1,297,307
Unique IDs	0.343	0.333
R-squared	223,238	214,910

*** p<0.01, ** p<0.05, * p<0.1.
Notes: The dependent variable is the logarithmic of the hourly wage. The match indexes are continuous and range from 0 to 1. All specifications include a vector of job characteristics (dummies for firm state, occupation groups and years), tenure in the current and the three previous jobs and its quadratic terms, and individual fixed effects. Robust standard error in parentheses.

3.5.4.3 Field of study

Robst (2007a) hypothesized that the returns to match depended on the transferability status of skills: the more transferable the skills, the smaller the penalty of being mismatched. The author validated this hypothesis for graduates in United Nations: Business, Engineering, Health, Computer Sciences and Law faced more than 20% wage penalties for working outside the field of study, while the wage effects are small or statistically insignificant in Liberal arts, English, Social sciences and Education. Such evidences suggest that the returns to field-of-study match are higher in fields that teach occupation specific skills, which are less transferable to other occupations.

Table 3.9 explores the heterogeneity in the field of study for our sample. Law and Production and engineering register high returns to major-job match, with coefficients 24.2%, and 17.2%, respectively. These fields are more specific and present a higher return to major-job match as well as in Robst (2007a). Except for these majors, the remaining ones show different patterns in comparision to Robst (2007a). For example, Education, Portuguese and foreign languages is among the highest returns in our sample (17.9%) and its major-job match coefficient is higher then the one for Business (14.0%).

Agriculture and related sciences and Health sciences also present a positive and statistically significant returns to major-job match (10.1% and 5.9%, respectively), and they are among fields that we expect to be more transferable, such as Humanities (12.3%), Social applied sciences (9.1%) and Journalism and information (8.0%). The return to major-job match for Computer sciences is not statistically significant, while the returns to major-job match for Sciences and mathematics and Others (which includes Design, Music, Theater and Tourism) are negative (coefficients equal to -5.4% and -13.7%, respectively).

The returns to job-to-job match is positive and statistically significant for graduates from all fields of study. Business presents the highest return to job-related experience (19.0%), followed by Production and engineering, Journalism and information, Computer sciences and Law (around 15%).

Table 3.9: Effects of major-job match on wages by field of study

	(1) Agriculture and related	(2)Business	(3) Computer sciences	(4) Education, Portuguese and foreign languages	(5) Health sciences	(6) Humanities
S^M_{iot}	0.101**	0.140***	0.007	0.179***	0.059***	0.123***
	(0.044)	(0.010)	(0.020)	(0.017)	(0.022)	(0.028)
S^L_{iot}	0.046***	0.190***	0.139***	0.046***	0.041***	0.085***
	(0.013)	(0.004)	(0.008)	(0.006)	(0.006)	(0.008)
Constant	3.185***	3.004***	3.353***	3.101***	2.969***	3.064***
	(0.108)	(0.047)	(0.139)	(0.086)	(0.077)	(0.116)
Observations	38,987	654,076	127,376	510,205	254,299	151,998
R-squared	0.339	0.390	0.475	0.394	0.329	0.371
Unique IDs	5,455	68,015	13,780	52,410	35,764	16,981
	(7) Journalism and information	(8) Law	(9) Others	(10) Production and engineering	(11) Sciences and mathematics	(12) Social applied sciences
S^M_{iot}	0.080***	0.242***	-0.137***	0.172***	-0.054**	0.091***
	(0.016)	(0.025)	(0.019)	(0.013)	(0.022)	(0.021)
S^L_{iot}	0.149***	0.123***	0.133***	0.156***	0.102***	0.116***
	(0.007)	(0.007)	(0.009)	(0.008)	(0.007)	(0.008)
Constant	3.317***	3.202***	2.946***	3.713***	3.225***	3.310***
	(0.097)	(0.108)	(0.155)	(0.082)	(0.087)	(0.099)
Observations	157,027	159,611	103,067	139,742	210,399	144,477
R-squared	0.380	0.335	0.359	0.467	0.369	0.377
Unique IDs	18,751	21,922	12,870	17,208	23,500	17,569

*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Notes: The dependent variable is the logarithmic of the hourly wage. The match indexes are continuous and range from 0 to 1. All specifications include a vector of job characteristics (dummies for firm state, occupation groups and years), tenure in the current and the three previous jobs and its quadratic terms, and individual fixed effects. Robust standard error in parentheses.

3.5.4.4 Type of job

The evidence shows that the structure of wages and pensions as well as the labor legislation are different for public and private employees, which affects occupational decisions and might generate misallocation in the economy (Cavalcanti and Santos (2021)). This way, the public sector might attract high productive and risk averse workers, who are looking for a more stable and higher wages. This evidence suggests that workers may deviate from the best matching jobs to follow a public career to enjoy these benefits, highlighting the relevance of investigating heterogeneous matching effects for public and private sector. Most Brazilian public employees hold a statutory type of contract. They are selected by admission exams, they enjoy job stability and receive higher wages than the average salary in the labor market. Moreover, except for jobs related to health care and law, most of public tenders that require a college degree usually do not specify the major. Thus, we expect lower effects of matching on log wages for employees in the public sector and hired under statutory contracts.

Table 3.10 presents the results for this investigation by economic sectors. The estimates suggest that the return to matching is higher among workers in industry and services sectors. Returns to matching are similar among workers in the private sector: the coefficient is 6.7% for workers in services and 7.8% for industry. Agriculture register a not statistically significant coefficient. On the other hand, public administration has the smallest return to major-job match in our sample (only 4.1%).

To deepen this discussion we also split the sample by types of employment contract and present the estimate by these groups in 3.11. The effects of major-job and job-to-job matches for workers in indefinite term contracts are statistically significant and amount to 7.6% and 15.3%, respectively. Public employees present a smaller return to matching: 4.8% for matching the major and only 1.1% for matching the previous work experience. Particularly those in statutory condition register a return to major-job match of 3.1%, but this coefficient is significant only at the 10% level. Lastly, we do not identify statistically significant effects neither for major-job nor for job-to-job match for the sample comprising workers from all sector but hired under fixed-term contracts.

Table 3.10: Effects of major-job match on wages by economic sector

	(1) Agriculture	(2) Industry	(3) Services	(4) Public Administration
S^M_{iot}	0.096	0.078***	0.067***	0.041***
	(0.067)	(0.010)	(0.007)	(0.013)
S^L_{iot}	0.103***	0.137***	0.144***	0.001
	(0.029)	(0.004)	(0.003)	(0.004)
Constant	1.328**	3.022***	2.683***	3.142***
	(0.527)	(0.118)	(0.070)	(0.055)
Observations	17,302	352,322	1,345,187	931,622
Unique IDs	0.405	0.464	0.365	0.369
R-squared	4,868	67,942	212,334	133,551

*** p<0.01, ** p<0.05, * p<0.1.
Notes: The dependent variable is the logarithmic of the hourly wage. The match indexes are continuous and range from 0 to 1. All specifications include a vector of job characteristics (dummies for firm state, occupation groups and years), tenure in the current and the three previous jobs and its quadratic terms, and individual fixed effects. Robust standard error in parentheses.

Table 3.11: Effects of major-job match on wages by type of employment contract

	(1) Indefinite Term	(2) Public Employee (All)	(3) Statutory Public Employee	(4) Fixed Term
S^M_{iot}	0.076***	0.048***	0.031*	0.008
	(0.006)	(0.014)	(0.018)	(0.038)
S^L_{iot}	0.153***	0.011***	0.026***	0.019
	(0.002)	(0.004)	(0.004)	(0.012)
Constant	2.715***	3.147***	3.214***	2.891***
	(0.069)	(0.058)	(0.067)	(0.418)
Observations	1,654,106	875,915	688,934	98,552
Unique IDs	0.378	0.389	0.443	0.135
R-squared	230,329	127,912	102,232	45,278

*** p<0.01, ** p<0.05, * p<0.1.
Notes: The dependent variable is the logarithmic of the hourly wage. The match indexes are continuous and range from 0 to 1. All specifications include a vector of job characteristics (dummies for firm state, occupation groups and years), tenure in the current and the three previous jobs and its quadratic terms, and individual fixed effects. Robust standard error in parentheses.

3.6 Effects of major-job match on turnover

The evidence also indicates that the education-job match is positively correlated to job satisfaction and turnover (see, for example,Ge et al. (2020) and

Choi and Hur (2020)). To explore this topic, this section estimates the effects of major-job and job-to-job matches on turnover applying an analogous econometric strategy. The turnover variable is accounted as a dummy and indicates whether employees move to a different firm or left the formal labor market in the next period.

Table 3.12 displays the results of this analysis. The effect of major-job match on turnover is negative and statistically significant (-7.2%). In contrast, the effect of job-to-job match is positive, indicating opposite patterns in the type of matching on turnover. The results are robust to variations in the specifications of the main regression (see table 3.13).

Table 3.12: Effects of major-job match on turnover

	(1)	(2)
S^M_{iot}	-0.072***	
	(0.004)	
S^L_{iot}	0.150***	0.149***
	(0.002)	(0.002)
Perfect Match - $S^M_{iot} = 1$		-0.066***
		(0.007)
Strong Match - $0.75 \leq S^M_{iot} < 1$		-0.056***
		(0.007)
Partial Match $0.5 \leq S^M_{iot} < 0.75$		-0.052***
		(0.007)
Weak Match $0.25 \leq S^M_{iot} < 0.5$		-0.029***
		(0.007)
Constant	0.024	0.023
	(0.020)	(0.021)
Observations	2,457,358	2,457,358
R-squared	0.014	0.014
Unique IDs	302,786	302,786

*** p<0.01, ** p<0.05, * p<0.1

Notes: The dependent variable is the turnover dummy and indicates whether employees move to a different firm or left the formal labor market in the next period. The dependent variable is the logarithmic of the hourly wage. The match indexes are continuous and range from 0 to 1. All specifications include a vector of job characteristics (dummies for firm state, occupation groups and years), tenure in the current and the three previous jobs and its quadratic terms, and individual fixed effects. Robust standard error in parentheses.

Table 3.13: Effects of major-job match levels on turnover

	(1)	(2)	(3)	(4)
S^M_{iot}	-0.067***	-0.068***	-0.073***	-0.077***
	(0.004)	(0.004)	(0.004)	(0.004)
S^L_{iot}	0.148***	0.119***	0.181***	0.395***
	(0.002)	(0.001)	(0.002)	(0.004)
Constant	0.021	0.030	0.013	-0.064***
	(0.020)	(0.020)	(0.019)	(0.020)
Number of previous jobs considered in S^L_{iot}	3	1	5	10
Sample	Obs. for years>2005	All	All	All
Observations	2,377,492	2,457,358	2,457,358	2,457,358
R-squared	0.014	0.015	0.014	0.016
Unique IDs	301,535	302,786	302,786	302,786

*** p<0.01, ** p<0.05, * p<0.1
Notes: The dependent variable is the turnover dummy and indicates whether employees move to a different firm or left the formal labor market in the next period. The dependent variable is the logarithmic of the hourly wage. The match indexes are continuous and range from 0 to 1. All specifications include a vector of job characteristics (dummies for firm state, occupation groups and years), tenure in the current and the three previous jobs and its quadratic terms, and individual fixed effects. Robust standard error in parentheses.

Finally, figure 3.4 shows the marginal effects of major-job match on turnover by years since graduation. Overall, the results indicate that the effects of major-job match on turnover is decreasing over time: as long as workers accumulate work experience since graduation, the probability to move to a new job decreases if major-job match increases. Moreover, in general, the effects of major-job match on the turnover reduction is stronger for senior workers then for inexperienced ones. Particularly, the figure highlights a positive relation between major-job match and turnover in the year of graduation for senior workers.

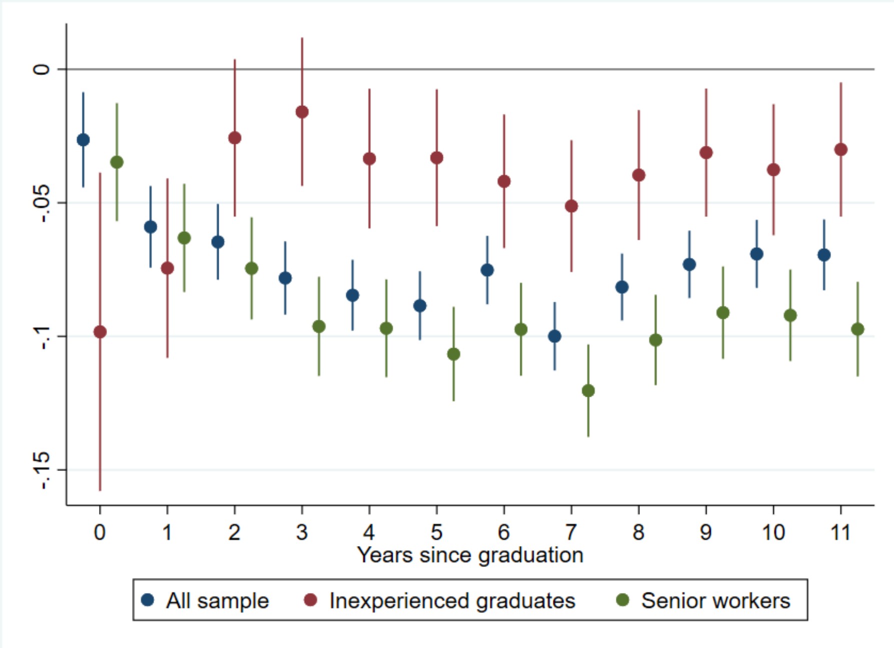


Figure 3.8: Effects of major-job match on wages by year since graduation

Notes: The figure plots the marginal effects of major-job match on turnover by year since graduation. To obtain these results we include an interaction between S^{M}_{iot} and the dummies for years to the estimation. The dependent variable is the turnover dummy and indicates whether employees move to a different firm or left the formal labor market in the next period. The estimate includes a vector of job control variables (dummies for firm states, occupation groups and years), tenure in the current and the three previous jobs and its quadratic terms, and individual fixed effects. Robust standard error in parentheses.

3.7 Conclusions

Matching worker skills to job requirements is a key factor to productivity and labor market returns. Particularly, the literature on field-of-study mismatch and its wage penalties has highlighted the relevance of this topic for discussing the efficiency in education investment to improve the match between the skills learned through formal education and the ones needed to perform job tasks. We add to this topic by exploring the Brazilian sample of workers who graduated between 2004 and 2006 and their employment trajectories up to 2018.

We contribute to the literature by innovating the methodology to compute the match index that combines a direct determination of the closest occupation to each major and a NLP approach to obtain the distance between occupations and, as a consequence, the similarity between major-occupation pairs. This empirical strategy allows us to measure both the major-job and the job-to-job match indexes and use it to estimate the effects of skill match on wages and turnover. Our results corroborate the main findings of the literature: the greater the major-job match, the higher the hourly wage and the smaller the turnover. On the other hand, the effects of job-to-job match is more mixed: while matching the previous experience to the current job also increases the hourly wage, the increase in the job-to-job match has a positive and significant effect on turnover. Besides, the accumulation of work experience over time do not imply in reduction of the return to major-job match, which suggests that on-the-job learning does not substitute major-job match. To sum up, our estimates mainly show the relevance of matching both the major and the previous work experience for wages.

Although we explore a unique dataset for graduates work trajectories, we acknowledged our results apply only to formal labor market. This way, we think additional investigation may add some evidence on this issue for entrepreneurs and independents workers. Future research can also expand our results by improving the NLP model used to measure the match indexes. Since we apply a NLP model that was trained to a wide general text, we believe that training a specific model to the occupation description would add more precision to the similarity measure we use in this paper. Finally, exploring the mechanisms that explain the heterogeneous effects we find in our estimates may contribute to additional relevant discussion for this topic in future.

References

Adamczyk, W., P. Ehrl, and L. Monasterio (2022). Skills and employment transitions in brazil. *ILO Working Paper* (65).

Almasi, P., A. Hadavand, S. Thomas, and O. Gharehgozli (2020). Relevance of education to occupation: a new empirical approach based on college courses. *Education Economics 28*(4), 370–383.

Altonji, J. G., P. Arcidiacono, and A. Maurel (2016). The analysis of field choice in college and graduate school: determinants and wage effects. In *Handbook of the Economics of Education*, Volume 5, pp. 305–396. Elsevier.

Bender, K. A. and J. S. Heywood (2011). Educational mismatch and the careers of scientists. *Education Economics 19*(3), 253–274.

Biagi, F., J. Muñoz, and G. Di Pietro (2020). Mismatch between demand and supply among higher education graduates in the EU. *European Union, Luxembourg*.

Cavalcanti, T. and M. Santos (2021). (mis) allocation effects of an overpaid public sector. *Journal of the European Economic Association 19*(2), 953–999.

Choi, S.-K. and H. Hur (2020). Does job mismatch affect wage and job turnover differently by gender? *Education Economics 28*(3), 291–310.

Devlin, J., M.-W. Chang, K. Lee, and K. Toutanova (2018). BERT: pre-training of deep bidirectional transformers for language understanding. *arXiv preprint arXiv:1810.04805*.

Gathmann, C. and U. Schönberg (2010). How general is human capital? a task-based approach. *Journal of Labor Economics 28*(1), 1–49.

Ge, Q., E. J. Jordan, M. Kim, and L. Shen (2020). Returns to job satisfaction in the presence of horizontal mismatch. *Applied Economics 52*(27), 2913–2930.

Guvenen, F., B. Kuruscu, S. Tanaka, and D. Wiczer (2020). Multidimensional skill mismatch. *American Economic Journal: Macroeconomics 12*(1), 210–44.

Iammarino, S. and E. Marinelli (2015). Education–job (mis) match and interregional migration: Italian university graduates' transition to work. *Regional Studies 49*(5), 866–882.

Kampelmann, S. and F. Rycx (2012). The impact of educational mismatch on firm productivity: evidence from linked panel data. *Economics of Education Review 31*(6), 918–931.

Kinsler, J. and R. Pavan (2015). The specificity of general human capital: evidence from college major choice. *Journal of Labor Economics 33*(4), 933–972.

Montt, G. (2017). Field-of-study mismatch and overqualification: labour market correlates and their wage penalty. *IZA Journal of Labor Economics 6*(1), 1–20.

MTE (2010). *Classificação Brasileira de Ocupações* (3 ed.). Brasilia: Ministerio do Trabalho e Emprego.

Nordin, M., I. Persson, and D.-O. Rooth (2010). Education–occupation mismatch: is there an income penalty? *Economics of education review 29*(6), 1047–1059.

Ortiz, E. A., M. Kaltenberg, C. Jara-Figueroa, I. Bornacelly, and D. Hartmann (2020). Local labor markets and higher education mismatch: what is the role of public and private institutions? Technical report, IDB Working Paper Series.

Reis, M. (2018). Measuring the mismatch between field of study and occupation using a task-based approach. *Journal for labour market research 52*(1), 1–15.

Robinson, C. (2018). Occupational mobility, occupation distance, and specific human capital. *Journal of Human Resources 53*(2), 513–551.

Robst, J. (2007a). Education and job match: the relatedness of college major and work. *Economics of Education Review 26*(4), 397–407.

Robst, J. (2007b). Education, college major, and job match: gender differences in reasons for mismatch. *Education Economics 15*(2), 159–175.

Roy, A. D. (1951). Some thoughts on the distribution of earnings. *Oxford economic papers 3*(2), 135–146.

Schweri, J., A. Eymann, and M. Aepli (2020). Horizontal mismatch and vocational education. *Applied Economics 52*(32), 3464–3478.

Somers, M. A., S. J. Cabus, W. Groot, and H. M. van den Brink (2019). Horizontal mismatch between employment and field of education: evidence from a systematic literature review. *Journal of Economic Surveys 33*(2), 567–603.

Souza, F., R. Nogueira, and R. Lotufo (2020). BERTimbau: pretrained BERT models for Brazilian Portuguese. In *Brazilian Conference on Intelligent Systems*, pp. 403–417. Springer.

Yakusheva, O. (2010). Return to college education revisited: Is relevance relevant? *Economics of Education Review 29*(6), 1125–1142.

Yamaguchi, S. (2012). Tasks and heterogeneous human capital. *Journal of Labor Economics 30*(1), 1–53.

Zhu, R. (2014). The impact of major–job mismatch on college graduates' early career earnings: evidence from China. *Education Economics 22*(5), 511–528.

Appendices

A Majors evaluated per year

Table A.1: Fields of study evaluated per year

2004	2005	2006
Agronomy	Architecture	Accounting
Dentistry	Bachelor in computer science	Archival science
Medicine	Bachelor in information systems	Biomedicine
Nursing	Biology	Business administration
Nutrition	Chemistry	Design
Occupational therapy	Computational engineering	Economics
Pharmacy	Engineering	Executive secretary
Phonoaudiology	Geography	Law
Physical education	History	Library science
Physiotherapy	Portuguese and foreign languages	Music
Social work	Mathematics	Psychology
Veterinary medicine	Pedagogy	Social communication
Zootechny	Philosophy	Teacher training
	Physics	Theater
	Social sciences	Tourism

Source: INEP. Authors' elaboration.
Notes: Social Communication includes the following areas evaluated separately: Advertising, Cinema, Editing, Journalism, Public relations, and Radio production.
Engineering includes the following areas evaluated separately: Agricultural engineering, Automation engineering, Biochemical and biotechnology engineering, Chemical engineering, Civil engineering, Computer engineering, Electronic engineering, Cartography, Surveying, Environmental engineering, Fisheries engineering, Food engineering, Forest engineering, Geological engineering, Industrial and wood engineering, Materials engineering, Mechanical engineering, Metallurgical engineering, Mining engineering, Petroleum engineering, Physical engineering, Power engineering, Production engineering, Sanitary engineering, Telecommunications engineering, Textile engineering, and Water engineering.

B The major-occupation matches and the occupation codes according to the Brazilian classification

Table B.1: The major-occupation matches

Detailed field of study	**Main Occupations**	**Codes in the CBO**
Accounting	Accountants	2522
Agricultural engineering	Agricultural engineers	2221
Agronomy	Agricultural engineers	2221
Architecture	Architects, town and traffic planners	2141, 2629

Continued on next page

Table B.1 – *The major-occupation matches (cont.)*

Detailed field of study	**Main Occupations**	**Codes in the CBO**
Archival science	Archivists and curators	2613
Automation engineering	Robotics engineers	2021
Bachelor in computer science	Computer systems analysts Computer systems engineers/architects	2124 2122
Bachelor in information systems	Computer systems analysts	2124
	Computer systems engineers/architects	2122
Biochemical and biotechnology engineering	Bioengineers and biomedical engineers	2011
Biology	Biologists Elementary school teachers Middle school teachers Secondary school teachers	2211 2312 2313 2321
Biomedicine	Bioengineers and biomedical engineers	2212
Business administration	Business professionals	2521
Chemical engineering	Chemical engineers	2145
Chemistry	Chemists Elementary school teachers Middle school teachers Secondary school teachers	2132 2312 2313 2321
Civil engineering	Civil engineers	2142
Computational engineering	Computer systems analysts Computer systems engineers/architects	2124 2122
Dentistry	Dentists, general	2232
Design	Design professionals	2624
Economics	Economists	2512
Eletronic engineering	Electronics engineers, except computer	2143
Engineering	N/d	n/D
Engineering - cartography	Mining and geological engineers, including mining safety engineers	2148
Engineering - surveying	Mining and geological engineers, including mining safety engineers	2148
Environmental engineering	Environmental engineers	2140
Executive secretary	Executive secretary	2523
Fisheries engineering	Agricultural engineers	2221
Food engineering	Food scientists and technologists	2222
Forest engineering	Agricultural engineers	2221
Geography	Elementary school teachers Geographers	2312 2513

Continued on next page

Table B.1 – *The major-occupation matches (cont.)*

Detailed field of study	**Main Occupations**	**Codes in the CBO**
	Middle school teachers Secondary school teachers	2313 2321
Geological engineering	Geoscientists, except hydrologists and geographers	2134
History	Elementary school teachers Historians Middle school teachers Secondary school teachers	2312 2035 2313 2321
Industrial and wood engineering	Agricultural engineers	2221
Law	Lawyers	2410
Portuguese and foreign languages	Elementary school teachers Middle school teachers Secondary school teachers	2312 2313 2321
Library science	Librarians and related information professionals	2612
Materials engineering	Materials engineers	2146
Mathematics	Elementary school teachers Mathematicians Middle school teachers Secondary school teachers	2312 2111 2313 2321
Mechanical engineering	Mechanical engineers	2144
Medicine	Medical doctors	2231, 2251, 2252, 2253
Metallurgical engineering	Materials engineers	2146
Mining engineering	Mining and geological engineers, including mining safety engineers	2147
Music	Composers, musicians and singers Elementary school teachers Middle school teachers Secondary school teachers	2627 2312 2313 2321
Nursing	Registered nurses	2235
Nutrition	Dietitians and nutritionists	2237
Occupational therapy	Occupational therapists	2239
Pedagogy	Education methods specialists Elementary school teachers Preschool teachers	2394 2312 2311
Petroleum engineering	Chemical engineers	2145
Pharmacy	Pharmacists	2234
Philosophy	Elementary school teachers Middle school teachers	2312 2313

Continued on next page

Table B.1 – *The major-occupation matches (cont.)*

Detailed field of study	**Main Occupations**	**Codes in the CBO**
	Philosophers	2514
	Secondary school teachers	2321
Phonoaudiology	Audiologists	2238
Physical education	Elementary school teachers	2312
	Middle school teachers	2313
	Physical therapists	2241
	Secondary school teachers	2321
Physical engineering	Physicists	2131
Physics	Elementary school teachers	2312
	Middle school teachers	2313
	Physicists	2131
	Secondary school teachers	2321
Physiotherapy	Physical therapist assistants	2236
Power engineering	Electronics engineers, except computer	2143
Production engineering	Industrial engineers	2149
Psychology	Psychologist	2515
Sanitary engineering	Civil engineers	2142
Social communication	N/d	n/D
Social communication - advertising	Advertising professionals	2531
	Sales and marketing managers	1423
Social communication - cinema	Film, stage and related actors and directors	2621
	Journalism professionals	2611
Social communication - editing	Editors	2616
	Journalism professionals	2611
Social communication - journalism	Journalism professionals	2611
	Editors	2616
	Film, stage and related actors and directors	2621
	Audiovisual media announcers, commentators and reporters	2617
Social communication - public relations	Journalism professionals	2611
	Film, stage and related actors and directors	2621
	Audiovisual media announcers, commentators and reporters	2617
Social communication - radio production	Film, stage and related actors and directors	2621
	Audiovisual media announcers, commentators and reporters	2617
	Journalism professionals	2611

Continued on next page

Table B.1 – *The major-occupation matches (cont.)*

Detailed field of study	**Main Occupations**	**Codes in the CBO**
Social sciences	Elementary school teachers Middle school teachers Secondary school teachers Sociologists	2312 2313 2321 2511
Social work	Social work professionals	2516
Teacher training	Education methods specialists Elementary school teachers Preschool teachers	2394 2312 2311
Telecommunications engineering	Electronics engineers, except computer	2143
Textile engineering	Chemical engineers	2145
Theater	Elementary school teachers Middle school teachers Secondary school teachers	2312 2313 2321
Tourism	Travel consultants and organizers	3548
Veterinary medicine	Veterinarians	2233
Water engineering	Civil engineers	2142
Zootechny	Zoologists and wildlife biologists	2233

Source: The authors.

C The highest and lowest matches

Table C.1: Examples of the highest and lowest major-job matches

Field of study	Occupation	S^M_{iot}
The highest matches		
Accounting	Accounting technicians	0.86
Chemical engineering	Industrial engineers	0.85
Production engineering	Chemical engineers	0.85
Textile engineering	Industrial engineers	0.85
Civil engineering	Techniciasn in civil construction	0.85
Bachelor in computer science	Director in information systems	0.85
Bachelor in informations systems	Director in information systems	0.85
Mechanical engineering	Mechanical techniciansin the manufacturing and assembly of machines, systems and instruments	0.83
Physical education	Occupational therapists and orthoptists	0.83
Materials engineering	Researcher in engineering and technology	0.82
The lowest matches		
Agronomy	Trade operators in stores and markets	0.08
Agricultural engineering	Trade operators in stores and markets	0.08
Forest engineering	Trade operators in stores and markets	0.08
Agronomy	Banking services cerks	0.13
Law	Equipment operators	0.15
Eletronic engineering	Middle school teachers	0.16
Telecommunications engineering	Middle school teachers	0.16
Business administration	Graphic print workers	0.16
Agronomy	Cashiers	0.17
Power engineering	Equipment operators	0.18

Source: INEP and MTE. Authors' elaboration.
Note: The table shows only matches with at least 50 observations in our sample.

Table C.2: Examples of the highest and lowest job-to-job matches

Current Occupation	Previous Occupation	S_{iot}^{L}
The highest matches		
Sales promoter	Sales representative	0.88
Accountant	Accounting technician	0.86
Production engineer	Chemical engineer	0.85
Civil engineer	Technician in civil construction	0.85
Information and technology analysts	Computation engineer	0.84
Mechanical engineer	Mechanical technician in the manufacturing and assembly of machines, systems and instruments	0.83
Human resources manager	Human resources professional	0.83
Telephony operator	Telemarketing operator	0.82
Administrative assistant	Transport logistics specialist	0.81
Administrative assistant	Executive secretary	0.80
The lowest matches		
Agrossilvipecuary engineer	Trade operators in stores and markets	0.17
Middle school teachers	Butcher	0.25
Education programmers, evaluators and advisors	Trade operators in stores and markets	0.25
Agrossilvipecuary engineer	Sales promoter	0.27
Electronics engineer	Sales promoter	0.29
Receptionist	Middle school teachers	0.33
Trade operators in stores and markets	Middle school teachers	0.34
Middle school teachers	Accounting assistant	0.33
Middle school teachers	Receptionist	0.33
Nurse	Trade operators in stores and markets	0.34

Source: INEP and MTE. Authors' elaboration.
Note: The table shows only matches with at least 50 observations in our sample.

D Detailed fields by aggregated fields of study

Table D.1: Detailed fields by aggregated fields of study

Field of study	Detailed field of study
Agriculture and related sciences	Agricultural engineering
	Agronomy
	Fisheries engineering
	Forest engineering
	Veterinary medicine
	Zootechny

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Table D.1 – *Detailed fields by aggregated fields of study (cont.)*

Field of study	Detailed field of study
Production and engineering	Architecture Civil engineering Engineering - cartography Engineering - surveying Geological engineering Environmental engineering Sanitary engineering Water engineering Automation engineering Biochemical and biotechnology engineering Chemical engineering Food engineering Materials engineering Mechanical engineering Metallurgical engineering Industrial and wood engineering Physical engineering Production engineering Textile engineering Mining engineering Petroleum engineering Eletronic engineering Power engineering Telecommunications engineering
Business	Accounting Business administration Executive secretary
Applied social sciences	Economics Psychology Social work
Computer and information sciences	Bachelor in computer science Bachelor in information systems Computational engineering
Education, Portuguese and foreign languages	Pedagogy Teacher training Portuguese and foreign languages
Health sciences	Dentistry Medicine Nursing Nutrition Occupational therapy Pharmacy Phonoaudiology Physical education Physiotherapy
Humanities	Geography History

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Table D.1 – *Detailed fields by aggregated fields of study (cont.)*

Field of study	Detailed field of study
	Philosophy Social sciences
Journalism and information	Archival science Library science Social communication - advertising Social communication - cinema Social communication - editing Social communication - journalism Social communication - public relations Social communication - radio production
Law	Law
Sciences and mathematics	Biology Biomedicine Chemistry Mathematics Physics
Others	Design Music Theater Tourism

Source: The authors.

Chapter 4

Conclusion

The higher education provides an advanced learning on specific subjects in order to equip workers with skills and knowledge to perform occupation tasks in the labor market. Some critical factors regarding to the improvement of public resource allocation, the market regulation and the efficacy of the system in preparing graduates to face the challenges of the labor market boost the relevance of evaluating whether public policy can improve the higher education results. This thesis has focused on two issues: the impact of accountability system and the returns to matching majors to jobs.

The higher education accountability provides information about the quality of undergraduate programs and supports public regulation of Brazilian HEIs. Our results suggest the SINAES impacts undergraduate programs in the years following the publication of the results, mainly for those around the cutoff that determines the minimum level required for federal approval of the program, i.e. around the cutoff determined by $CPC_{score} = 1.945$. The programs that receive a low score ($CPC_{level} < 1.945$) in a certain period achieve higher quality indexes in terms of student performance, infrastructure, faculty and quality overall in the next evaluation cycle. On the other hand, programs just above this threshold increase the program offer in comparison to programs just below the same threshold. These results suggest that program administrators respond to the threat of punishment related to this threshold. Even though we expected administrators to use their results as an advertisement, we do not find consistent impacts from reaching higher levels of quality, such as $CPC_{level} = 4 or 5$, on either program effort or candidate perceptions of future returns. Our main results are stronger for private HEIs, which we argue are related to the competitive pressure and positive incentives (such as access to public programs that offer scholarships and student loans) that private institutions face.

Finally, matching college skills to job requirements is a key factor to productivity and labor market returns. We add to this topic by exploring the Brazilian sample of workers who graduated between 2004 and 2006 and their employment trajectories up to 2018. We also add to the literature by innovating the methodology to compute the match index that combines a direct determination of the closest occupation to each major and a NLP approach to obtain the distance between occupations and, as a consequence, the similarity between all major-occupation pairs. This empirical strategy allows us to measure both the major-job and the job-to-job match indexes and use them to estimate the effects of skill match on wages and turnover. Our results corroborate the main findings of the literature: the greater the major-job match, the higher the hourly wage and the smaller the turnover. Besides, we find that on-the-job learning does not substitute major-job match. To sum up, our estimates mainly show the relevance of matching both the major and the previous work experience to the current job in the formal labor market.