



Online Education and Student Performances : between effectiveness and equality

Denitza Arguirova

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Online Education and Student Performances: between effectiveness and equality

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L'Université Gustave Eiffel n'entend donner aucune approbation ni improbation aux opinions émises dans cette thèse. Ces opinions doivent être considérées comme propres à leur auteur.

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Denitza Arguirova

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Abstract

Education provides the foundation for skills development and employment integration. With the increase in technology and the recent COVID pandemic, online education, along with other alternative educational modalities, has been increasing in the traditional education environment. Although the demand for such alternative modalities in education has risen, the impact of such provided education on the graduates and their prospective employment is yet to be evaluated.

The objectives of this thesis is to analyse the effectiveness and equity of online education, and to understand the impact it may have on the students' performance and future employment. The literature in the field of alternative modalities, such as online and hybrid models, is growing but is still sparse. In this regard, the thesis is focused primarily on the USA and France, using available national data, surveys, and experimental data.

The first chapter evaluates to what extent the effectiveness and equality in education can be improved through online education, using the COVID pandemic as a natural experiment where all education institutions were affected by the same restrictive context. Moreover, it provides a literature review regarding the factors that influence the effectiveness and equality of traditional education systems and if alternative education modalities, such as online education, can suggest improvements to these factors.

One of the main measurements of effectiveness in education is student performance, as it quantifies the extent to which a student has been able to acquire the capacities and learning objectives of a given subject. In this regard, the second chapter investigates alternative teaching modalities' impact on student grades. It contributes to the empirical literature by conducting a case study on a sample of master level students at a French university. Traditional teaching modalities have been severely upended due to the recent pandemic, which raises the question of whether alternative teaching modalities can be beneficial or detrimental to student performance. Alternative empirical models are used to isolate the impact of the teaching modalities and the covid pandemic on student grades. The findings

suggest that teaching modality has an overall negative impact on grades, while the pandemic has increased the grade compared to previous years.

The third chapter conducts a correspondence test across three French cities to indicate whether there is differential behaviour of potential recruiters based on students' educational background, i.e. online versus traditional in-person degrees. The candidate profiles are data scientists and IT technicians. It is found that having an online degree may increase the probability of receiving employment. More importantly, the medium sized companies have a higher probability of giving a positive callback to data scientists with online degrees compared to data scientist candidates with a traditional degree. For similar companies, the probability of receiving employment is reduced for IT technicians.

Keywords: : online higher education, education effectiveness, education equality, student performance, covid pandemic, statistical discrimination; correspondence testing

Résumé

L'éducation constitue le fondement du développement des compétences et de l'insertion professionnelle. Avec l'augmentation de la technologie et la récente pandémie de COVID, l'éducation en ligne, ainsi que d'autres modalités d'enseignement alternatives, ont augmenté dans l'environnement traditionnel. Bien que la demande pour ces modalités alternatives d'éducation ait augmenté, l'impact de ce type d'enseignement sur les diplômés et leurs perspectives d'emploi reste à évaluer.

L'objectif de cette thèse est d'analyser l'efficacité et l'équité de l'enseignement en ligne, et de comprendre l'impact qu'il peut avoir sur les performances des étudiants et leur futur emploi. La littérature dans le domaine des modalités alternatives, telles que les modèles en ligne et hybrides, est en augmentation mais reste encore peu abondante. À cet égard, la thèse se concentre principalement sur les États-Unis et la France, en utilisant des données nationales disponibles, des enquêtes et des données expérimentales.

Le premier chapitre évalue dans quelle mesure l'efficacité et l'égalité dans l'éducation peuvent être améliorées par l'éducation en ligne, en utilisant la pandémie de COVID comme une expérience naturelle où toutes les institutions éducatives ont été affectées par le même contexte restrictif. En outre, il fournit une revue de la littérature concernant les facteurs qui influencent l'efficacité et l'égalité des systèmes éducatifs traditionnels et si les modalités d'éducation alternatives, telles que l'éducation en ligne, peuvent suggérer des améliorations à ces facteurs.

L'une des principales mesures de l'efficacité dans l'enseignement est la performance des élèves, car elle quantifie la mesure dans laquelle un élève a pu acquérir les capacités et les objectifs d'apprentissage d'une matière donnée. À cet égard, le deuxième chapitre étudie l'impact des modalités d'enseignement alternatives sur les notes des élèves. Il contribue à la littérature empirique en menant une étude de cas sur un échantillon d'étudiants de niveau master dans une université française. Les modalités d'enseignement traditionnelles ont été remises en question en raison de la récente pandémie, ce qui soulève la question de

savoir si les modalités d’enseignement alternatives peuvent être bénéfiques ou préjudiciables aux performances des étudiants. Des modèles empiriques alternatifs sont utilisés pour isoler l’impact des modalités d’enseignement et de la pandémie de covidie sur les notes des étudiants. Les résultats suggèrent que les modalités d’enseignement ont un impact négatif sur les notes, tandis que la pandémie a augmenté les notes par rapport aux années précédentes.

Le troisième chapitre réalise un test de correspondance dans trois villes françaises pour indiquer s’il existe un comportement différentiel des recruteurs potentiels en fonction du parcours éducatif des étudiants, c’est-à-dire des diplômes en ligne par rapport aux diplômes traditionnels en personne. Les profils des candidats sont des data scientist et des techniciens informatiques. Il s’avère que le fait d’avoir un diplôme en ligne peut augmenter la probabilité d’obtenir un emploi. Plus important encore, les entreprises de taille moyenne ont une probabilité plus élevée de donner un rappel positif aux data scientist avec des diplômes en ligne par rapport aux candidats data scientist avec un diplôme traditionnel. Pour des entreprises similaires, la probabilité d’obtenir un emploi est réduite pour les techniciens informatiques.

Mots clés: enseignement supérieur en ligne, efficacité de l’enseignement, égalité de l’enseignement, performance des étudiants, pandémie de covid, discrimination statistique; test de correspondance.

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Glossary

APOGEE *Application pour l'organisation et la gestion des enseignements et des étudiants. It is a university software package that was developped in 1995 by the Agency for the Mutualization of Universities and Establishments in France. Its purpose is to manage the registration of student profiles and data.*

FE *Fixed effects*

ICC *Intra-class correlation*

ICT *Information, communication and technology.*

IFIS *l'Institut Francilien d'Ingénierie des Services. A department in UGE.*

INSEE *L'Institut national de la statistique et des études économiques. It is in charge of production and publication of statistics in France since 1946.*

IPEDS *Integrated Postsecondary Education Data System*

IT *Information Technician*

LANGUE *Langues, Cultures et Sociétés. A department in UGE.*

LMS *Learning management system*

LSDV *Least square dummy variable*

M1 *Master 1. The first year of a master degree in France.*

M2 *Master 2. The second year of a master degree in France.*

MOOCS *Massive open online course*

NAF *Nomenclature d'activités française. It is a nomenclature of economic activities in France that was developped to classify and organized economic and social information.*

NCES *National Center for Education Statistics.*

OC *OpenClassrooms. A French education technology company.*

OECD *Organisation for Economic Co-operation and Development*

OLS *Ordinary least squares*

RE *Random effects*

EL-SD *Employer learning statistical discrimination model*

SCECO *Sciences Economiques et de Gestion. A department in UGE.*

UGE *Université Gustave Eiffel*

UNESCO *United Nations Educational, Scientific and Cultural Organization*

VIF *Variance inflation factor*

General Introduction

Context

Education provides the foundation for skill accumulation and productivity, which spills over into societal benefits and economic growth. The economics of education has long been studied since the 1960s due to the pioneering work of Gary Becker and Jacob Mincer. The focus of the field has been predominantly in terms of rates of return to acquiring education, human capital accumulation and education financing. One of the biggest constraints of the human capital paradigm is that it is based on the assumption of the existence of perfect markets, which is not the case in reality due to many types of market failures¹. When this assumption is removed, other social factors, such as family background and family resources, become pertinent factors in explaining in more detail the situation of the individual and their preferences for education. In this regard, it is evident that individuals will not have the same opportunity to education due to personal and family constraints. As a response to these market failures, public policies could address this situation through re-distributive policies, and/or provide alternatives, such as improvement in institutional resources.

The human capital model is determined through educational choices. According to Chec-

¹Market failures in the context of human capital arise from moral hazard and degree of control over the human capital. Moral hazard arises when the individual undertakes education at the cost of someone else, such as parents or the bank if a loan is taken out. In this regard, only the individual will know to what extent he/she is truly able to succeed in their education path. The individual also possesses a certain degree of control over their own human capital which, unlike physical capital, can only be used if the individual is employed, thereby making the individual a wage earner (Checci, 2006). In other words, the human capital may not be employed to its fullest extent based on the extent to which the individual is willing to work.

chi (2006), the main determinants of educational choices are individual unobserved ability², time spent in education (with decreasing returns)³, educational resources⁴, and human capital background⁵ such as parents' education background. This is considered to be the education production function, where the inputs are the determinants mentioned, and the output is the change in individuals' human capital (Lazear, 2001; Prichett and Filmer 1999). Moreover, Checchi (2006) argues that these determinants are imperfect substitutes, because if one factor has low levels, another can compensate in order to maintain a certain level of human capital. For example, the unobserved ability of a learner can be compensated for by an increase in educational resources to support the learner. In this regard, factors can influence one another. This can be seen in the increase in the time spent in education due to the improved educational resources. Or, if the family background is highly educated, usually students would remain longer in education. In this regard, and as part of the educational resources factor, the instructional modalities⁶ can also influence all the inputs of the education production function. As students have different unobserved abilities, some may react positively or negatively to the change in the instructional modalities. This can enhance the learning of some students. Moreover, the innovation in the pedagogical instruction and the technological supporting systems could induce shorter study periods among learners due to a more effective education and learning. Lastly, students from better-endowed family backgrounds can easily adapt to alternative modalities. Due to the scale of outreach and flexibility in alternative educational modalities, it can also provide access for those students that are less endowed

²This is the individuals' talent that is unobservable.

³According to Card (1999), students remain longer in education with the expectation of a higher rate of return. This is especially the case for students that would have higher unobserved ability. But there are decreasing returns to the time spent in education. In other words, an additional year of education decreases the rate of return in terms of expected income. Moreover, an additional year of education impacts students differently based on individual unobserved ability and family background, specifically pertaining to financing opportunities to attend university for longer.

⁴Educational resources refer to materials and services provided to the student by the academic institutions for learning.

⁵The impact of family education background on individuals' unobserved ability has been investigated in terms of genetically transmitted unobserved talent (Mulvey, Miller, and Martin (2001), through family genetics, or simply an individuals' own endowment of unobserved talent.

⁶Instructional modalities refer to the way in which the teaching is performed. This can be simply defined as online, hybrid, or in-person. Or, it can be a combination of teaching modalities. Nonetheless, the teaching modality chosen needs to be well-equipped to be effectively executed.

due to family educational and financial backgrounds.

From the perspective of the student, the choice of undertaking higher education is also an investment that carries a cost. The main reason is that the opportunity cost of foregone present income with the expectation that with the higher education attained, the future income will be higher. Moreover, the theory stipulates that the productivity of the worker will be enhanced due to higher education levels. As with every investment, the cost of acquiring education pertains to direct and indirect costs. The direct costs include tuition fees, living costs, materials, and transport. The indirect costs refer to the opportunity cost of studying instead of working, i.e. the foregone income. Alternative education modalities can reduce both types of costs. In terms of direct costs, alternative education modalities can alleviate these costs for students in terms of reduced mobility costs, increased digitization of materials and sources, and saving on campus costs. Moreover, due to the flexibility provided in alternative education, the program is no longer restricted to time and space, allowing for more students to be registered. By this logic, even the tuition fees could be reduced due to increase in the number of student registrations, i.e. economies of scale in outreach. Lastly, the effectiveness of the alternative modalities can provide more outcome-based results and ultimately equip student capacities for labor market needs.

Unfortunately, not everyone has the opportunity to benefit from alternative education modalities. Differences arise due to the lack of familial financial resources to fund education opportunities, even in the traditional case. Checchi (2006) argues that this is an initial income inequality that, if not corrected by public intervention, will reduce the access to education and persist throughout generations as it will have a subsequent effect on future income. Limiting the acquisition of education, and thereby human capital accumulation, for financially constrained families will result in a market failure according to classical human capital theory. In this case, the society will be inefficient in the use of the human capital in the economy. As a solution, the state intervention through appropriate taxation and redistribution policies can alleviate these financial constraints. Alternatively, increased support in ICT to universities and families could facilitate the transition into alternative modalities

to acquire education without interruption. Overall, this would increase the human capital investment for the society as a whole.

Looking at the education offer more closely, classical human capital theory has yet to investigate the pertinence of differing education modalities and how they impact the education choices and outcomes. An alternative approach to education can impact the effectiveness, equity and efficiency of a traditional education. Moreover, this could also have a direct impact on the teachers, thereby influencing education quality, and student performance and experience. Lastly, and as a result to the alternative educational outcomes, the opportunities in the labor market could differ due to the signals and perceptions of alternative education modalities by future employers. In this light, and with the rise in digitized education programs, the impact of alternative education modalities will be investigated in this thesis.

Background on Alternative Typologies of Education

Education is changing faster than expected. With the growing use of the internet and innovative technologies, a new digital era in the education and learning arena is rising. Since the mid-1990s, the importance of online education has been gaining momentum, as more of the academic content becomes readily available through online mediums, providing alternative methods for learning and broader access to education for students. This has provided the foundations for a new pedagogical paradigm for education as a whole in regards to new education modalities, methodology, processes, roles, and responsibilities. In this regard, although education has become more readily available, the effectiveness in the transition from such diverse methodologies of education to work, and how the skills and knowledge required might transfer to the labor market, is yet to be confirmed.

Distance education is not a new phenomenon. It has existed even before the technological revolution in the form of correspondence by mail. Some researchers would argue that distance education has even existed prior to the invention of the internet, through writing, printing, and telegraphy, although this is not within the scope of this research (Hafner and Lyon, 1996;

Hiltz and Turoff, 1993). This kind of correspondence education provided very low interaction between students and teachers, and was rather frowned upon, making it seem as insufficient education (Thompson, 1990). Only later on, in the 1980s and 1990s, when research on the field surfaced⁷, and with the digital advancement and global access to the internet, was online education able to gain speed and spread in use (Peters, 2003). Computer use and networking led to higher connectivity, increasing human communication and collaboration. Moreover, it provided tools that expanded the scale of distance education to support beyond just a few courses and ultimately entire degrees fully delivered online (Wallace, 2003). In this regard, many more students can be assisted at the same time. These technological tools enhanced the online education space and content, through communication and conferences, i.e. email, Zoom, and content management systems, i.e. Google Drive, Moodle. Moreover, it facilitated the processes of student record-tracking, attendance, assessments, and student performances. As Kim and Bonk (2006) described it, the online education realm experienced an “e-storm” of new ways to link pedagogy, technology and learner needs.

A New Pedagogical Paradigm

Online education is a method of instruction provided from a distance, usually using one or more digital tools to connect teachers and learners through a virtual environment. The definition of online education has been widely discussed due to differing characteristics and tools used. Primarily, researchers define online education on the basis of location, i.e. whether the instruction is provided physically in class versus at a distance (McIsaac and Gunawardena, 2013). Others enhance the definition through an emphasis on essential characteristics of online education, such as open virtual space communication (Moore and Kearsley, 2012) and temporal advantage (synchronous versus asynchronous) in teaching (Finch and Jacobs, 2012). In general terms, the definition can be perceived from a pedagogical or technolog-

⁷Research of the field of distance education did not officially start until the 1980s. At that time official research journals, such as the American Journal of Distance Education, founded by Michael G. Moore, and Distance Education, pioneered by Desmond Keegan, were formally established.

ical perspective. Some researchers define online education as a pedagogy that generically uses information and communication technologies (ICTs) (McCarty, et al., 2006). Therefore the focus is mainly on the technological perspective and the extent of use of technological tools. This interpretation pertains to the use of virtual classrooms, chats, and educational platforms for material logging, i.e. Moodle, including methods and tools for educational organization and pedagogy (Holmberg 2005). This thesis will define online education as any use of technological means to teach academic material, outside of the traditional classroom. The terms online education, online learning, e-learning, and distance education will be used interchangeably throughout the study.

With the expanding use of the internet, more of the academic material, teaching and learning has been transformed to different forms of providing and receiving education. The traditional format of providing education in a physical classroom has been altered to different degrees of distance education by incorporating more of the newly available technology and tools into pedagogy. Hybrid education is a mix of traditional education modality with the use of digital tools for communication and interaction. In this regard, the extent to which digital tools are used within a teaching practice can determine to what extent the education provided is more traditional, hybrid or online. The three main types of education can be generally defined as;

- Traditional: education provided in-class with physical presence, without the use of digitized content, delivery and learning
- Hybrid: blended learning using a mix of digitalized tools for delivering education and conducted partially online and face-to-face
- Online: education is supported by digital tools, and learning is conducted entirely at a distance and through a virtual medium (online)

Higher education is increasingly adopting more the hybrid and online formats of delivering education. These alternative modalities increase the access towards the courses and degrees

that are offered online. It does so due to the main characteristics of online education, as specified by Harasim (2000):

- Place independent
- Time independent (synchronous/asynchronous)
- Computer mediated environment

These attributes influence online interaction, conceptualization/learning and collaboration between learners and instructors. From the perspective of accessibility, online education provides location and time flexibility, which would otherwise be a barrier to students that cannot attend courses due to distance and time constraints. Moreover, the computer mediated environment provides a medium for group discussions and a sense of community, which can stimulate motivation and participation (Harasim, 2000). The management of these attributes is an organizational challenge in order to ensure that it functions correctly for all stakeholders involved.

For whom and what's the benefit/cost?

Online education has provided new foundations for the roles and responsibilities of the stakeholders in education. There are three main stakeholders in delivering and receiving online education: the higher education institution (HEI), or university/college, the instructor and the learner. The roles and responsibilities of each stakeholder are changing, with different advantages and disadvantages. This part will investigate the implications of online education on the roles of each stakeholder.

Each stakeholder is concerned with at least one of the three main characteristics of online education: access, quality and cost. There are benefits and costs to transitioning into online education for each of the stakeholders. The university's investment in cloud-based learning management systems (LMS) provides flexibility in access to teachers and students from any

place and at any time. Moreover, it can be cost effective in terms of materials and administration support. Therefore, the virtual environment depends on the university's development of LMS and online support. In regards to the teachers, Duffin (2020) found that demand from students and the employers for specific skills are drivers for which teachers are willing to offer online courses. The modality under which faculty will teach has a great impact on the quality of the pedagogy delivered. Therefore, the faculty needs to also be prepared, whether that is through university or external funding, in having the appropriate training and tools to effectively deliver their teaching to students.

The Institution

Higher education institutions are institutions that provide tertiary education and accreditation. They are public or private and usually take the form of universities, colleges, technical training or vocational institutions. These institutions are responsible for providing the instructors and the learners with administrative and digital support in order for educational content to flow between the providers, the instructors, and the receivers, the learners.

The core business of the higher education institution is to provide learning and credentials for the level of education achieved. In both aspects, digitization can be helpful. For starters, digitizing education can increase the number of students accepted into online courses and degrees due to the unlimited nature of virtual space and asynchronous pedagogy. This is both an opportunity and a challenge for universities. On the one hand, an increase in the number of students can increase the annual revenue due to economies of scale. On the other hand, maintaining the infrastructure to teach students online could be quite costly due to the rise in fixed costs. This would further require regulation for quality assurance. Additional benefits of online education, such as automated assessment systems, data analytics for improved student and teacher support, classroom management tools⁸ and administration data control⁹ (Gallagher and Palmer, 2020), provide further efficiency in the processes and

⁸For example: communication tools, such as Zoom, but also information sharing platforms, such as Moodle.

⁹Online education can generate data and feedback for the improvement of the management and func-

logistics for HEIs. This is predominantly seen through the business model of the MOOCs. The effectiveness of fully digitalized credentials in higher education when transitioning into the labor market is not yet confirmed. Nonetheless, universities have adopted and increasingly support the unbundling of degrees through micro-credits. This is also highly valued by the employers, which is consistent with the lifelong learning approach and recognition of specific skills. In other words, digitization can provide more options for capacity building for employers, especially if the education is more outcome based.

The Instructor

Through the institutions, the instructors could attain and continuously maintain lifelong learning, as they are the distributors of the pedagogy itself. Thus there is a opportunity to adapt universities and their support towards faculty skill specialization and improvement (McCarty, et al., 2006; Ros, Bouadi, Brunet, 2021). The educators and faculty need to harness the technological advancement in education, including the new methods of education provision and communicating. This calls into question the readiness for the educators in providing education in such ways. The flexibility of online education is not strictly driven in one direction from teacher to student, but rather provides a network and environment in which information overall can be shared even for the development of the educators themselves.

Traditionally, instructors would teach in face-to-face environments and have physical contact with the learners. In the virtual classroom, the role of the instructor has changed from a teacher to a facilitator. In the online environment, the traditional presentation style does not work, tends to decrease discussions, and could increase dropout rates. Instead, instructors should alter their approach and design content in a way that would stimulate discourse while being able to moderate, facilitate and mediate. Koschmann et al. (1994) found that when instructors engage learners through controversial and constructive discussions, this team work is stimulated, thereby increasing commitment and learner interest.

tionality of the system within the universities (Bell and Fedeman, 2013), thereby increasing efficiency and feedback for administrative improvement

There are advantages for the instructor in using online education. In a study by Harasim (2000), professors acknowledged that using online education as an alternative modality provided them with new technological skills, such as the use of different digital tools and adopting alternative pedagogical approaches, such as engaging more with students. Moreover, it drives instructors to focus on fostering relationships with students (Bailey and Card, 2009). In terms of evaluations, automated assessments are also time saving for the instructor. Moreover, customized feedback can increase student-specific development, thereby increasing interaction and collaboration within the class (Rao and Tanners, 2011). With the use of digital tools, online education provides an environment for discussion even between instructors, whether that is within university or between other universities, such as online conferences. The outreach and scale of information sharing have become borderless.

The challenges imposed by online education on instructors are mainly in regards to course material preparation and the learning curve of how to use digital tools. There needs to be organizational support from the university and training provided in advance to instructors in order to ensure technological preparedness and smooth course delivery. The initial workload in preparing traditional courses is already very high and labor intensive, therefore the use of technological tools could alleviate this weight through automation. DiBiase and Rademacher (2005) found, through analysing instructor records of a three-year asynchronous online course, that instructors were able to attain a 12% gain in preparation efficiency of the course material. Moreover, there was no significant decrease in the student satisfaction of the course delivered, meaning that the quality of the course was well maintained throughout the years. This shows that after overcoming the learning curve of the digital tools available, the workload is less, and instructors can benefit from such automation and content sharing.

The Learner

The learner is a consumer of the education provided by the instructor. The design and delivery of the educational material is done by the instructor, which has a direct impact

on the learners' achievement and satisfaction of the education. In order to have successful student learning, social presence and interaction are key (Mullen and Tallent-Runnels, 2006). The social presence is the level of student participation. The interactions can be defined into three types: student-student, student-teacher, and student-content. These aspects will be considered in more detail later on in this chapter.

Online education has had some profound impacts on the learners in higher education. The primary impact is the disconnection from the physical classroom and the instructor, which can drive students into a sense of isolation, demotivation and ultimately dropout. On the other hand, it has been argued that online education can also stimulate discussions and provide a space for students that are normally not talkative and shy of initiative inside the classroom. The presence and participation level in a virtual environment can lead to an increase in performance, which can be seen as a demonstration of the ability to stay connected, thereby increasing motivation to establish and maintain online presence. Moreover, the virtual space is an equal space for discourse without social barriers such as judgement or discrimination. This is particularly important for students that are disadvantaged or disabled, who would not have the opportunity to communicate easily otherwise (Guo, Bricout, and Huang, 2005).

There are advantages of online education for the learner. Firstly, it provides the learner with a sense of autonomy. In other words, it forces young individuals to be better managers of their time and workload. Just like instructors, online education provides the learner with new skills in the use of digital tools. It provides flexibility in terms of access and time. This can be critical, especially for those students for whom travel is long and costly. In terms of access, and with the condition that internet and a computer are readily available, using online education delivery can have a greater outreach to students, thereby decreasing inequality in accessibility to education. Lastly, due to the virtual classroom, there is equitably-distributed learner participation due to increase in discussion rates and open space collaboration (Bell and Fedeman, 2013).

Some of the main drawbacks are mainly due to connectivity, such as slow internet or more technical issues regarding the use of the digital platforms and tools. In Harasim (2000), the

students who were interviewed reported that they had initial anxiety in navigating through the online classroom and support tools, but this improved with continuous use. In this regard, students should be provided with guidance on the use of digital tools provided from the HEI in order to avoid delays in delivering and receiving education. Another issue is cheating during online assessments, which has not been addressed properly and for which controls are yet to be determined. Lastly, many debates have discussed the extent to which computer mediated communication eliminates the human aspects and connection with the teacher and students. This depends on the nature of subject, as some researcher have found that more quantitative courses would in any case require less interactivity and therefore the students would have a lower participation level (Dumford and Miller, 2018).

The rise of the MOOCS

The rise in the demand for online courses and degrees induces a rise in the market share of the education technology market. In 2016, the global investments into education technology were already at USD 18 billion (Li and Lalani, 2020). The global online education market value was projected to reach USD 350 billion by 2025, and even USD 1 trillion by 2027, with a compound annual growth rate of 21% due to the impetus of the COVID-19 crisis (ibid). The education technology market has been fuelling the development of digital tools, and powerful learning management platforms based on massive data, cloud computing and artificial intelligence. For example, MOOCs provided by Coursera use machine learning to analyse student data, automatically grade it and provide customized learning material. The potential of online education is great, whether that is through video conferencing and communication tools, virtual teaching, or online learning software. The rising investments in the edtech market provide an avenue for improvement in the efficiency and effectiveness for traditional higher education in terms of pedagogy and tools. Although, according to the European University Association, the investment in increasing digitalized learning is primarily seen as enhancement to the traditional higher education rather than replacing it with

an entirely alternative method of education (Gaebel, 2015). These investments are usually generated through private companies, and therefore are primarily targeted in improving the link between higher education and the workforce expectations (Gallagher and Palmer, 2020). Although, usually the private company's incentive in investing in online education is mostly in regards to vocational and adult training, it simply shows that online education can be another modality in which distance education can be provided at scale and with outcome-based learning.

Thesis contribution and structure

Alternative teaching modalities in higher education have been widely used, although relatively little research has been done on the effectiveness and subsequent outcomes and consequences of such modalities. The recent pandemic exposed the difficulties and challenges that higher education institutions had to overcome. Nonetheless, the extent to which alternative education modalities should be adopted is complicated due to two main difficulties: the complexity of defining alternative modalities and the lack of data in the field at the higher education level.

Firstly, alternative modalities expand the concept of traditional education by specifying the modalities of teaching and learning in education economics. The modalities are usually categorized into three general categories: online, hybrid and in-person. The extent to which each course or program partakes in either of the categories will depend on each teacher and institution. The impact of each modality will also depend on the students' and teachers' characteristics and experience with the specific modality. When looking at the labor market, the perception of alternatively obtained higher education degrees will be determined also by the characteristics and experience of the recruiter in those education modalities in order to properly evaluate the candidate competencies.

The lack of data is also an impediment in testing appropriately the alternative modalities. The extent to which a modality is used is not usually registered in the university databases.

Moreover, teacher and student surveys need to be conducted to capture their characteristics, experience and satisfactions with certain tools and methods. These surveys are on a case by case basis, which makes comparability between courses, programs and institutions difficult. The result is that the data regarding alternative modalities are very scattered and only provide a glimpse of the situations and cases of specific institutions and programs. This lack of data makes it hard to adopt education and employment public policies that would help the education institutions improve due to the difficulty in evaluating the effectiveness of the existing alternative education programs in traditional higher education context. Moreover, the crisis provided a clear disruption and potential control group against which to statistically test the impact of alternative modalities on students' performance and subsequent labor market outcomes. Moreover, the influx of public policies in advocating the importance of digitization and closing the digital skills gap induces further research and potential increase in integrating alternative education modalities.

In this regard, this thesis aims to contribute to the existing literature and provide insight into the effectiveness of alternative education modalities. There is also a particular focus on higher education, which is the least-studied level of education regarding this topic. The main guiding question of the thesis is whether alternative education modalities are effective, and if they provide equitable access to higher education. Several sub-questions have guided the development of the thesis. From the labor supply side, do the alternative education modalities effectively prepare students with the competencies necessary in order to transition into the labor market? To what extent should certain modalities be adopted, and for which type of classes? Do modalities provide equal access to all the students that want to enter higher education, or is it an additional barrier? Turning to the labor demand side, are recruiters open to hiring a non-traditional candidate?

The objective of this thesis is to evaluate the effectiveness of alternative education modalities, and the effect of these modalities on the labor market outcomes of higher education graduates. There are two empirical chapters and one literature review chapter containing the theoretical approaches in education economics and the impact of the recent pandemic

in education. Due to the lack of pandemic-influenced data in higher education, the focus country of the first chapter is predominantly the USA, based on national survey data. While in the empirical studies, however, France was the country of focus where data was generated for the purposes of the thesis to overcome the lack of data. The variables studied in the chapters to capture effectiveness and equity are not exhaustive, and there is room for the inclusion of further variables and factors that can be investigated if data permits.

The first chapter focuses on the equality in access and effectiveness of online education as an alternative modality to traditional higher education. The USA was selected as a country of reference due to the large national surveys that were conducted on different university types¹⁰ and levels¹¹. The purpose of this chapter is to provide an overview of the impact of the pandemic on higher education and to review the existing literature on online education on the basis of how effective it is and whether it aids in providing better education access. The research finds that the pandemic had differing impacts on institutions due to their level of preparedness, in terms of technology, and pedagogical agility. In addition the teacher and student experiences with technological tools and alternative learning methods differ due to the digital skills gap. More importantly, according to national surveys, the teaching staff and students are willing to integrate more online education tools as ways to improve the effectiveness of traditional education. Overall, online education can provide accessibility, and thereby lessen the inequality in access to higher education, but this would need to be supported at the institutional level and should not depend on the students' circumstances. Alternatively, if students are unable to ensure their own access to online education, then this would only increase the inequality in access and the digital divide.

Due to the lack of empirical research on online education, the concepts evoked and analysed in the first chapter leave a large margin of potential investigation and questions. Firstly, have universities in other countries experienced the same impact from the pandemic? And what has been their experience with alternative education modalities? More importantly,

¹⁰University types including community colleges, private and public institutions

¹¹Different levels of tertiary degrees, such as associate, bachelors, and masters

have the student performances, as an indicator for future employment, been impacted and whether their skills set have truly been acquired?

The second chapter provides some answers by taking into consideration a case study focusing on France, and more specifically on the Université Gustave Eiffel for the time period between 2017-2020. The data were collected from three different departments; the Departments of Languages Culture and Society, Engineering, and Economic Sciences and Management. Student data anonymity was respected as the data were collected from the university administration. The modality at the course level was collected through a teacher survey that was sent to each teacher that taught a specific course for the time period. This provides a range of different types of courses at the masters level. A total of 798 courses were identified with a teaching modality, which resulted in 16,328 unique student grades. The chapter uses three distinct empirical models. The first model uses an OLS regression to capture the combined impact of the pandemic and teaching modalities on student performance across time, September 2017 - June 2020. Due to the confounding nature between distance teaching modalities and covid, two additional models were estimated to isolate the impact of covid and teaching modalities. The second model uses an OLS regression across courses solely considering the pandemic semester, January - June 2020. Lastly, the third model uses a least squared dummy variable model to isolate the impact of the pandemic semester on student performances. The pandemic was found to have a significant and positive impact on student performances, where the students from the languages and economics departments performed overall better (0.5 points of a grade) compared to the engineering department. This could be due to the typology of the courses within those departments and to the extent to which the course material requires physical interactivity for learning. In order to capture the impact of the teaching modalities, and to isolate the pandemic, an unbalanced panel data is used, where the model is identified by cross-course variation. The time period is the same for all courses and set in the semester in which the pandemic started, January - June 2020, in order to subject all courses to the same shock. The evidence suggests that students who took courses under hybrid and online teaching modalities experienced a negative effect on their

performance. When student and random effects are added, the impact of these modalities only strengthens at an even higher significance level.

The last model attempts to isolate the impact of the pandemic by following the same cohort of students across time and investigating the covid shock on the individuals' performance within the cohort. The findings suggest that the pandemic has a positive effect on students' grades by increasing the grade by 0.72 points of a grade for the cohort. The reason behind this increase in grades cannot be clearly investigated due to the lack of data on the typology of evaluations used for students and limited student characteristic data. Although the three models provide interesting results, the analysis can be improved through more information regarding the course evaluation typology, frequency and difficulty. Moreover, the teacher quality is not captured here due to limited time and information regarding teachers that have taught the courses. Nonetheless, the chapter provides new approaches in evaluating the pandemic and alternative teaching modalities on graduate performance in the French context. The findings and analysis also provide the foundation for future and more in-depth causal analysis.

As a follow-up to the second chapter, the third chapter will evaluate the labor market demands and perceptions of applicants that apply with an online versus traditional education background. The objective of the study is to see whether the recruiters differentiate between graduates of online or traditional degrees at the masters and bachelors level. The study uses a spontaneous correspondence test, in which fictitious candidate CVs are sent to recruiters. Within the CV, the differentiating factor is the education type based on modality, which is used as a signal to see whether there will be differential treatment between pairs of candidates. The Université Gustave Eiffel is the traditional education provider, while the French-based company, OpenClassrooms, is the fully online degree provider. The programs chosen from the two institutions are similar in curricula, except in the modality of teaching and learning. Reputation effects are not captured in this study, although the industries to which the applicants were sent were diversified. This was done to limit the probability that sample firms were already acquainted with either educational institution. Two different pro-

fessions were tested in the Lille, Lyon and Marseille regions: data scientist at the master level and IT technician at the bachelors level. To evaluate the effect of the education type signal, the fictitious candidate stated their education type in the email text and in their CV that was attached to the email sent to the recruiter. The firms to which the spontaneous applications were sent were identified using the French nomenclature of industries and activities ¹². A total of 1,754 unique companies, where 756 searching for the data scientist candidates and 998 searching for the IT technician candidates, were contacted. In total, 310 responses were received, of which the data scientist profession received more responses (33%) compared to the IT profession (28%). Both candidates received more responses if they had online education background compared to a traditional one. A linear probability model was used to interpret the impact of the education modality on the probability of obtaining a positive response from the recruiters. The results suggest that for both professions having an online education background would experience an increase on the probability of obtaining a positive callback, although it is statistically not significant. This may be due to the relatively small sample size. Most importantly, through these findings, the study does not find evidence of significant differentiation between candidates with respect to online or traditional education background.

Overall, the evidence in this thesis sheds light on the importance of alternative education modalities, especially after the recent pandemic, and the potential that these modalities can add to the traditional education methods and structure. These modalities are an alternative way in which to improve the effectiveness and equity of higher education and graduates' labor prospects.

¹²The nomenclatures of the French industries are sourced from the French national Institute of statistics. Under each nomenclature category, a specific sub-category of activities was chosen to source the companies to which the candidacies were sent out . The industries that were chosen for the data scientist were: manufacturing, energy, research and development, transportation, insurance and finance (see Annex 3.D for more information). For the IT technician profile, the following industries were chosen: information and communication, administrative services and support (see Annex 3.E for more information).

Chapter 1

Online education: Is it an effective and equitable alternative to traditional higher education? The case of the COVID-19 impact on higher education.

1.1 Introduction

The COVID-19 pandemic has accelerated the implementation of online education in the higher education arena. The question is whether it should remain as an educational option, or even become more adopted throughout higher education systems. In order to properly evaluate the relevance of online education, there are two important factors to consider: the effectiveness of online education, in the sense of reaching desired student outcomes, and its impact on educational equity as a measure of equal access to quality education. This chapter aims to analyse online education through the lens of these two concepts and review the

literature that has been done to evaluate the effectiveness and equity impact of alternative educational modalities.

In 2020, the health crisis forced more than 188 countries to bring traditional schooling and classroom attendance to a halt (OECD, 2021). This disrupted the traditional education delivery for over 1.5 billion learners worldwide (UNESCO, 2020). Moreover, the World Bank (2020) announced that it would lead to a “learning poverty” due to an increase in the learning gap. In response, universities attempted to use different digital methods to continue education delivery and to minimize the educational inequalities. Students continued their education at home using digital devices and online education sources, such as learning management systems, i.e. Google Classroom and Moodle, and communication tools, i.e. Zoom and Microsoft Teams. Resorting to such alternative modalities of education resulted in differing experiences across students, lecturers, universities. These differing experiences depended on the institutional preparedness and existing prior online pedagogical experience.

In this regard, challenges evolved at the institutional level. Pre-existing institutional issues, such as different socio-economic backgrounds of students, drive the differences in the accessibility of quality education (Reimers, 2022; Chamorro-Premuzic and Frankiewicz, 2019; Halima et al., 2009). This educational inequality could induce future socio-economic inequalities, such as in measured income. This is further supported by the human capital literature and the return on education, only reinforcing the importance of education as a foundation to employability and thereby socio-economic status. Consequently, if academic institutions are not prepared to provide quality education through digital means, then the transition into online education would only amplify educational inequality. According to a UNESCO (2020) report, 65% of lower middle-income countries and 25% low-income countries had set up online learning platforms. Therefore the learning management platforms, and thereby online education, are not a new invention, although the extent of use and the transition into using such tools and teaching modalities has only started to be adopted more in the last few decades. Moreover, having established online platforms does not necessarily ensure connectivity to these platforms for students. This was primarily due to the lack of digital device

accessibility, internet connectivity, and the digital skills gap. The crisis exposed educational inequality in the light of the digital divide.

In addition to equal opportunity in access to education, the educational effectiveness impacts the knowledge and skills attained that would later on influence the return on the investment for a learner. Effectiveness will be considered as the degree to which the educational delivery was successful in terms of educational objectives (OECD, 2017). It differs from education efficiency which refers to attaining education objectives at the lowest cost. To evaluate for effectiveness, the effect of the resource inputs need to be evaluated against the expected education outputs. The resource inputs encompass all the resources provided by the educational institution to the student, such as infrastructure, teachers, and technology. Given a change in technology, keeping all else equal, the effectiveness of the change in the teaching modality will subsequently impact the expected outputs, and thereby educational objectives. One of the most frequently-used measurements of education output is student performance measured in grades from different assessments (Alhassan et al., 2020). There are other indicators that can also be used as measures of effectiveness in education, such as graduation rates and student and teacher satisfaction surveys. The way the resource inputs are allocated and used can determine whether there is an impact on the quality and equity of using them in the academic setting. The quality of the education depends on the effectiveness of the education delivery and students' readiness to learn. In other words, the education inputs, such as infrastructure, technology and teachers, need to be prepared for different instructional modalities in education delivery, and the students need to be able to learn through these modalities effectively. This implies that the students' learning skills would need to be more adaptable to different learning environments, thereby having a certain level of learnability and adaptability in terms of the educational delivery. The ability to learn and adapt in different contexts can also be transposed into the skills necessary with the rapidly changing and unpredictable labor market needs.

In order to alleviate the digital divide and improve effective delivery, digital literacy must be improved for students, instructors, and institutions. At the institutional level, as a goal to

enhance effectiveness and efficiency of the education provided, the infrastructure should be sufficient and teacher training should be readily available, with at least some minimum training required. According to EDUCAUSE Core Data Service Benchmarking Report (2017), in the USA less than 5% of the college budgets are used for IT expenses, indicating that the education sector is the least digitized sector, thereby exposing it to large risk in times of crisis and technological disruption. The survey had 775 participating higher education institutions, and they used the Carnegie classification system ¹ to group the institutions by education type and level, among other indicators. Although the sample size was quite small, it aims to shed light on the lack of institutional IT investment and training for all teaching staff. Supplementary teacher training in technological tools and pedagogical engineering would reduce the digital divide among teachers, although it also requires that teachers are willing to be adaptive and innovative in their pedagogical approach.

In regards to the students' technological readiness, according the US Department of Education (2020), 37.2% of postgraduate students have had experience with at least one distance education course. Student enrolment in massive open online courses (MOOCs) increased from 300,000 to 220 million between 2011 and 2021 worldwide (Shah, 2021). This shows that increasingly more students have online learning experience at the course level. Although the popularity of MOOCs is rising, effectively transposing similar learning content into a university environment is found to be unsatisfactory for students. A Strada Student Viewpoint survey (2020), collecting more than four thousand university student responses in the beginning of the fall semester of 2020 found that 1 in 3 students considered their learning to have worsened due to online instruction. This shows not only the difficulty that institutions and teachers had in coping with the transition to online instruction, but that students were not also prepared to experience an academic semester, program or year entirely conducted online. One of the major impeding factors consistently reported for learning in student surveys has been stress and motivation levels (Cengage, 2021). All in all, the institutions, educators and

¹The Carnegie classification framework was developed in 1970, and uses data from colleges and universities across the USA to categorize institutions, monitor changes in time and evaluate differences between academic institutions.

students were not readily prepared to transition into a fully online educational experience thereby exposing the higher education system to its lack of technological readiness.

In the wise words of Albert Einstein “in the midst of every crisis, lies great opportunity.” The pandemic provided the opportunity for academic improvement. In the aftermath of the crisis, it does not seem that traditional education will return to its previous form. And maybe this is for the better, considering the exposure to alternative tools, teaching modalities and pedagogical methods that emerged from the crisis. A Cengage (2021) survey ² found that 46% of the students and 32% of the teachers agree that there should be more digitalization of materials and increase of technology use in higher education. Another survey conducted by Harvard Future of Teaching and Learning task force also found that 82% of the faculty are keen on integrating the digital tools used during the pandemic to their in-class sessions (Harvard, 2022). Although a drastic situation of fully online degrees does not seem reasonable for the traditional education environment, there is a desire to improve the effectiveness and efficiency of higher education with more technological integration. A golden middle path frequently discussed is the hybrid model, whereby both the traditional and online approaches are integrated at the course and degree level. Although the shortcomings of traditional education have become apparent during the crisis, potentially this also gave way to the opportunity to improving and modernizing education through the lessons learnt from the crisis.

The pandemic has shed light on many avenues for improvement for academia. As traditional higher education begins to adopt the features of online education at a larger scale, the purpose of this chapter is to provide an analysis of these potential improvements through the existing literature. It will specifically focus on the impact of COVID-19 on the effectiveness and equity of online education on higher education, learning disparities, and equal work opportunities after graduation. It will contribute by identifying avenues for further research once more data are available, especially at the higher education level. Currently, discussions

²Cengage, in partnership with Bay View Analytics, surveyed 1,286 faculty and administrators and 1,469 college students across 856 US universities.

and research are primarily based on best practices rather than on empirical evidence of the suggested practices. This has been due to the difficulty in finding a suitable control group as well as the influences of selection bias and measurement error. Moreover, the effectiveness of the digital tools used in online instruction have not been effectively evaluated and require further comparative research. As different forms of digital tools were used, it was nonetheless complicated to generalize the impact of alternative instruction modalities and tools at this stage.

The chapter is designed in the following manner: Section 2 will provide background statistics on the context and the impact of the pandemic on the education. Section 3 will present empirical research and findings in regards to equality and effectiveness of online education. Lastly, Section 4 will conclude and suggest further research avenues and recommendations.

1.2 Context

In order to evaluate the impact of the pandemic on higher education, indicators regarding the effectiveness and equality are evaluated in turn. At the level of the education institutions, the cost of this unexpected transition from traditional to online learning has been observed through learning losses, volatility in student performances, and differentiated enrollment and graduation rates. Although the initial cost of the pandemic came as a shock, the potential benefits are still to be reaped from the aftermath of technological exposure to student, faculty and universities.

Learning loss

The impact of the health crisis is visible through the disruption in the students' learning. This can be observed through the rise in learning loss, reflected through a decline in the students' capacities and overall knowledge due to a discontinuity in education progress. In other words, it captures the difference in learning achieved before the crisis and learning during the crisis. Duffin (2021) estimated in January 2021 that there was a learning loss

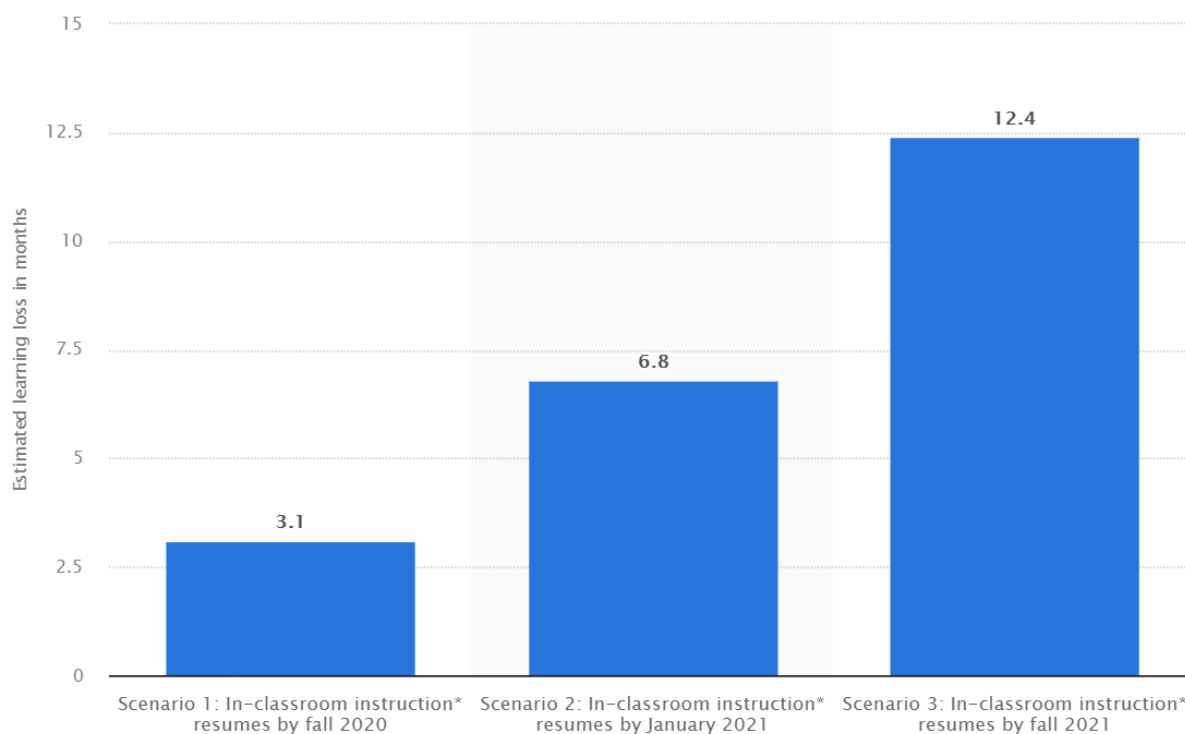
of approximately seven months in the USA (Figure 1.1). This is equivalent to almost an entire academic year. It was further estimated that this would increase to over 12 months if the in-classroom instruction only resumed in the fall of 2021 (ibid). Learning losses can have heavy repercussions on employability due to the loss in effective learning time thereby resulting in lower skill development and accumulation.

Distance education can be used as a means of mitigating the lost learning time for students by focusing on the necessary learning outcomes that should be achieved. This is only ensured given that the students have access to the teachers and instruction material. Otherwise it would exclude those who do not have access, thereby increasing educational inequality. In this regard, Patrinos et al (2021) argue that online education is an imperfect substitute to the traditional instruction based on the vulnerability and socio-economic status of the student. Those that are in the most vulnerable groups will only experience further deterioration in their learning due to the accessibility issues to online instruction and materials.

Student performance

The student performance is a measure of the students' results on assessments. As the assessments differ between institutions, the experiences will therefore be different. Moreover, the modality in which the assessment was conducted will also influence the results. At the student level, the primary factors that impacted student performances are absenteeism, inadequate performance on assessments, and student satisfaction. Tracking students for physical presence in a virtual environment can be difficult. Even if students are logged into a platform, it is uncertain whether they are present and attentive to what is being taught. Attendance is key in order for students to be able to grasp the material, i.e. through in-class discussions, and ultimately ensuring that they have a strong understanding for better performance results. Arulampalam et al (2012) used quantile regression on an economics class in the UK and found that class absence has adverse effects on performance although these effects are causal only for the upper part of the conditional performance distribution. Students have

Figure 1.1: Estimated learning loss from COVID-19 between 2020-2021, the USA case



Source: Duffin (2021)

been polled regarding their experience in virtual class environments, and there are mixed reviews on whether it is effective for the learners.

Regarding the assessments, the student performance varied widely due to the challenges in controlling assessments at a distance. Cheating, for example, is a major limitation to online education. However, solutions are being developed through the expansion in the edtech market, such as proctored examinations. Unfortunately, proctored examinations are costly, and therefore not many universities have these type of technologies installed. Moreover, it is worrisome as this limitation may have inflated the student grades thereby providing incorrect signals to the labor market regarding the preparedness of the students (Brown and Hesketh, 2004). According to Burgess and Sievertsen (2020), these effects will result in consequences for the new graduates such as lower job matching efficiency, higher job separation rates, and potentially lower incomes. It is therefore critical that there are policy implications to what

extent the funding towards universities should be invested in technological improvement for examinations and assessments.

This performance volatility can also be explained by institutional and pedagogical factors, such as administrative student support and the quality of the education delivered. Some higher education institutions may have been better prepared, through already existing online education courses, development of learning management systems (LMS), and strong administrative as well as technical support. Others may not have had such opportunities due to a lack of infrastructure and funding. Moreover, the faculty may have already had experience in delivering online courses, which has a direct impact on the quality of the education delivered. Orlov et al (2021) found that if teachers have previous online teaching experience it can be used to mitigate the negative impact on the student performance (0.611 compared to 0.765 standard deviation points). The difference in the student academic performances can also be explained through the type of courses that may be easier to move suddenly online, such as theory-based courses, compared to other courses where this transition impedes interaction for critical analysis and problem solving. Using a hierarchical model across 11 STEM courses at a Canadian university, Tomal et al. (2021) found that with the transition to online delivery there was an increase in the average grades for courses that require lower level cognitive skills³, such as statistics and mathematics. For courses requiring higher-level cognitive skills, and therefore more physical interaction, grades were observed to decrease, such as computing science and architectural and engineering technology courses. The decrease was larger for underachieving students, showing an achievement gap.

In addition, student satisfaction has a direct impact on the students' performance and retention (Astin and Magolda, 1993). Many factors have been identified to contribute to student satisfaction, such as interaction with teachers (Astin, 1993; Finaly-Neumann, 1994; Williams and Ceci, 1997), and campus experience (Bean and Bradley, 1986). But when considering a virtual environment, the factors determining student satisfaction would then rely more on practical aspects, such as level of interactivity, quality of education provided and

³The cognitive skills were defined and classified by Bloom's taxonomy of knowledge (Krathwohl, 2002).

its efficiency of delivery (Bollinger and Martindale, 2004). In this regard, the students must be adaptable in using digital tools in order to maintain motivation and avoid frustration. Palmer and Holt (2009) used a multivariate linear analysis to show that student confidence in their ability to communicate and learn online was a significant factor and positively influenced student satisfaction. On the contrary, according to regression analysis by Kuo et al. (2013), student-to-student interaction and self-regulated learning do not contribute to overall satisfaction. Bollinger and Martindale (2004) argued that satisfaction drives motivation, and therefore student motivation is a predicting factor of student success that needs to be maintained. As the pandemic had a major impact on student mental health, it resulted in lack of motivation, increase in depression and disengagement due to distancing (Brooks et al., 2020), ultimately, driving students into dissatisfaction, lower academic achievements and potential drop out.

Enrollment rates

The demand for online education can be seen through the increase in the enrolment in distance education courses (Figure 1.2). In 2020, 72.8% of students from 5,961 post-secondary institutions enrolled in distance education courses ⁴ (NCES, 2020). When this figure is divided by distance education status and student level, it showed that at the undergraduate level, approximately 43% were enrolled exclusively in online courses, while about 30% were enrolled in only some distance taught courses. For comparison, at the graduate level this is about 52% and 19%, respectively (Table 1.1).

These figures suggest that there are more students enrolled in fully online education courses for graduate level compared to undergraduate level. According to a research study across six American academic institutions ⁵ from Boston Consulting Group and Arizona

⁴The data were collected by the U.S. Department of Education, National Center for Education Statistics, Integrated Postsecondary Education Data System (IPEDS) from 5,961 Title IV institutions in the United States.

⁵The six academic institutions are comprised of three colleges and three universities. They are the Arizona State University, University of Central Florida, Georgia State University, Kentucky community and technical college, Houston community college, and Rio Salado community college. These institutions are pioneers of

Table 1.1: Enrolment in distance courses in 2020

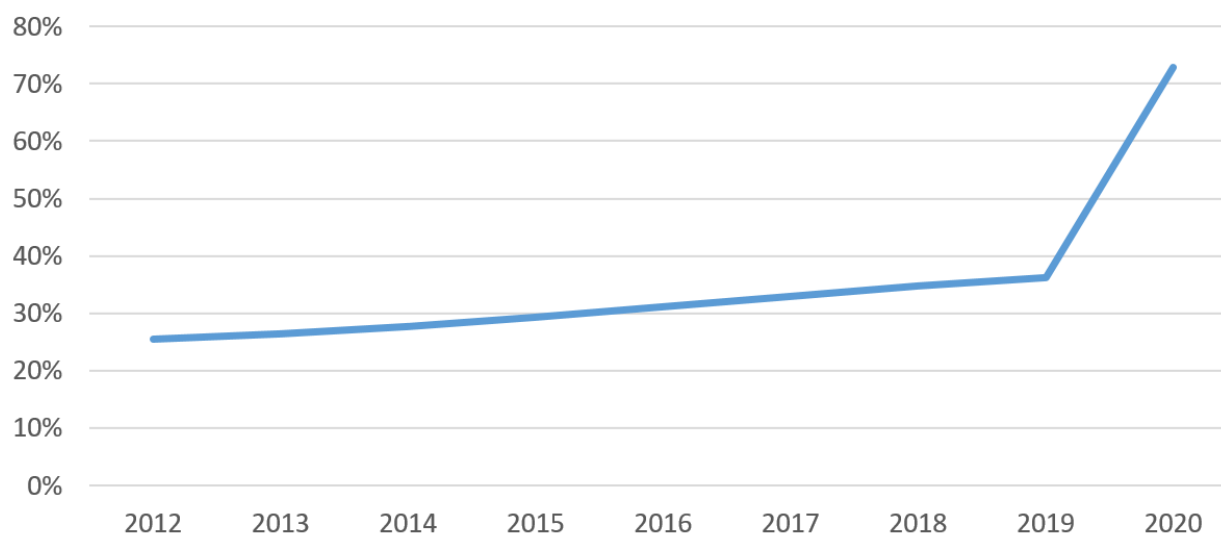
	Undergraduate	Graduate
Enrolled exclusively	43%	52%
Enrolled in some	30%	19%
Not enrolled in any	27%	29%

Notes: This table presents data collected from Title IV institutions in the United States. Source: U.S. Department of Education, National Center for Education Statistics, Integrated Postsecondary Education Data System (IPEDS), Fall Enrollment component provisional data (2020)

State University (2018), the number of students taking online courses has shown a consistent annual increase of 5%, even though the overall post-secondary enrolment on average has been decreasing by 2% from 2014 - 2018. It seems that online education could have been a driver for the rise in enrollment rates for higher education. Many factors can explain the decrease in enrolment rates, such as the need for students to work while studying, especially at the graduate level, and hence the decrease in students seeking the traditional type of education. This is particularly common for non-traditional students, who are balancing family and work simultaneously. Online education can provide a remedy through the adoption and integration of digital tools to meet the needs of students in such situations and eventually increase the overall enrolment for higher education.

The demand for online education delivery was already rising even prior to the COVID pandemic. In 2013, Allen and Seaman (2013) found that 32% of graduates attending a higher education institution took at least one online course. More specifically, a report by Snyder et al. (2018) revealed that the percentage of students taking one or more online undergraduate classes increased from 16.5% in 2008 to 45.6% in 2016. Moreover, the percentage of undergraduate students taking fully online degree programs increased from 3.8% in 2008 to 10.8% in 2016. At the graduate level, students that went through programs entirely online increased from 6.1% in 2008 to 27.3% in 2016. The graduate and postgraduate levels of education seem to prefer distance learning which may be due to the autonomy of the students in their learning methods. Another study conducted by Pew Research Center (2011) found that 89% of universities offered courses taught in different online modalities, such as fully online, online education at the higher education level.

Figure 1.2: Percent of students enrolled in distance education courses



Source: U.S. Department of Education, National Center for Education Statistics, Integrated Postsecondary Education Data System (IPEDS), Fall Enrollment component final data (2012 - 2019) and provisional data (2020)

hybrid, and other forms of distance learning instruction (Parker, Lenhart, and Moore, 2013). The driving factors for providing online courses, investigated in a 2008 study by NCES, were found to be student demand over flexible schedules (68%), access to education (67%), greater availability in courses and potential increase in student enrolments (45%)(Parsad, Lewis, and Tice, 2008).

Moreover, Learning House, Inc. and Aslanian Market Research (2018) conducted a survey of 1,500 online students at the graduate level, and found that 86% of the students agreed that their online degree equaled or exceeded their expectations. In other words, online education seems to be more accepted by the graduate level students. Through a survey, Duffin (2019) found that 52% of US graduate students were content with online college-level education, and that it rather provided a better learning experience than their in-person college level classrooms. The reasons why students choose online programs include affordability, reputation of programs, and rapidity of degree acquisition (Duffin, 2020)⁶.

In the aftermath of the pandemic, alternative teaching modalities are becoming more

⁶The survey was conducted in 2019 and consisted of 1,500 online student respondents.

accepted. The Digital Learning Pulse survey⁷ conducted by Cengage, Bay View Analytics and the Online Learning Consortium found that 68% of the students polled were in favor of hybrid learning post-pandemic (Kelly, 2021). Moreover, about two thirds of the teachers and students polled reported an interest in incorporating more technology and digital materials in the curriculum for both learning and teaching (ibid). These flexible characteristics of teaching modalities provide incentives for students to demand such education, and for universities to reach students at scale.

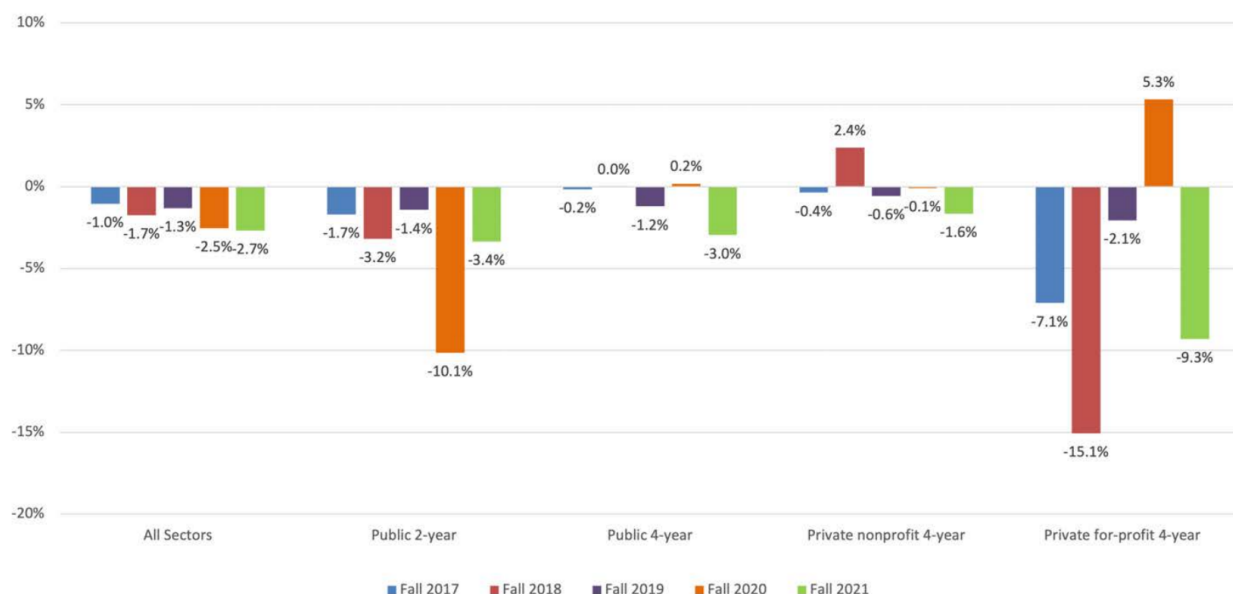
Nonetheless, the enrolment rates in traditional universities have been consistently decreasing, especially for certain education levels and institution types. According to NSC Research Center (2022)⁸, the overall post-secondary enrolment rates decreased by 2.7% since 2020 across all education sectors in the USA (Figure 1.3). This accumulates to a 5.2% decrease in enrolment over the past two years due to the pandemic. One of the contributing factors, at the undergraduate level, could be the decrease in enrolment for high school graduates. According to the current population survey⁹ of the Bureau of Labor Statistics (2021), surveying about 60,000 households, indicated that the enrolment of high school graduates dropped from 66% in the fall of 2019 to 62% in the fall of 2020. Looking more closely, the public two year institutions (10.1%), which primarily consist of associate degrees, were the strongest hit in terms of decrease in enrolment rates when comparing the fall semester of 2019 to 2020. The negative impact on enrolment persists for this category although at a much lower rate (3.4%). Interestingly, and contrary to others' experience, the public and private four year institutions experienced an increase in enrolment rates of 0.2% and 5.3%, respectively. The

⁷Cengage produced the Digital Learning Pulse survey, in partnership with Bay View Analytics and the Online Learning Consortium to analyse the responses of faculty, students and administrators on the changes of higher education due to COVID-19. The survey polled 1,469 students and 1,286 faculty and administrators across 856 United States institutions.

⁸NSC Research Center survey was conducted across three years (2019-2021) of tracking unweighted enrolment count nationally in the USA. It draws from 12.6 million student enrolments reported as of 25 March 2021 from 76% of the institutions that report annually to the Clearinghouse. Institutions actively submitting enrollment data to the Clearinghouse account for 97 percent of all enrollments at Title IV, degree-granting institutions in the U.S.

⁹The current population survey is conducted monthly. It gathers data on employment, unemployment, degree recipients, enrolments and graduations. High school graduates can range from 16 – 24 years old. Recipients of degrees can range from 20 – 29 years old.

Figure 1.3: Percentage change in total enrolment rate by institution type, Fall 2017 - 2021



Note: the percentage change is based with reference to the previous year. Both full time and part-time students are considered in the enrolment count. Undergraduate and graduate levels are considered together in the data represented in the table.

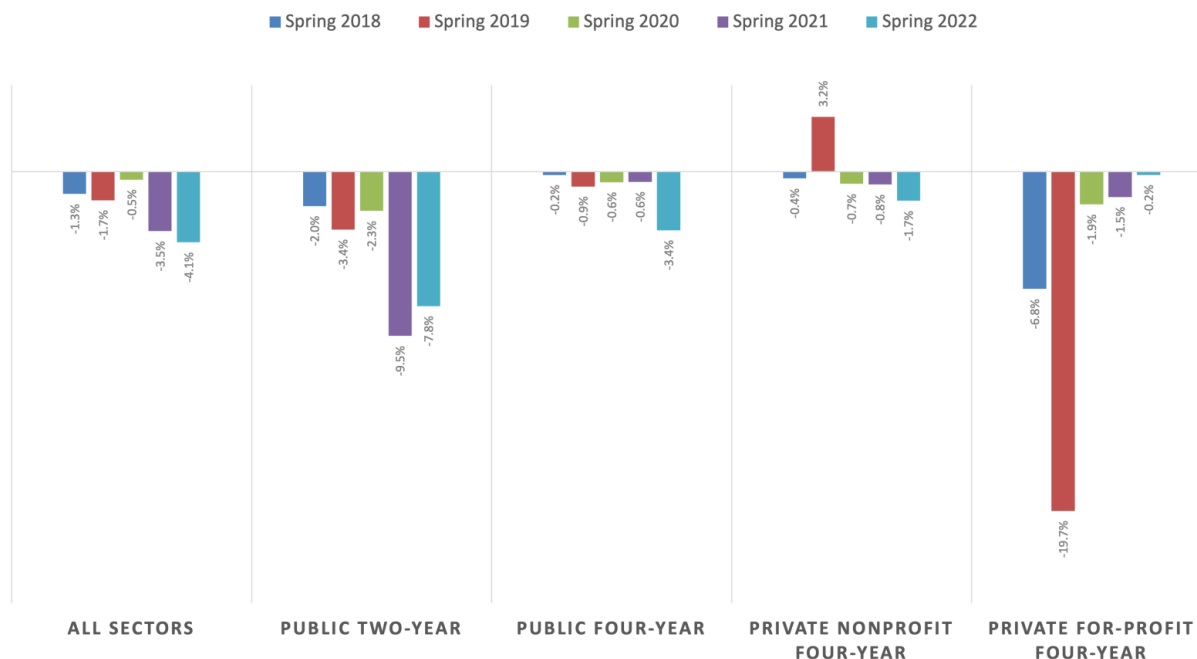
Source: NSC Research Center (2022)

enrolment rates for both decrease by 3.4% and 9.3% a year after the pandemic, however.

When considering the spring cohorts, the enrolment rates have also been decreasing. The NSC Research Center (2022) issued the spring 2022 enrolment data which confirms a continuing decline in enrolment rates (4.1%) across all education sectors (Figure 1.4). As with the fall semester, the sector whose enrolment rates are most affected is the two year public institutions.

When considered by institutional type, it is primarily the enrolment rates of undergraduate certificate and associate degrees that have drastically decreased. As these are lower levels of education, and usually for vocational learning, it clearly shows a learning inequality as the learning gap between higher and lower levels of education begins to widen at a faster rate. Moreover, there is a small decrease of 2.2% in the bachelor credential type, with overall undergraduate enrolment rate changing by 5.9% when compared to last year (Figure 1.5). At the same time, the graduate enrolment rates have increased by 4.4% (Figure 1.6).

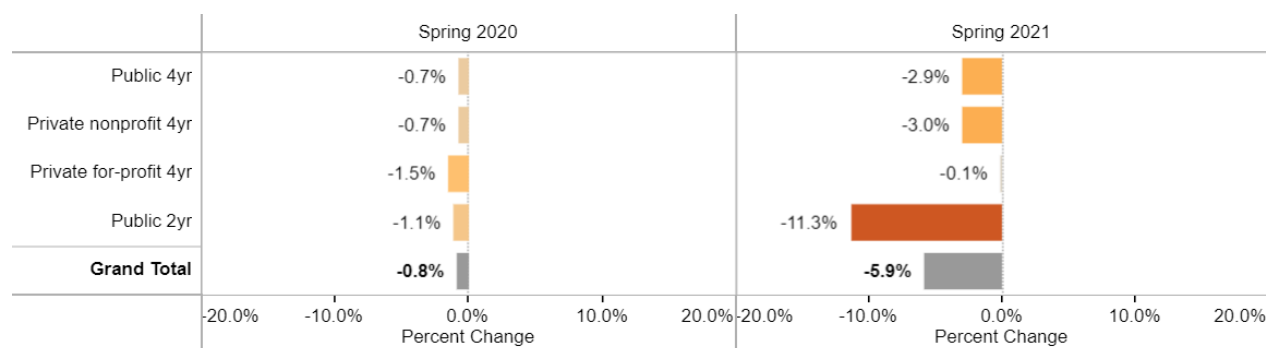
Figure 1.4: Percentage change in total enrolment rate by institution type, spring 2018 - 2021



Note: the percentage change is based with reference to the previous year. Both full time and part-time students are considered in the enrolment count. Undergraduate and graduate levels are considered together in the data represented in the table.

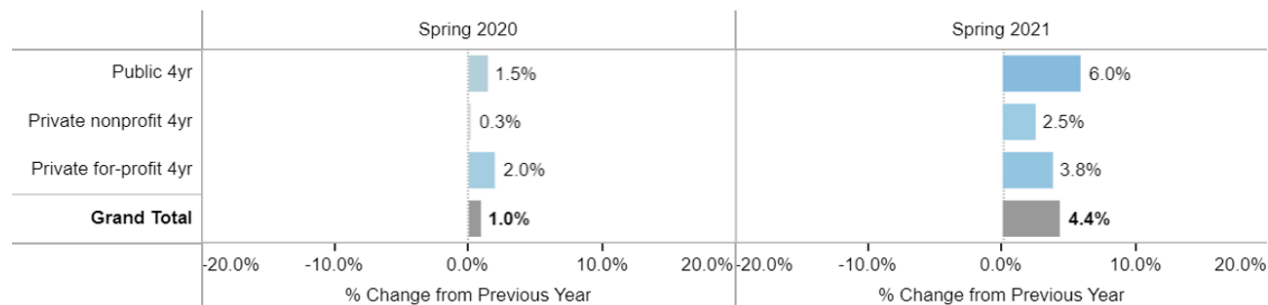
Source: NSC Research Center (2022)

Figure 1.5: Undergraduate enrolment rate changes in USA, comparing spring 2020 to spring 2021



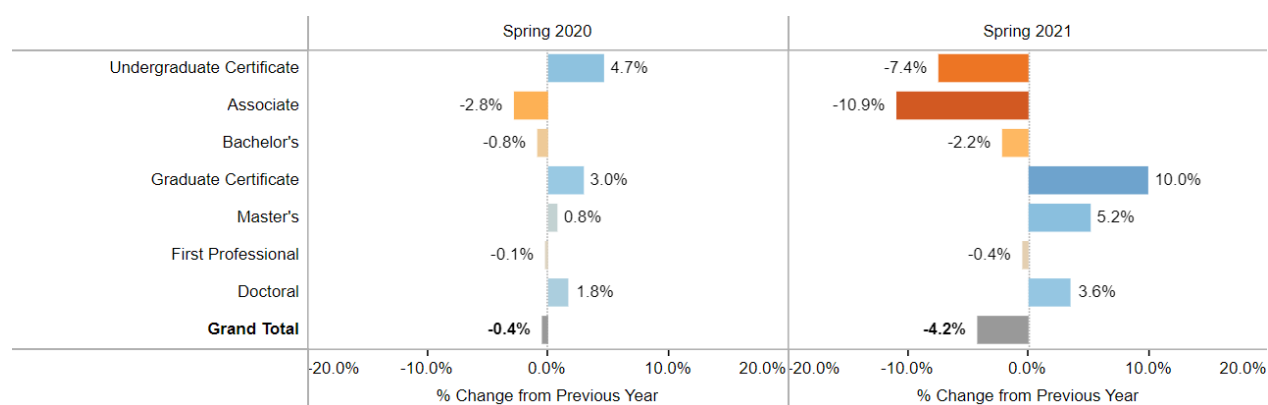
Source: NSC Research Center (2022)

Figure 1.6: Graduate enrolment rate changes in USA, comparing spring 2020 to spring 2021



Source: NSC Research Center (2022)

Figure 1.7: Enrolment rate changes by credential type in USA, comparing spring 2020 to spring 2021



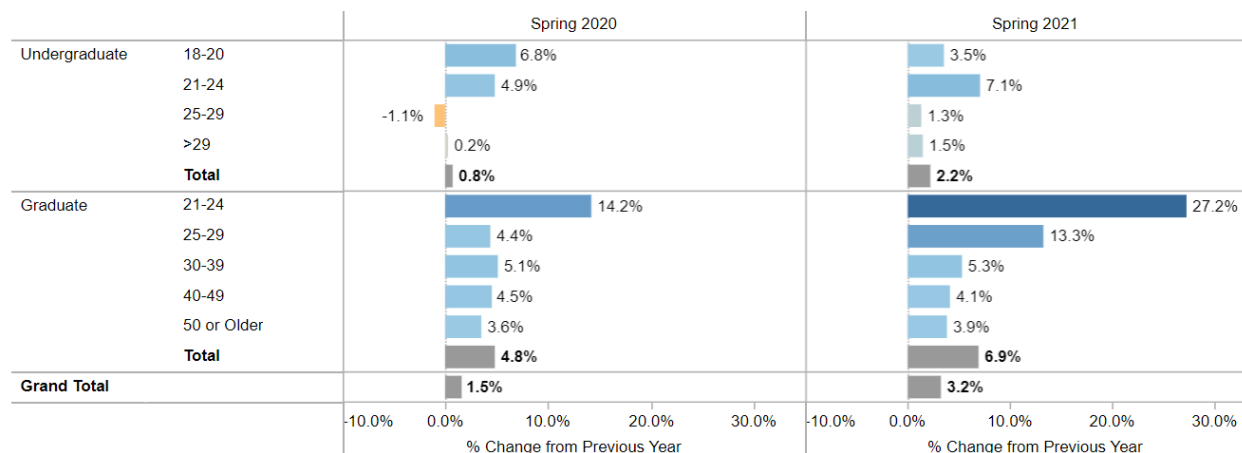
Source: NSC Research Center (2022)

When considering the enrolment rates by certification type (Figure 1.7), the overall enrolment decreased further (4.2%) from spring 2020 to spring 2021. The change in the graduate enrolment rate is the highest at the graduate certification level (10%), followed by Masters (5.2%) and Doctoral (3.6%) levels. Even at a time of crisis, the post-secondary education enrolment rates seem to be rising, especially at the higher education levels. In contrast, the associate and undergraduate certificate levels of education decreased drastically with change in enrolment rates of 10.9% and 7.4% respectively.

If only the primarily online education institutions ¹⁰ are considered, the NSC Research

¹⁰The primarily online institutions are institutions that predominantly provide online courses and programs. It is an identification used in the IPEDS 2018 enrolment survey. In order for the institution to be considered a primarily online institution, the NSC Research center (2021) requires that it has more than 90% of the students, at both undergraduate and graduate level collectively, enrolled in online courses only, prior to the pandemic. There are 27 of such institutions that are used in the NSC Research (2021) Center report.

Figure 1.8: Enrolment rate changes by age and education level, comparing spring 2020 to spring 2021



Source: NSC Research Center (2022)

Center (2022) finds that there has been a continuous increase in the enrolment rates to these institutions across all ages and education levels when comparing spring 2020 to spring 2021 (Figure 1.8). It has particularly increased for traditionally aged graduate students (27.2%). Considering that the graduates would have had experience already with the sudden switch to fully online instruction in spring 2020, it could be understandable that the graduates in spring 2021 see such an increase in the enrolment in primarily online education institutions. This is consistent with the previous studies mentioned earlier regarding the rise in the demand for online education at higher education level.

Graduation rates

Graduation rates are even more pertinent when it comes to ensuring that students are able to graduate well equipped to ultimately find employment. Moreover, graduation rates are a good indicator regarding the quality of the degree and the effectiveness of instructional delivery. Carter (2018) claims that the graduation rates among students from online degrees may seem higher due to the decrease in the obstacles that impede good performance, such as travel time and learning at one's own pace. Nevertheless, Puzziferro (2008) argues that Majority are identified as for-profit four year institutions.

this is only relevant for students that are usually academically strong, highly confident and independent in their learning. Even prior to the crisis, there had already been debates regarding the differing graduation rates from online degrees provided from higher education institutions, whether that is based on the level of the degree ¹¹ or the status of student registered ¹² (Haynie, 2015; Lynch 2020). During the academic year 2019-2020, the undergraduate graduation rate for first time degree earners ¹³ dropped by 1%, which is the first time it has dipped since 2012 (NSC Research Center, 2021). Inversely, the graduation rate for students with previous degrees and stacked credentials ¹⁴ increased by 2.7% despite the crisis (ibid). Nietzel (2020) argues that this halt in the completion rates is primarily due to the impact on traditional aged students ¹⁵ and community college students. Indeed, the community college and associate degree institutions are the ones that have suffered the most compared to other institutions. These are indications of the disparity caused by the pandemic between different types of students based on their chosen educational path.

1.3 Effectiveness and equity of distance education

Online education provides new alternatives to teaching and learning (Palvia et al., 2018). This new era of the digitalization of education has brought forward many opportunities, as well as many uncertainties, especially regarding its effectiveness in learning outcomes. These uncertainties are due to the difficulty in measuring and thereby ensuring the actual efficacy of the online education on the learning outcomes and skill accumulation. Moreover, due to the sudden transition into online education, the impact of the pandemic shed light on some serious inequalities within and between academic institutions. The effects of the

¹¹From credentials, associate degrees, bachelors, masters, for example.

¹²In other words, traditional or non-traditional student. Non-traditional students are defined as those that are also balancing work and family alongside their education. Traditional students do not have obligations outside of academic environment.

¹³First time undergraduate degree earners are students who obtain their first postsecondary award from a Title IV, degree-granting institution in the U.S.

¹⁴Previous degrees and credentials refer to associate degrees, bachelor degree or a similar level of certification.

¹⁵Traditional aged undergraduate students are primarily students 20 years old and younger.

pandemic will not be seen immediately, but could have profound impact on the transition to employability for students and their preparedness for work. Investigating the inequality caused by the pandemic and the effectiveness of online education can provide ways forward to improve the traditional education systems.

The globalization of online education gives way to the distribution of and access to learning opportunities around the world. There have been some studies analysing and comparing the different improvements in education as a result of adopting more online methods and tools for students (McCarty, et al., 2006, Palvia et al., 2018). According to a survey ¹⁶ done by McKinsey in November 2021, teachers and university students are looking forward to more digital integration in the classroom and learning experience (Brasca et al 2022). These advances can lead to an improvement in the pre-existing inequality in access to education given the institutional investment in providing digital access to students and teachers. With further support from international organizations, such as UNESCO and in line with the “education for all” mandate, online education can be a driver to provide equal learning opportunities not only within a country, but also cross nations. With technological advancement, online education has the potential to shape education to become borderless.

Traditional education has been standardized for many decades. It is a one-size-fits-all model in the sense that it provides a particular level of very similar, if not identical, information to students at the same pace (Fourtané, 2021). In other words, it is a paradigm suited to educate students on relatively the same basis and ultimately prepare them for job posts based on their student performance. By contrast, the online pedagogy could be much faster, learner-driven, personalized, and virtually more collaborative. The instruction method for teachers can then be changed from predominantly lecturing to facilitating the learning path of students. This flipped class method provides a much stronger focus on the initiative of the student and their learning interests, rather than imposing a one-size-fits all learning model

¹⁶The survey was conducted in November 2021 for a period of 10 days. Both faculty (634) and university students (818) were surveyed regarding their experiences with digital tools in their teaching and learning. The participants were from different types of colleges and universities, such as private, public and minority serving.

on all students. This flexibility in learning opens doors to alternatives such as studying from a different location, at one's own pace and ultimately for the students' needs. The effectiveness of such a personalized method of teaching at the student level would require a lot of comparative research on the factors that work and therefore make higher education a success.

This section will provide a review and evaluation of the existing literature that has investigated the effectiveness and equality of online education delivery at the higher education level.

Equality in access to online education and its repercussions

Education is a basic human right that should be accessible to all. In this regard, in order to provide equal opportunity to education, it should not depend on the learners' circumstances. Being virtual, online education has a scale of reach that can be unlimited, thereby providing the opportunity to access for virtually anyone. In reality, this is not the case for many individual and socio-economic reasons. The COVID-19 pandemic increased the inequality in two major ways: the access to education and the home environment.

In order to access a virtual class, students must be able to afford to have a computer and sufficient internet access and bandwidth to follow those classes and teachers must be effective in teaching in such environments. The unpreparedness in equipping learners for a virtual education environment enhances the digital divide, which is based on family income and school preparedness. At the family level, there are students who are unable to afford to have stable internet or computer in order to follow online classes (Wegerif, 1998). At the higher education institution level, the university preparedness is necessary in order to avoid disruptions. In reality, not all universities were able to attain the same level of preparedness, thereby increasing the inequality in the online education that was provided to students from universities with funding versus other universities that did not have sufficient funds to provide laptops and virtual support.

The repercussions of the digital divide increase the learning losses between student co-

horts, thereby increasing the skills gap. In this regard, it is likely that the inequality in skill accumulation will rise, which can have a direct impact on the work opportunities as well. Many researchers would argue that the digital divide and the learning loss are now too deep to be reversed. The impact of this digital inequality and learning loss could have major implications on the transition to work and beyond. Others view online education as a way to restore the learning loss and reinforce education through alternative teaching and learning modalities. Certainly, the impact of the crisis has scathed the learning paths of many learners, but it is also provided the academic arena an opportunity to experiment with technology and potentially benefit from it in the long run.

Studies have shown the importance of education and its impact on the skills. UNESCO estimated that within the first year of the pandemic and school closures, more than 70% of the student population ¹⁷ were facing disruption in their education path. As known through the human capital theory, an increase in a year of education has positive financial returns. Inversely, a loss in education time can have detrimental impact on the skill development of students and job prospects. More specifically, Carlsson et al. (2015) quantified the learning loss due to school closures and estimate a causal effect of schooling on skill acquisition, based on the number of preparation days necessary to prepare for a test in Sweden. They found that if 12 weeks fewer of schooling were dedicated to learning, then this would imply a 6% standard deviation on the test results. Moreover, the learning losses can reach up to 60% more for students from disadvantaged and less educated homes. The family background and environment when studying from home is critical for the learner. The issue is two-fold: the infrastructure at home and the impact of family educational background. The infrastructure at home ensures access distance education and materials. Unfortunately not all students are able to have such readily available materials in order to have access to their learning. This digital divide would only drive greater inequality in regards to the access to education, which should be readily available rather than a limitation.

Moreover, the parents' background can have a strong impact on the learner's environment

¹⁷The student population includes from primary to tertiary, globally.

while learning at a distance. There have been many studies on the impact of parental education on the education outcome of the children (Bjorklund and Salvanes, 2011). Even beyond technical skills, the environment at school also provides invaluable soft skills and experiences that can only be accumulated when placed in the academic environment. This also means that some parents may not know how to help their children academically as they have not been endowed with the responsibility of teaching before. According to Oreopoulos et al. (2006), key differences include the amount of time available to devote to teaching, the non-cognitive skills of the parents, availability and access to resources, and the amount of knowledge that the parents may have on the subject. There is great inequality in the case of the background of certain families and hence their impact, direct or indirect, on the students' performance and motivation for learning. Consequently, this difference in the home environment will inevitably lead to an increase in the inequality of human capital growth for the affected cohorts.

Effectiveness of Online Education: reaching expected learning outcomes and employment

The effectiveness of online education is primarily determined by academic achievement and student satisfaction. Using such determinants as a way to evaluate online education effectiveness is limited due to many experimental design pitfalls and setbacks. For example, determining a comparative basis on which to evaluate the effectiveness of distance education is within itself a difficult task to define. Through the use of 355 comparative studies, Russell (1999) found that there was no significant difference in the achievement and satisfaction of students whether education was provided in-class or at distance. Moreover, using a panel data set and estimating random effects and fixed effects models, Lenton (2015) finds that there are large differences in student satisfaction scores across subjects and universities. Therefore the satisfaction levels should not be used as a ranking method. Instead, student-staff ratio and student employability are strong influences. Bernard et al (2009) conducts a meta-analysis to

show that it is not about comparing distance to classroom instruction, but rather analysing cases for improvement in student learning through optimization in distance education. It is found that in general, research methodologies that are used to investigate the effectiveness of online education are inadequate, in the sense that it is difficult to show causal inferences due to confounding variables that are not accounted for in the delivery methods of education, design in pedagogy and learning environments. Moreover, due to the degree of specificity, distance education evaluated at a program level provides a more uncertain outcomes than at course level research (Phipps and Merisotis, 1999). Nonetheless, this section will assess the effectiveness of online education through analysis on factors such as class interactivity, assessments, and preparedness for employment.

Student interaction is a critical part of formal education. Students are able to communicate, network, cooperate and ultimately learn from one another when they are able to interact. There is a social and instructional purpose to interacting, whether that is between students or students and instructors (Gilbert and Moore, 1989). Online instruction can be argued as an impediment to the full potential of interaction between students and the instructor, although studies have shown that the interactive element of learning does not hinder the achievement levels of students (Yacci, 2000). The evidence of interaction would be measured and seen more in attitudes and student satisfaction instead of in student performance. Nonetheless, in order for the effectiveness of online education to succeed, the students must have a satisfactory experience which is supported through interactivity.

There are three main forms of interaction in education: the student-student, student-teacher, and student-content interaction. In traditional education, the student-student interaction depends mainly on face-to-face, synchronous learning. It has benefits, according to social theories of learning, such as cultivating motivation and increasing cognitive learning as well as a constructive environment when learning among other students (Kanuka and Anderson, 1999). The perks of online education is that it can maintain the traditional aspect of student-student interaction, but with a synchronous or asynchronous component. Synchronous modality has been seen with the rise in video conference tools for teaching,

especially during the pandemic. The asynchronous method is predominantly used through the discussion boards and chats in tools such as Moodle and Slack.

When considering the student-teacher interaction, this has been traditionally the case of in-classroom, face-to-face teaching and dialogue. The goal of this type of interaction is for the teacher to be able to stimulate and enhance interest and motivation in students regarding certain subjects. In online education, the interaction between the teacher and the student is critical in order to ensure the proper pedagogical and emotional support, in addition to the maintenance of participation. Distance education theorists, such as Anderson (2003), Moore (1989) and Holmberg (2003), emphasize the importance of the student-teacher interaction on motivational and emotional support, but that it should be measured through attitude test rather than student achievements.

Lastly, student-content interaction is when the student is able to enhance their understanding and perspective of a certain subject through their interaction with the content of the subject (Moore, 1989). The result of this type of interaction is the creation of skills for the student as a result of active investment into the academic material. The level of the skills can range from hard to soft skills that are attained throughout the educational period. It should be noted that the interactions are all interdependent and cannot function solely on their own for an effective educational experience. Rather, different combinations of the interactions could result in much more effective educational outcomes (Anderson, 2003). As per Anderson's (2003) ¹⁸ equivalency theorem, the educational outcomes will be similar regardless of the different combinations and intensities of the interactions, sometimes even more cost and time effective. The main condition to the equivalency theorem is that at least one of the three main interactions is maintained at a high level. Improving further on other interactions will evidently enhance the educational experience but not necessarily in a cost and time effective manner when compared to the less interactive learning treatments.

Technology provides an opportunity to transform student-teacher and student-student

¹⁸He continues further to develop the other types of interactions, such as teacher-content and content-content interaction.

interactions into a stronger student-content interaction. Bernard et al (2009) used a meta-analysis to investigate the effect on achievement through different combinations of interactions and found that only student-student and student-content were significant. Essentially the student-teacher interaction was not significant in producing better educational achievements. Therefore, the push towards online education should be seen as a call for innovative methods to create more cultivated experiences and improved interactivity for students and teachers alike.

The interaction level would differ between synchronous, asynchronous and blended distance education. Holden and Westfall (2006) argue that the grounds on which we compare the interaction between types of distance education are different and should be considered carefully. The interaction would be much larger in synchronous and blended distance education compared to fully asynchronous model. In the case of asynchronous education, the interaction can be built in through information and communication technology that should be made available to students for continuous offline communication and interaction as well.

Effectiveness can also be assessed through assessments and thereby student performance. Examinations and other types of assessments provide information regarding the students' progress and understanding of the subject. Therefore student performances on assessments are a critical indicator towards the students' preparedness, but moreover it shows the effectiveness of the teaching that was done. During the pandemic, many assessments were delayed, cancelled or transformed into homework based assignments. Examinations done online will likely have a larger variance in the grades than usual, due to the absence of appropriate way of controlling for cheating on online exams. Bunn et al (2014) studied the cheating behaviour of micro-economic students and found through a logit model that cheating is inversely related to GPA and directly related to the perception of the number of students who routinely cheat. Mitigating these risks has yet to be addressed, although with the enhancement of online education tools, there could be more tools for exam taking, i.e. proctoring exams, but which would also require higher investment at the institutional level to implement.

In terms of readiness for work, the graduates after the pandemic will be graduating at

the beginning of a great recession and would therefore need to be agile in their skills and adaptability to such an environment. The perks of online education are that it cultivates skills of self-teaching, self-motivation and adaptability, which are pertinent in times of employment downturns. Evidence suggests that poor market conditions at labour market entry cause workers to accept lower paid jobs, and that this way may lead to permanent effects for the careers of some. More importantly, the effectiveness of the online education in terms of student performance upon graduation is an indicator of preparedness for entry into the labor market. This type of signaling effect is critical in sending the appropriate signals to potential future employers. Research shows that employers use educational credentials, such as degree classifications and grade point averages, to sort applicants (Piopiunik et al. 2020) as a way to reduce hiring costs. The increase in the noise of the applicants' signals will therefore potentially reduce the matching efficiency for new graduates on the labour market, who might experience slower earnings growth and higher job separation rates. This is costly both to the individual and also to society as a whole (Fredriksson et al. 2018). Oreopoulos et al. (2012) show that graduates from programs with high predicted earnings can compensate for their poor starting point through both within- and across-firm earnings gains, but graduates from other programs risk experiencing permanent earnings losses from graduating in a recession.

Overall, the effectiveness of education has profound impact on the student capacities, their academic experience and performance, and ultimately their preparedness for employment. Although the research around these indicators of effectiveness is rich, it remains to struggle to show external validity due to small and concrete samples. More research at a larger scale would be necessary although that would also be quite costly.

1.4 Conclusion and Recommendations

The pandemic provided an opportunity to reflect on the effectiveness and equality of the current education system. From the institutions' preparedness, to the teachers' adaptability and the students' outcomes, the sudden switch to fully online education revealed many

pre-existing and new issues in the institutional organization, teaching and learning. This disruption in traditional teaching methods delayed and even induced learning losses between 7 to 12 months, especially for lower achieving students who require further support. Moving entirely online increased the inequality between students that are able to support such learning at home and those that are not, based on being able to afford the necessary internet and equipment to be able to follow the lectures. In this regard, online education is beneficial to students that can support this alternative modality. This would increase online access to courses, materials and teachers, thereby decreasing the inequality among the students that have access to such modality of learning. In other words, online education can bring more inclusion on the basis of access, and this can be further scaled. On the other hand, and if the students are not able to support such a modality, it can increase the digital divide, whereby accessibility to education is limited. This would in turn increase inequality to access and ultimately exclude these cohorts from accessing any online courses or materials. Ultimately, distance education can mitigate the learning losses by providing a medium to validate the learning outcomes. In order to do so, accessibility to online education should not be dependent on the students' circumstances but rather provided at the institutional level.

The effectiveness of online education depends on all three stakeholders; the institution, teachers and students. During the pandemic, different types of education institutions, whether universities or community colleges, were impacted differently due to their respective available resources in supporting staff and students. This gives rise to between-institution inequality, which is fundamentally based on the funding availability to have a resilient education program and provide for flexible teaching methodologies. This further emphasizes the insufficient institutional investment in ICT, in order to provide digital tools, platforms, and training, in order to close the digital divide in terms of staffs' technological skills. The impact of the level preparedness at the institutional level trickles down to the teaching staff and their effective practices. The sudden transition to online instruction in the middle of the academic year did not provide sufficient time to transform the pedagogy and the teaching practices

of teachers, in order for the online education delivery to be effective. Teaching staff with previous online education experience were able to convert their practices much more easily due to a lower learning curve in the use and management of different learning management systems and modalities.

Students' performances is an indication of the effectiveness of the education provided. Studies have shown that students' performances varies on the basis of different factors, such as student attendance, grades on assessments, and satisfaction with the education received. Attendance has been found to be important for students due to the benefits in learning through interactions between peers and teachers. With limiting the physical attendance during the pandemic put students in a feeling of isolation, which could have negative effects on the learning, motivation and ultimately performance. Assessments were difficult to perform at a distance, which resulted in large variations in grades. This could have results for many reasons, including cheating. Therefore using the grade as the only indicator to assess students' performance and their capacities could be misleading. Moreover, it could have implications on the employment of these students that signal certain skills sets that they may not actually have. There is still a lot of investment necessity to create robust examination systems that would impede cheating and other technical difficulties in taking exams online. Overall, surveys have predominantly shown that students were unsatisfied with their experience of online education.

Even though it was difficult to become accustomed to an online modality in the traditional education context, surveys have shown that both teachers and students are willing to integrate more digital tools in their courses. The main reasons are to increase the effectiveness and the efficiency of teaching and learning. Moreover, with greater accessibility through online education, this means that it can be provided at scale which could in turn also be beneficial at the institutional level as more students can be accommodated per class. In the aftermath of the pandemic, more institutions are starting to use more digital tools and searching for ways to improve education and training in different teaching and learning modalities. The modernization of education will also improve the digital skills of both teachers and students.

Ultimately, online education should not replace traditional education, but rather help in areas in which traditional education can be made much more effective. The technological medium and tools can open opportunity for a better outreach and potentially better outcomes for students.

This chapter has attempted to synthesize the approaches to evaluating online education in light of the recent pandemic. Using the current literature, different avenues of further research have been pointed out. Nonetheless, this chapter itself has its own limitations. Firstly, it is primarily based on USA data sets, as it has the most data currently available. Further improvements to this analysis would be to expand the region of focus, currently predominantly the USA. It would be much more fruitful to have comparable data with other comparable country settings. This would provide a greater knowledge base and comparisons between lessons learnt. In addition, more data are necessary at the tertiary level of education. A majority of the studies have focused primarily on early childhood, primary and secondary education. Once more data become available, the effect of the pandemic can be better analysed with more rigorous empirical studies.

Chapter 2

The Impact of Alternative Education Modalities on Student Performance

2.1 Introduction

Higher education is a period for students to gain foundational knowledge and capacities in preparation for employment. There has been profound literature on the importance of higher education and its returns on investment, in terms of individual and national gains (Becker, 1960, Schultz, 1961; Denison, 1962). In general, the higher the level of education attained, the greater the expected gain which is usually measured in income at the individual level and in economic growth at the national level. In this regard, and due to the initial high, risky, and illiquid investment in higher education, the expectation is that it would provide a doorway into work opportunities with future higher returns (Becker, 1975; Mincer, 1975). Yet there are certain barriers applicants need to pass through, on the basis of specific criteria, in order to transition onto the employment phase. One of these criteria is typically academic standing, usually measured through academic excellence and performance. Academic performance is an indicator, usually measured by grades, showing the students' efforts and achievements of the learning outcomes. It is determined by an ensemble of quantifiable factors such as attendance, assignment completion, midterm results, and final exam grades. Keeping all

else fixed, these factors are a result of a two facet contribution: the student effort and the teacher ¹ effort. Although the majority of the research studies have focused on student-side factors ², there is little literature on the evaluation of teachers ³, specifically on the different teaching modalities with respect to student performance at the higher education level. In this regard, this study will examine different teaching modalities and the extent to which a teaching modality implemented in a class will alter the student grade as a measure of academic performance.

The recent pandemic reinforced the use of technological tools and alternative teaching modalities in the academic arena, especially with university closures. This induced an increase in the overall demand for digitalization of education, thereby enforcing alternative methods of teaching due to the global context. In the United States, according to the National Center for Education Statistics (2022), the number of postsecondary students enrolled in at least one distance provided course doubled from 6 million in 2019 to 11.8 million in 2020. Students that were solely enrolled in distance courses tripled, from 2.4 million to 7 million, within the academic year of 2019-2020 (ibid). Although there has been a rising demand for online education, it has been a challenge for universities to provide this alternative (Diaz-Infante, et al., 2022). In response, governments implemented educational continuity plans in order to ensure connectivity between students and teachers, including providing student support, aid with information and communication technologies, access to stable internet connection, and computer equipment (Reich et al., 2020; Jacques and Ouahabi 2021). For example, the France Université Numérique (FUN) Campus is a digital platform used extensively by higher education students and professors to share course content, do interactive activities, and acquire practice and skills. Moreover, the French Ministry of Higher Education, Research and Innovation had already launched a project in 2019 called Connected Campuses with

¹A teacher comprises the professors and teacher assistants. In other words, any person that teaches core material, whether in a lecture or a supporting tutorial, on which there is a grade provided.

²Research has focused on specific factors, including but not limited to, student satisfaction (Jacques et al., 2020), student emotional and mental experiences (Le Vigouroux, et al., 2021; Bourion-Bédè et al., 2021), student motivation (Jacques et al., 2020), attendance to class, physical distance from the classroom.

³The studies that exist regarding teacher quality primarily focus on teacher satisfaction, previous experience of teachers with respect to the subject matter taught.

the goal to eliminate the physical barriers for access to education by providing certified distance education in localised spaces. For the academic year 2021-2022, there were already 89 connected campuses in France (Campus France, 2021). Although access to digital tools and resources was made readily available to ensure educational continuity, there were still pedagogical challenges induced through such digital tools and social media (Sistek-Chandler, 2020). In particular, teachers had to balance education continuity and quality, while at the same time reinventing their pedagogical approaches, improve digital competencies for course delivery, and maintain contact with their students. Hence, with this steep increase in the digitalization of education and pedagogical challenges, this chapter aims to investigate alternative modalities ⁴ through a case study on the performance of masters level students at a French university.

In order to investigate teaching modalities, student performance must be defined appropriately. As there are a variety of determinants of academic performance, the literature can be split into internal and external influencing factors. When referring to internal factors, it is student specific and thereby focused on individual characteristics. External factors can be further divided into two categories; (a) surrounding environment, and (b) academic institutional practices. The individual characteristics mainly studied are gender and age as they are easily observable and measurable (Pirmohamed, et al., 2017; Nunez-Pena, et al., 2016). There are also unobservable individual characteristics that are determinants of student performance, such as motivation and cognitive ability. In terms of differing motivational factors, Yoo and Wenhao (2013) used 190 surveys and found that there were significant gender differences in intrinsic motivation, while extrinsic motivation was impacted by age differences. There are also psychological individual characteristics, as described by Bandura's (1986) social cognitive theory that generate a certain attitude and hence impact on the student performance (Devi et al., 2017). These types of characteristics, such as self-regulation, self-efficacy, and self-motivation, are much harder to evaluate as it is innate, or rather an

⁴For this chapter, the teaching modalities investigated are split into three categories; presence, hybrid and distance.

endowed, individual cognitive ability, and hence difficult to quantify. Nonetheless, Sothan (2019) used multivariate regression analysis based on a sample of over 329 undergraduate students, and found that personal traits such as self-efficacy and study effort are positively associated with academic performance, while student-independent factors, such as teacher evaluation, were not. Inevitably, the student's motivation and thereby performance depends to a degree on the students personality and approach to learning. Chamorro-Premuzic (2007) used an experimental study based on 221 undergraduate medical students from two UK universities to investigate whether there are correlations between personality traits and learning approaches of students as a determinant of their preferred teaching modality. Within the big-five personality framework ⁵ (John and McCrae, 1992; Goldberg and Rosolack, 1994), the study uses the psychometric instrument factors ⁶ to estimate the individuals' learning approach ⁷ as defined by Biggs (1987). These student-specific instruments were used to evaluate the relationship between personality traits, types of assessments, and academic performance (Chamorro-Premuzic and Furnham, 2009). The findings confirm that the student-specific characteristics can have a heavy impact on the students' approach to learning, but also on their preference on the teaching method, which in turn can also impact learning and academic performance. Hence, both the student effort, based on individual characteristics, and teachers' teaching modality clearly depend on one another to ensure the level of academic performance.

The external influences affecting the student performance are split between factors found within or outside the academic setting. Examples of external factors to the academic setting, include family background and socioeconomic level. Studies have found that there is an achievement gap between individuals from advantaged and disadvantaged socioeconomic backgrounds due to family influence and disposable resources (Datcher, 1982; Astone and McLanahan, 1991). This touches upon the education inequality amongst students that

⁵In the field of psychology, the five-factor model of personality traits was developed in the 1980s as part of the psychological trait theory in order to evaluate academic behaviour.

⁶Neuroticism, Extraversion, Openness, Agreeableness, and Conscientiousness

⁷Biggs (1987) defines the learning approach in fourth categories; deep, surface, and achieving motives and strategies

arises from the parents educational background and the income variation, which are positively correlated with the students' performance (Björklund and Salvanes, 2011; Guimaraes and Sampaio, 2011). Even when controlling for resource differences, Cheung and Andersen (2003) found that family background persists in having a significant impact on academic performance. In this regard, the family environment is critical in ensuring an appropriate learning environment, especially when learning is done at home and at a distance. It is even more important in the case of alternative teaching modalities, as students need to be well equipped in order to use and learn from digitized material.

This chapter will focus on factors within the academic setting, specifically on the relation between academic institutional practices and student performance. The factors within the academic setting can include physical aspects, such as classroom size, institutional facilities, and availability of resources. There are also intangible institutional factors, such as teachers' quality and their teaching modalities. With the increase in technological integration in academia, the teaching modality has become more accessible and flexible, permitting for different ways in which to teach, interact and evaluate students (Lee et al., 2010; Francescucci et al., 2020). Some studies have found that distance learning has been beneficial to certain types of learners while detrimental to others (Clarke et al., 2001; Dumford and Miller, 2018), due to different teaching styles affecting the overall engagement of the course.

However, evaluations of the impact of alternative teaching modalities ⁸, i.e. distance, hybrid and in-person, on student performance has not been rigorously investigated. It is important to study this topic because it is becoming largely adopted by universities without concrete evidence on its impact on students and their performance. Due to the recent crisis, the use of technologies in the classrooms has risen. Public policies are supporting the adoption of these technologies as a way to facilitate access to higher education, by funding infrastructure and teacher training. For example, the EU renewed its initiative regarding the Digital Education Plan for 2021 - 2027 as a way to enhance digital skills in preparation for the development of a high performing digital education ecosystem (European Commission,

⁸The alternative teaching modalities have been identified and thoroughly discussed in chapter 1.

2021). This is to facilitate university infrastructure and hence teaching quality when using alternative teaching modalities. This begs the question, how do different modalities impact the performance of the students? Can this impact be improved or used in a way that is beneficial to all university students, even those that may be restricted by time, physical distance, or ability? By evaluating the alternative teaching modalities and using student performance as an indicator can shed light on the benefits and limitations of teaching methods and the learning approach to students. It can also suggest how to ensure that the education system becomes more resilient against future crises and is readily adaptive. Moreover, this research can provide insights into the improvement on teaching efficiency in terms of minimizing costs for a better value of teaching and learning. Lastly, evaluating alternative teaching modalities can provide accessibility, especially for those students limited by time and distance, and provide economies of scale for a greater outreach to students beyond the physical classroom.

The purpose of this chapter is to contribute to the empirical literature on teaching modalities through a quasi-experimental modelling using student grades from three different departments of the Université Gustave Eiffel (UGE). It will do so two folds by evaluating; (1) the impact of the alternative teaching modalities (distance, hybrid, and in-person) on student performance using a pooled OLS approach, and (2) capturing the impact of covid on student performances using a pooled panel data from September 2017 - June 2020. The pandemic has added a level of complexity to the research design as the impact of covid cannot be distinguished from time or certain imposed teaching modalities, such as distance, due to confounding. This will be further discussed in the research design section. In this regard, there will be several model designs to shed light on the impact of these two distinct approaches to the topic.

This chapter is organized in the following manner: it will provide insight on the existing, yet limited, empirical literature specifically pertaining to the relationship between alternative teaching modalities and student performances. Section 3 will be dedicated to the overall research design for the study, allowing for multiple design models to better illustrate the influence of alternative teaching modalities and the pandemic. Section 4 will provide data

description of the data collected for the study, followed by Section 5 showing the results of the different models. Section 6 will conclude and provide recommendations for further research.

2.2 Literature Review

There has been a fundamental shift in the instructional modality overall. The focus is no longer centered on the instructor, with students passively learning the material. Instead, it is increasingly becoming more student centered with greater emphasis on active learning. Personal management skills, such as self-motivation and self-direction, over academic objectives, are fostered in active learning, thereby adding value to classroom dynamics once the educational material has already been covered outside of the classroom session. This provides more time for in-depth discussions, clarifications and inquiries during the class session. In this regard, the extent of active learning depends on the teaching modality adopted and hence the influence on the performance of the students.

Active learning depends greatly on the students' learning preferences. Studies have found that the learning preferences differ across students based on their level of educational maturity and years of study (O'Shea, 2003; Marriott, 2002). Otter et al. (2013) found that students felt more obliged to be self-managed, but also felt very disconnected from their classmates and teachers. Moreover, and similar to the teacher's experience, studies have found that students do not feel comfortable with using online study as they do not feel that they have the sufficient competencies, which limit their ability to learn (Zhang and Perris, 2004; Holley and Oliver, 2010). Studies around instruction methods, efficiency of tools, and student satisfaction have shown mixed results based on factors such as course content and digital infrastructure (Connolly et al., 2007). All in all, alternative teaching modalities can therefore be not only cultivating students and staff with additional personal, interpersonal, and technological skills, but it can also be cost effective.

The literature on the impact of alternative education modalities on students has been investigated since the rise of learning management platforms and digital tools in the late

1990s (Davis et al, 2009; Dobre, 2015). The majority of the studies have done qualitative research to evaluate the difference in student performances based on the extent to which online instruction is adopted. This could be evaluated in terms of the technological tools used in the classroom, homework completion, and final exam scores (Alpert et al., 2016). In this regard, it seems that the literature cannot determine whether one modality is more effective, on average, than another, due to issues of variations in the types of instruction⁹ conducted and outcomes measured¹⁰. This poses a shortcoming in the research methodologies as there is a lack of control on extraneous variables, lack of randomness in the selection of subjects, and hence reliability of instruments used. Consequently, there is a direct impact on the research findings particularly due to lack of external validity, comparability and scalability. Lastly, the research methodologies range from purely observational research to quasi-experimental studies to, in relatively few instances, randomized studies due to the limitations of the research designs regarding instructional modality impact on student performances.

Due to the multifaceted complexity of evaluating teaching modalities against different students in time, there are few empirically strong studies on this topic in existence. Very few rigorous experimental studies used random design to explore the impact of alternative instructional modalities in university courses on learning outcomes. Firstly, Figlio, Rush, and Yin (2013) conducted an experimental study on an introductory microeconomics class by comparing traditional to recorded lectures that were uploaded online. Students were randomly assigned to either traditional (97 students) or recorded class (215 students) cohorts. The instructor and any class supporting material, i.e. quizzes, assignments, practice exams, or help, i.e. from a teacher assistant, were kept constant. This was a way to keep all aspects of the course identical for each student group in order for the only differing factor between the

⁹The definition of different teaching methods differs across research studies due to the variety of ways in which teachers can deliver a course. For example: online instruction can be conducted through simple recording of a lecture and uploading it into the learning management system of the university for all students to access. At the same time, the online instruction can be much more advanced with interactive video calls, webinars, and discussion forums. Online instruction can also be conducted synchronous or asynchronous depending on the content and activity of the course.

¹⁰The learning outcomes can differ based on different universities' approaches and objectives for learning outcomes of each class.

two cohorts to be the method of instruction. They found that students who took the course in person performed better ¹¹ on average, both on the midterm (roughly 3 points more) and the final exam (2.5 points more), compared to those who took the course entirely online. This was particularly the case for males, Hispanics, and lower-ranking students. This is in line with the literature on the achievement gap on the basis of ethnic background and below average achieving students (Figlio and Loeb, 2011; Kaupp, 2012; Xu and Jaggars, 2013). The validity of this experiment is susceptible to information contamination and positive peer effects between student cohorts. These are issues that are out of the study's control, but could impact the study results. Apart from the need to improve external validity, similar experimental studies are needed for comparability.

In this regard, Bowen et al (2014) conducted an experimental study comparing hybrid and traditional teaching on an introductory statistics course. The 605 participants were randomly assigned into either the hybrid or traditional cohort. Using machine-guided instruction of one hour of face-to-face instruction per week, for the same course across six public university campuses, the study was able to test the hybrid instruction through a more sophisticated online interactive system, as compared to Figlio et al (2013) video recorded course. An OLS estimation, course specific dummy variables, and clustering around the standard errors were used in order to capture differences between the two cohorts, such as in teacher quality since the instructors were different between the cohorts due to difficulty in teacher randomization. This is a limitation to the study, as the instructor has a large influence on the students based on the instructor's experience with hybrid teaching modality. Moreover, as there are different instructors for each cohort, there could be an impact on the grading method. Considering that all the exam results turned out quite similar, however, the researchers are confident that this issue does not seem to carry much weight. In terms of student performances, they found that both instructional cohorts have similar impact. Although, in terms of course completion rates, the hybrid cohort had a 5% higher completion rate than the traditional format. Ultimately, the study concluded that hybrid format instruction increases access

¹¹The grading is based on a 100 point scale.

to higher education and improves educational productivity by achieving the same learning outcomes at a much lower cost.

Conducting classes online or hybrid mode means that students will have less time in-class and reduced interaction with the teacher and other students. Joyce et al. (2015) conducted a randomized experiment of 725 college students in an introductory microeconomics class to assess the impact of class time on student performance based on the extent of access to online course material. The traditional format consisted of lectures conducted twice a week, while the compressed version of the class consisted of a single lecture, but with extensive access to course materials online, including lecture slides, teacher videos, and supporting material. In other words, the design attempted to simulate a hybrid mode of the class by minimizing the number of lectures and predominantly providing the course material online instead of during a live lecture. They found no significant differences on the final exams scores for students who took classes in hybrid mode when compared to in-person. Instead, the traditional format cohort scored approximately 3 points ¹² higher on the midterm compared to the hybrid cohort. Interestingly, approximately 17% of the students from the hybrid format were penalized for missing attendance compared to the 9% from the traditional format. These absences can have an impact on the performance due to missed material. This emphasizes the importance of engagement in the course work, especially for non-traditionally taught courses where the students are not physically bound to attend the classroom. Although, according to Bandoura's Social Cognitive Theory (Bandoura, 1991), attending classes does not necessarily mean that learning is taking place. Therefore the necessity of physical attendance to learn is questioned.

The course content and design are critical in determining how the modality will impact the student performance. In terms of the course characteristics, the majority of the literature has examined primarily introductory courses at the undergraduate level (Driscoll et al., 2012). Moreover, the compatibility of the type of course with a specific teaching modality could impact the learning process of students. In other words, if the course is scientific in

¹²The grading is based on a 100 point scale.

nature, and involves physical interactions and work, i.e. laboratory experiments, then alternative teaching modalities would be limiting. Tomal et al (2021) argues that average grades tend to be higher for online courses that entail lower level cognitive skills, such as statistics and mathematics. For courses requiring higher-level cognitive skills, and more physical interaction, grades were observed to decrease. Moreover, Figlio, Rush, and Lin (2010) argue that the transition into online education will impact more significantly the initially lower achieving students compared to the higher achievers. Furthermore, without distinguishing initial performance of students, Sockalingham (2012) finds that 71% of the variance in assessment is due to the course content and design. Therefore based on the nature of the course, a change in teaching modality could impact students differently.

2.3 Data Collection

The study is based on a French multidisciplinary university, the Université Gustave Eiffel, which was established in January 2020 and has campuses around France. In addition to being a university, its founding partners also include; six research institutes, three engineering schools, and an architectural school ¹³. Overall, the university reported to have about 17,000 students, out of which 3,500 are master students (UGE, 2020). In addition, there are 2,300 teachers, researchers and support staff (ibid). The goal of the university is to have a large range of expertise by educating different student profiles such as youth, experienced adults, and civilians.

The study is based on the UGE campus close to Paris at a site called Cite Descartes. In the study framework, one engineering institution and two training and research departments agreed to collaborate. These are:

- Department of Economic Sciences and Management ¹⁴,

¹³The six institutes are under the umbrella of Institut français des sciences et technologies des transports, de l'aménagement et des réseaux (IFSTTAR). The three engineering schools are Ecole Nationale des Sciences Géographiques (ENSG), Ecole des Ingénieurs de la Ville de Paris (EIVP), and ESIEE Paris. The architectural school is Ecole d'Architecture Villes and Territoire (EAVT).

¹⁴Officially, Science Economiques et Gestion (abbreviation, SCECO)

- Department of Engineering ¹⁵,
- Department of Languages, Culture and Society ¹⁶

Each department has specialized master's degrees in their respective domain. The courses are adapted to include options for apprenticeships, internships, and/or further research depending on the type of degree and options available. All master's degrees are provided at M1 and/or M2 levels. The LANGUES department is the smallest as it offers six masters, consisting of different languages, interpretation, and commerce. The SCECO department offers 11 master's , predominantly in economics, data analysis, and management. The largest department from the sample is IFIS, and it offers 16 masters, focusing on a wider range of subjects such as social economic, innovation management, and tourism. Each department could also have master's programs that are affiliated with other institutions.

The data were collected through two sources: the university APOGEE database ¹⁷ containing information on all registered students ¹⁸, and an online survey that was sent to teachers to identify their teaching modalities for the courses that they taught (Annex 2.A). Using these two sources of data, the database used for this study was generated. The APOGEE database disclosed student information such as student characteristics ¹⁹ and student grades from September 2015 until June 2020. There are two possible grades per student. The first grade is the original final grade for a course that a student attained. The second grade is an adjusted grade that takes into account any retakes of the assessments for the course. After robustness checks, there is no significant difference in the results of the models, whether the first or second grade is used as a dependent variable (Annex 2.B). In order to provide equal opportunity to each student for taking an assessment, the study will only use the first grade in the proposed models.

¹⁵Officially, Institut Francilien d'Ingénierie des Services (abbreviation, IFIS)

¹⁶Officially, Langues, Cultures et Sociétés (abbreviation, LANGUES)

¹⁷The APOGEE database is used to collect all information on registered students, including profiles, grades, and other information regarding the student's academic progress.

¹⁸For privacy reasons, student numbers were made anonymous.

¹⁹Student characteristics that were disclosed were fictitious student number, sex, and age.

Figure 2.1: Numbering periods (semesters) across academic years

Semester (Period)	1	2	3	4	5	6	7	8	9	10
Year	Sept - Dec 2015	Jan - Jun 2016	Sept - Dec 2016	Jan - Jun 2017	Sept - Dec 2017	Jan - Jun 2018	Sept - Dec 2018	Jan - Jun 2019	Sept - Dec 2019	Jan - Jun 2020

Source: Author's creation

The objective of the survey was to capture the teaching modality used by the teachers for the courses they taught from September 2017 – June 2020. The survey was developed using the teacher registry by course. It consisted of three multiple choice questions organized by academic year. Within each particular year, all the courses that the teacher had taught were listed in order for the teacher to identify the teaching modality for each course. The options for modalities were distance, hybrid, or in-person. The definitions of each modality were provided to each teacher to avoid misunderstanding. A final question was added to capture the teaching modality for all prior academic years to 2017. The goal was to standardize the assumption that the teaching method prior to 2017 was indeed primarily face-to-face. A standardized email was sent to all UGE staff, exterior teachers, and temporary teachers for which a contact email address was identified. The survey was sent out in March 2021 for a duration of three weeks with weekly reminders.

2.4 Data Description

This section will only focus on the constructed database for the purposes of the case study. To better capture the impact of covid, an academic year is split into two semesters, which will be referred to as periods from this point onward. These are numbered according to the academic years for which students grades were provided (Figure 2.1). Final assessments and ultimately the student grades for courses are given at the end of each period. The survey identified course modalities for periods 5 to 10, which will be the focus of the study. The covid pandemic started in March 2020, equivalent to period 10.

Using the APOGEE and survey databases, the study's database was constructed by matching the teacher survey responses to the course codes, and the student grades. This

Table 2.1: Number of courses identified by modality

Year	Period	Distance	Hybrid	Presence	Total Courses
Sept - Dec 2017	5		1	128	134
Jan - Jun 2018	6	1	1	82	90
Sept - Dec 2018	7	2	4	181	194
Jan - Jun 2019	8	2	9	99	118
Sept - Dec 2019	9	32	69	82	192
Jan - Jun 2020	10	35	40	30	115
Total Courses		72	124	602	798

Source: APOGEE and Teacher Survey

Table 2.2: Number of grades identified by modality and period

Year	Period	Distance	Hybrid	Presence	Total by Period
Sept-Dec 2017	5		14	2,573	2,587
Jan-Jun 2018	6	16	28	1,690	1,734
Sept-Dec 2018	7	62	91	3,700	3,853
Jan-Jun 2019	8	39	178	2,061	2,278
Sept-Dec 2019	9	752	1,523	1,488	3,763
Jan-Jun 2020	10	689	874	550	2,113
Total by Modality		1,558	2,708	12,062	16,328

Source: APOGEE and Teacher Survey

resulted in identifying the teaching modalities for 798 courses (Table 2.1) from September 2017 – June 2020. As expected, there are few courses identified to have been taught using distance or hybrid modality prior to the pandemic in period 10. In addition, more courses were identified for the first semester of each year versus the second semester. This could be due to internship requirements during the second semester, which reduces the amount of classes taken at university.

Within the 798 courses, the number of observations, student grades, is 16,328 (Table 2.2). It is observed that very few courses were identified to have been taught in distance and hybrid modes prior to 2019. The grades considered are only those that were taken at the first attempt, without make-up assessments considered.

Interestingly, there was a surge in the number of courses taught in distance and hybrid modalities the semester prior to the pandemic (period 10). This identification issue was

investigated and no inconsistencies were found in the data collection process or the survey response-to-course matching. Therefore, the responses were cross checked against the modalities specified for a particular course in semester one of 2018 (period 7) with respect to semester one of 2019 (period 9). Presumably, the course would have been in-presence for both periods 7 and 9, as it is prior to the pandemic. There was a difference in the response for 18 teachers, who were re-contacted to ensure the correctness of their response.

According to the responses of nine teachers out of the 18 that were recontacted, there are two main reasons for the difference in the modality between those periods. Firstly, it was due to the transportation strikes in the last quarter of 2019. This limited school attendance for many students and teaching staff, as all public transportation was cancelled or drastically reduced (Godin and Nossiter, 2019). Moreover, due to the strikes, the courses could not be delayed or cancelled for working students whose studies are funded by employers, hence the need for alternative modalities. Therefore, due to an increase in absences and employment constraint, the teachers were advised to resort to hybrid or even remote teaching. Secondly, the heads of some master degrees recommended hybrid/remote teaching for reasons such as providing students with more free time, especially if they already had the skills in the course subject, such as for working students. Ultimately, the reasons seem to justify the sudden increase in the hybrid and distance modalities for period 9.

When analysing the grade averages by master level and modality, within each period, the M1 level seems to always have a lower average grade than M2 level for all modalities (Table 2.3). For both master levels, the second period within a year predominantly has a higher average grade compared to the first period. Although, specifically during the pandemic, the average grade for the M1 level courses that were taught virtually dropped from 12.23 in period 9 to 11.84 in period 10. Courses taught under hybrid and in-person modalities had an increase in the grade average during the same periods for M1 level. For the M2 level, there was an increase in the grade averages across all modalities for which courses were identified. This shows an interesting contrast between M1 and M2 levels and how they were impacted, on average, from one period to the next, during the pandemic.

Table 2.3: Average grade and standard deviation by modality period and master level

Year	Period	Master Level	Distance	std	Hybrid	std	Presence	std
Sept-Dec 2017	5	M1			10.81	3.45	12.42	3.05
		M2					13.1	2.63
Jan-Jun 2018	6	M1	13.34	2.41	14.13	1	12.96	2.96
		M2					13.33	2.38
Sept-Dec 2018	7	M1	10.18	1.72	14.73	1.11	12.86	2.62
		M2	13.75	2.78	14.8	0.54	13.3	2.55
Jan-Jun 2019	8	M1	13.27	3.02	13.65	1.92	12.48	2.94
		M2	14.12	1.81	15.02	2.92	13.45	2.37
Sept-Dec 2019	9	M1	12.23	3.04	12.76	2.79	12.82	2.63
		M2	13.13	3.07	13.45	2.25	13.33	2.68
Jan-Jun 2020	10	M1	11.84	3.24	13.11	2.58	13.57	2.52
		M2	14	2.51	13.5	2.45	13.85	2.04

Note: The modalities are D for Distance, H for Hybrid and P for Presence. Along side each modality, the respective standard deviations are represented. The master levels are M1 or M2. The periods are following the same time represented in Figure 2.1. Source: APOGEE and Teacher Survey

Lastly, there are greater standard deviations for distance modality between periods and master levels compared to other modalities. More specifically, under the distance modality, the standard deviation is consistently higher for the second semester for M1, while consistently lower for the second semester in M2. This is expected as there are usually fewer courses taken during M2 compared to M1, which gives opportunity to greater volatility due to fewer grades issued. For the M2 level, the standard deviation is higher for the second semester within the hybrid modality while lower for the second semester under the presence modality. This provides an indication that the grades are more dispersed for the courses taught under hybrid versus those taught under presence modalities. A higher grade variance also indicates higher uncertainty, which could be interpreted as larger error. This error can be interpreted in different ways, such as students truly having difficulty with alternative teaching modalities, the impact of the pandemic situation on student motivation and other drivers, and lastly on the teacher error in grading, if the teachers were more or less lenient to the student during the pandemic.

2.5 Model Design and Approaches

In order to provide a holistic understanding of the impact of the pandemic and the teaching modalities on student performance, three approaches are proposed: (1) a pooled OLS regression to capture the combined effect of teaching modalities and covid, (2) isolating the impact of teaching modalities through a panel fixed effects model across courses within the semester affected by the pandemic, and (3) a least square dummy variable model to shed light on the impact of covid on a sample of students followed across time.

Impact of Teaching Modalities and Covid on Student Performance

A pooled OLS regression was used to evaluate the impact of both teaching modalities and covid shock on student performance from September 2017 - June 2020. As the teacher modalities are identified from the survey that was sent to all teaching staff, it can be assumed that there is fair randomization in the data collected by design. The model is designed to follow individual students in time. In this regard, the observations and student grades can be correlated between courses for the same student. Following previous research (Abadie et al., 2017), and due to this study's fairly random sampling and experimental design of this study, clustering is essential at the student level. The reasoning is due to each student having multiple grades in periods and courses. In this regard, and to address the correlation among observations, the error terms of each student were clustered. This was done to eliminate any potential influence from one grade to the next. There can be many reasons that explain the potential correlation between grades; the student may have stronger intrinsic competencies in one course over another, the courses may have overlapping content, some assessments may be more difficult, and some teachers may be more lenient compared to others across time. Dummy variables are added to control for department, master level, and gender. Lastly, a covid dummy is used to capture the period when the covid pandemic started, January - June 2020.

The model is designed to identify the combined effect of alternative teaching modalities

and the covid shock on individual student grades. It is represented as follows in Eq. (2.1):

$$y_{it} = \beta_0 + \beta_1 H_{it} + \beta_2 D_{it} + \beta_3 C_t + \sum_j \beta_j \lambda_{jit} + \mu_{it} \quad (2.1)$$

where the dependent variable y_{it} is the grade of the student i for a specific time period t . The range of the dependent variable y_{it} is between 0 and 20. The modalities are dummy variables representing whether a course for which a student has a grade has been taught in either hybrid H_{it} or distance D_{it} modality for each time period. The in-person modality is the reference category. The covid dummy C_t is 1 for only the semester in which the pandemic started, and zero for all precedent semesters. Control dummy variables λ_{jit} are included, such as department, master level, and student gender for each time period ²⁰.

Isolating the Impact of Teaching Modalities on Student Performance

In order to standardize the impact of covid, a second model is specified to capture the impact of teaching modalities only. This model will only consider period 10, which is when the pandemic began and thereby subjecting all courses and students. In this way, the model eliminates, by design, any potential confounding between the covid shock and certain teaching modalities, such as distance and hybrid modality.

Using an unbalanced panel data across courses, rather than time, the model adopts a pooled OLS approach. In other words, the model follows the student grades across all the courses for which a modality was identified, during period 10. The panel is unbalanced across courses because not all students will take the same courses. It is especially common for the second semester of the academic year, as there are usually elective (optional) courses and/or internship requirements. In order to ensure variability in the data, only students who have taken at least one course in all three modalities have been considered. Variability is necessary for when course-demeaning is applied once fixed effects are incorporated in the model.

²⁰The reference categories are the Department of Engineering (IFIS), master level 1 (M1), and female gender.

Similarly to the previous model, this second model is designed to identify the impact of the course modality on the student grade of the course. It is represented as follows in Eq. (2.2):

$$y_{ic} = \beta_0 + \beta_1 H_{ic} + \beta_2 D_{ic} + \sum_j \beta_j \lambda_{jic} + \mu_{ic}, \quad (2.2)$$

where the dependent variable is the grade of the student i for a specific course c . The modalities are dummy variables representing whether a course for which a student has a grade has been taught in either hybrid H_{ic} or distance D_{ic} modality, with presence modality being the reference category. Controls λ_{jic} are added for each student by course.

In order to adjust for unobserved heterogeneity within courses, the model uses within fixed effects. Due to the fixed effects transformation, unobserved heterogeneity regarding student characteristics, such as innate ability, previous educational background and motivation levels, are eliminated. The base model, with the explanatory dummy variables representing hybrid H_{ic} and distance D_{ic} modality, incorporates the unobserved fixed effect α_i such that

$$y_{ic} = \beta_0 + \beta_1 H_{ic} + \beta_2 D_{ic} + \alpha_i + \mu_{ic}. \quad (2.3)$$

Following the fixed effects transformation (Wooldridge, 2013), the average grade across courses for each student i is taken, such that

$$\bar{y}_i = \beta_1 \bar{H}_i + \beta_2 \bar{D}_i + \alpha_i + \bar{\mu}_i, \quad (2.4)$$

where the average grade \bar{y}_i of each student i is the mean across all of the courses for which the student has a grade in period 10. As the student unobserved effect i is fixed across all the courses within period 10, we can eliminate the student fixed effects through a within-transformation

$$y_{ic} - \bar{y}_i = \beta_1 (H_{ic} - \bar{H}_i) + \beta_2 (D_{ic} - \bar{D}_i) + \mu_{ic} - \bar{\mu}_i \quad (2.5)$$

where the unobserved effect α_i has now disappeared. The result is a fixed effect within estimator that uses course variation in grades for each student. This ensures within group

variation in the data for the fixed effects transformation to work. In order to ensure consistent and unbiased fixed effect estimators, the fixed effects model assumptions are verified in Annex E.

Following Wooldridge (2013), the model is extended to incorporate random effects to compare which estimator is more efficient. In this case, the student unobserved effect α_i is assumed to be uncorrelated with the modality across all courses. In other words, the covariance between all modalities that the students have experienced and the unobserved effect is equal to zero, such that

$$Cov(x_{ic}, \alpha_i) = 0, \quad x \in \{P, H, D\}. \quad (2.6)$$

Moreover, a key random effects feature is the composite error term. The composite error is defined as $v_{ic} = \alpha_i + \mu_{ic}$, containing both the unobserved effect α_i and the error term μ_{ic} . Under the random effects assumptions,

$$Corr(v_{ic}, v_{is}) = \frac{\sigma_\alpha^2}{\sigma_\alpha^2 + \sigma_\mu^2}, \quad c \neq s \quad (2.7)$$

where the correlation between the composite errors of each random effects regression for each course must be uncorrelated with one another. Since the unobserved effect is in the error term, the composite errors in this cross sectional data set could be autocorrelated across courses. As the model is focused on a discrete number of courses, rather than time periods, there is no lagged version of the courses within the same period. Therefore, serial correlation is not applicable by design. Spatial correlation is also not applicable by design as there is no natural ordering in the courses within the same period. However, there could still be some autocorrelation in the error term of the random effects model, such as the correlation between distinct courses that are taught by the same professor. In this regard, the intraclass correlation coefficient is computed to verify if multilevel modelling is necessary (further in Section 6.2).

Impact of COVID on Student Performance: Least Square Dummy Variable Estimator

As covid is confounding with hybrid and distance modalities by design, the third model investigates the impact of covid on student performance separately through a fixed effects least square dummy variable model (LSDV). The model design is based on following the same students across four semesters from September 2018 – June 2020. The students sampled will have started their Master 1 in September 2018 and continued into their Master 2, graduating in June 2020. This means that the students are in Master 1 for periods 7 and 8, and in Master 2 for periods 9 and 10. The impact of covid is captured in period 10, equivalent to the last semester of the M2 (January – June 2020). This provides a natural counterfactual for the same individuals in time by solely considering the impact of covid on student performance.

Therefore, the main specification reads as follows

$$y_{it} = \beta_0 + \beta_1 P8_i + \beta_2 P9_i + \beta_3 P10_i + \alpha_i + \mu_{it}, \quad t = 1, 2, 3, 4 \quad (2.8)$$

where the dependent variable y_{it} is the grades of students based on the period and the variables $P8, P9, P10$ are dummy variables for each semester (the omitted category is period 7, equivalent to September 2018, to avoid the dummy variable trap). The model explicitly takes into account the cross section unobserved heterogeneity among observations, student grades, by allowing for each student to have his/her own intercept α_i .

For each student i , the average grade over the time periods is taken, such that

$$\bar{y}_i = \beta_1 \bar{P8}_i + \beta_2 \bar{P9}_i + \bar{P10}_i + \alpha_i + \bar{\mu}_i \quad (2.9)$$

where the dependent variable is the average grade y_i of each student i across all the periods. As the student unobserved effect i is fixed across all the periods, we can eliminate the student fixed effects through a within transformation:

$$y_{it} - \bar{y}_i = \beta_1 (P8_{it} - \bar{P8}_i) + \beta_2 (P9_{it} - \bar{P9}_i) + \beta_3 (P10_{it} - \bar{P10}_i) + \mu_{it} - \bar{\mu}_i, \quad t = 1, 2, 3, 4 \quad (2.10)$$

As the LSDV estimation is the same as the fixed effects estimation, including the standard errors, it follows the same approach and assumptions (Annex 6). With the dummy variables

regression, the heterogeneity in the data is better explained as there is a dummy variable for each cross-sectional unit, thereby providing a better description of the grades for each semester.

2.6 Descriptive Statistics on Sub-Samples

Descriptive Statistics: Pooled OLS panel data

The pooled OLS panel data focuses on the impact of teaching modalities on student performances, including the effect of the covid shock. After cleaning the data, the pooled OLS panel data model sample resulted in 16,331 grades with an identified modality. The sum of the in-presence modality differs between Table 2.4 and Table 2.5 due to missing semester information for three courses in 2018 in the Language department. As seen in Table 2.5, the grade count obtained from the in-presence modality is much larger than the other modalities (12,065 grades). As expected, the distance modality has the lowest grade count (1,588 grades). The department with the highest representation across all three modalities is the Engineering department. This is understandable as, for the time frame considered, it has more master's degrees (IFIS: 27, LANGUES: 16, SCECO: 22). It also has a much higher number of students registered ²¹ over the time frame compared to the other departments, independent of master level affiliations (IFIS: 1,421, LANGUES: 376, SCECO: 712). The share of each modality per department also shows that the Engineering department had a higher distance share (15%) and hybrid share (19%) with respect to the shares of the same modalities in the other two departments. The Language and Sciences departments seem to have adopted the predominantly in-presence modality for their courses (80% each) when compared to the Engineering department (66%).

When considering the grade count by period (Table 2.5), similar patterns are observed between the modalities across time. During the academic year when the pandemic began

²¹The student number is unique and counted only once throughout the time period September 2017 - June 2020. If a student remained for Master 2, it is not counted to avoid duplication.

Table 2.4: Grade count by Department and Modality from 2017-2020

Department	Distance	Hybrid	Presence	D (%)	H (%)	P (%)
IFIS	1,092	1,403	4,930	0.15	0.19	0.66
LANGUES	159	208	1,509	0.08	0.11	0.80
SCECO	307	1,097	5,626	0.04	0.16	0.80
Total	1,558	2,708	12,065			
Sum of all Modalities	16,331					

Note: The percentage columns represent the share of the modality represented in the sample. Source: APOGEE and Teacher Survey

Table 2.5: Grade count by Period and Modality

Year	Period	Distance	Hybrid	Presence	Total	D (%)	H (%)	P (%)
Sept-Dec 2017	5		14	2,573	2,587		0.01	0.99
Jan-Jun 2018	6	16	28	1,690	1,734	0.01	0.02	0.97
Sept-Dec 2018	7	62	91	3,700	3,853	0.02	0.02	0.96
Jan-Jun 2019	8	39	178	2,061	2,278	0.02	0.08	0.9
Sept-Dec 2019	9	752	1,523	1,488	3,763	0.2	0.4	0.4
Jan-Jun 2020	10	689	874	550	2,113	0.33	0.41	0.26
Total		1,558	2,708	12,062	16,328			

Note: The percentage columns represent the share of the modality represented in the sample. Source: APOGEE and Teacher Survey

(period 9 and 10), with respect to the previous academic year (period 7 and 8), there was a large overall increase in the annual number of grades across distance (1,441 grades versus 101 grades) and hybrid (2,397 grades versus 269 grades) modalities, while in-presence experienced a natural decrease (2,038 grades versus 5,761 grades). The in-presence modality maintains the highest share across all periods, except during periods 9 and 10, when hybrid is predominantly used (41%).

The evolution of the average of the grades per period is provided in Table 2.6 to illustrate if there was a disruption in the overall mean of courses conducted in either modality. From the courses identified with a modality, the average grades of courses taught in hybrid experienced a steep increase just before the covid pandemic, reaching as high as a 14.75 grade in period 7. Interestingly, as the pandemic arrived during period 10 (January - June 2020), it is observed that distance modality taught courses experienced a slight decrease in the average grade

Table 2.6: Average Grades by Period and Modality

Period	Distance	Distance (std)	Hybrid	Hybrid (std)	Presence	Presence (std)
5			10.81	3.45	12.75	2.88
6	13.34	2.41	14.13	1.00	13.11	2.74
7	13.11	2.95	14.75	0.98	13.07	2.59
8	13.83	2.28	13.95	2.24	12.97	2.71
9	12.52	3.08	13.17	2.51	13.04	2.66
10	12.49	3.20	13.33	2.51	13.68	2.34

Source: APOGEE and Teacher Survey

level, from 12.52 in period 9 to 12.49 in period 10. On the contrary, the average grades of courses taught in in-presence and in hybrid increased from period 9 to period 10, from 13.17 to 13.33 for hybrid and 13.04 to 13.68 for in-presence. The dispersion of the average grade is most significant for distance modality, especially during the pandemic, where the standard deviation for distance modality reached 3.20. This shows that students may have been impacted drastically and that not all students would have been accustomed well to the courses taught in distance.

The covid dummy and the teaching modalities could have confounding effects. Using our sample for this model, the correlogram in Figure 2.2 shows that the covid dummy has a low positive correlation with distance (0.30) and hybrid (0.25), while a negative correlation with presence modality (-0.41). Moreover, it is also quite correlated with the semester dummy (0.50). In this regard, the semester as a dummy variable will not be considered in the specification.

Descriptive Statistics: Pooled OLS across courses

The pooled OLS model across courses is based solely on period 10, the semester impacted by the pandemic, to investigate the impact of different teaching modalities on student performance. In this period, 83 courses for which a modality was identified from the teacher survey (Table 2.7). Within the courses, there are 1,667 observations (Table 2.8) providing a sufficient grade count by modality. It is not surprising that hybrid is the highest identified teaching modality (706 grades) during this time as the pandemic began in mid-March 2020,

Figure 2.2: Correlation between covid dummy variable, semester dummy, and modalities

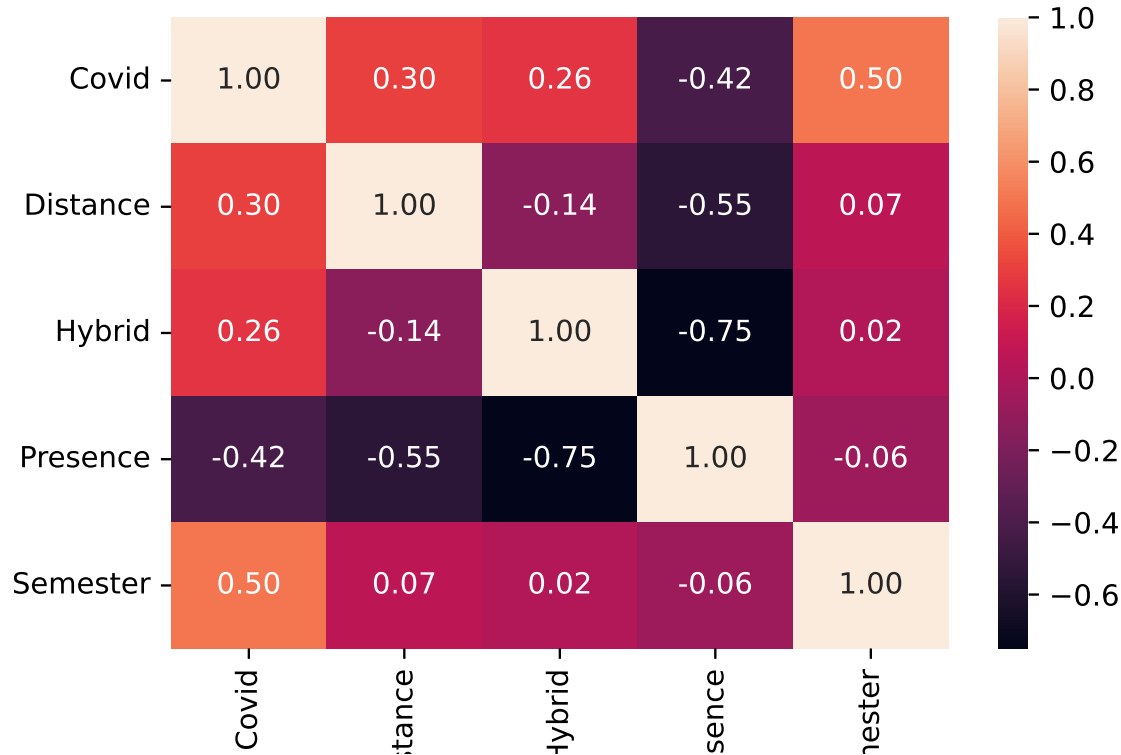


Table 2.7: Course count by Modality and Department for period 10

Period	Department	Distance	Hybrid	Presence	Total
10	IFIS	7	14	4	25
10	LANGUES	5	2	8	15
10	SCECO	10	17	16	43
Total Course Count		22	33	28	83

although there were also courses identified to have been taught in presence (530 grades) and distance (431 grades) throughout the semester. In terms of the department, the highest grade count is captured by the Science department (SCECO) with 929 grades. It is also the department with the highest representation in terms of grades across all modalities. The number of students in this sample is 403.

In terms of student characteristics on the total grade count, there are 1,083 grades obtained by females, while 584 grades are obtained by males from the courses used in this

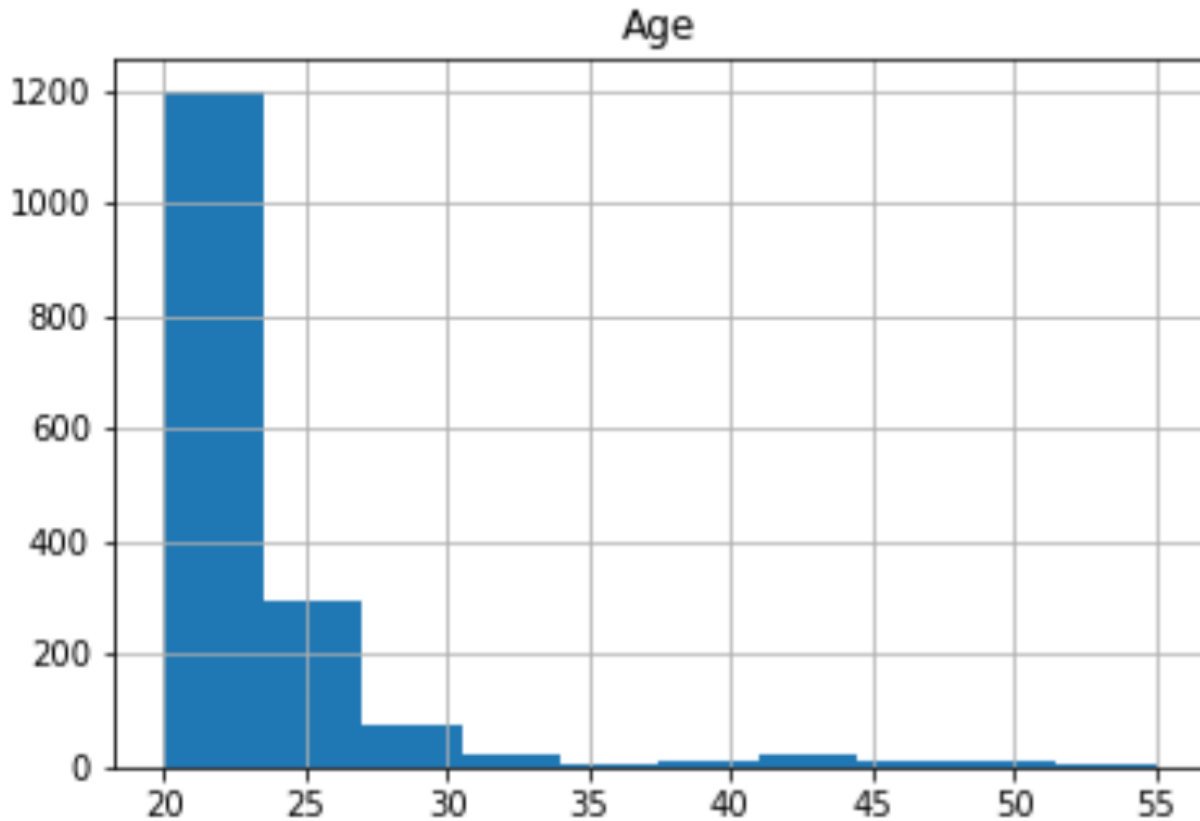
Table 2.8: Grade count by Modality and Department for period 10

Period	Department	Distance	Hybrid	Presence	Total
10	IFIS	154	305	122	581
10	LANGUES	57	14	87	158
10	SCECO	220	387	321	928
Total Grade Count		431	706	530	1,667

sample. The age of the students in the sample is highly skewed to the right, as expected, since most students taking an M1 or M2 degree are usually between 20 and 25 years old (Figure 2.3).

Lastly, as students' grades are clustered within courses, the level of correlation between students' grades was verified through the intraclass correlation coefficient, ICC (Table 2.9). It represents the level of correlation between units, i.e. grades within the same group, and reliability, i.e. measuring the quality of the grades within the same group by checking if the grades are reproducible. The ICC has been used as a measurement of consistency and replicability of measurements, especially in medical studies (Koo et al., 2016). It is generally measured by dividing the variance between units by the sum of the variance between and within units. In other words, it seeks to find to what extent the variance in the dependent variable is attributable to between-unit versus within-unit differences. Therefore, the goal is to see to what extent the total amount of variance in grades is due to between or within courses. According to Liljequist et al. (2019), an ICC value below 0.5 is considered to have a low correlation and a poor reliability, while ICC values greater than 0.8 suggest high correlation and good reliability. It serves as an indication on whether multilevel modelling and clustering around the error terms would be necessary for this model design. The courses, which are defined as the number of judges/raters, can be considered to be either fixed or

Figure 2.3: Histogram distribution of Age for period 10



Source: APOGEE

random. The two-way random effects model (`single_random_raters`) randomly selects courses and can be generalized to other courses with similar characteristics. The two-way mixed-effects model (`single_fixed_raters`) only considered the courses that are of interest, thereby eliminating the generalization of the courses to other courses, even if they have similar characteristics. In both cases, the intraclass correlation coefficient is relatively low, 0.25 and 0.17 respectively. This indicates that the correlation of the grades within the courses is low, which meets the purpose of verifying that there is low potential correlation between student grades within courses (83) that were taken by students (403). Although the reliability is poor, this simply confirms that the grades are not reproducible by the same student. This can be explained by different reasons that could impact the grade differently, such as the student's temporary psychological state during each of the assessments leading to the final

Table 2.9: Intraclass correlation coefficients, using sample dataset for pooled OLS across course

Type	Coefficient	p-value	lower bound	upper bound
Single_raters_absolute	0.16	0	0.14	0.18
Single_random_raters	0.17	0	0.14	0.19
Single fixed raters	0.25	0	0.22	0.28

Number of subjects	403
Number of judges	83

Table 2.10: Number of same students by department, followed across periods 7 - 10

Department	Student Count
IFIS	181
LANGUES	58
SCECO	112

grade obtained for a course, or the way the teachers marked each assessment of each student might have differed. Nonetheless, and for the purposes of testing for correlation within the courses, the ICC confirms that there is no need for clustering to be done with the data, which means it is possible to accept the model design without multilevel structuring.

Descriptive Statistics: Least Square Dummy Variable Model

The LSDV model follows the same batch of students ($n = 351$) for which there are grades across four periods (1,404 observations), which is equivalent to two academic years, September 2018 - June 2020. The total number of students by department are represented in Table 2.10. There are more female students (238) than males (113) in the sample. The average age is about 22 years old (Table 2.11).

Table 2.11: Distribution of Age for the same students followed across periods 7 - 10

	Age
count	351
mean	22.7
std	2.1
min	20
25%	21
50%	22
75%	24
max	37

2.7 Discussion

Results: Impact of Teaching Modalities and Covid on Student Performance

The pooled OLS regression of the panel data was conducted under different specifications to investigate how and to what extent different teaching modalities and the covid shock impact student grades (Table 2.12). The reference teaching modality across all specifications is the in-presence modality. The number of observations in the first specification are 16,331 grades as no period information is required. Due to the missing semester information for 3 Language department courses, all specifications that include variables defined by a period, such as specifications 2 - 4 and 6, have an observation count of 16, 328 grades. Specification 5 differs in the number of observations (12,565) only because period 9 is excluded from the time frame. The reasoning was based on the potential low reliability of the data that were received from the teacher survey identifying the course modalities. Overall, there is a high coefficient of determination (R^2) for specifications 4 - 6 compared to the first three specifications.

Table 2.12: Pooled OLS estimation of the impact of teaching modalities on student performance, including Covid shock.

	<i>Dependent variable:</i>					
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	13.014*** (0.042)	13.004*** (0.043)	12.981*** (0.044)	11.982*** (0.148)	11.943*** (0.164)	11.980*** (0.148)
Distance	-0.439*** (0.106)	-0.522*** (0.100)	-0.342*** (0.107)	-0.063 (0.109)	0.248 (0.263)	-0.249** (0.099)
Hybrid	0.310*** (0.081)	0.252*** (0.077)	0.340*** (0.083)	0.333*** (0.079)	1.039*** (0.126)	0.258*** (0.072)
Covid		0.210*** (0.077)	0.702*** (0.115)	0.628*** (0.113)	0.619*** (0.118)	0.167** (0.076)
Distance:Covid			-0.848*** (0.192)	-0.832*** (0.188)	-1.115*** (0.312)	
Hybrid:Covid			-0.696*** (0.151)	-0.630*** (0.145)	-1.316*** (0.181)	
LANGUAGE				0.607*** (0.078)	0.652*** (0.084)	0.609*** (0.078)
SCECO				0.616*** (0.148)	0.805*** (0.171)	0.624*** (0.148)
Master2Level				0.524*** (0.059)	0.543*** (0.066)	0.519*** (0.059)
SexM				-0.586*** (0.078)	-0.649*** (0.084)	-0.587*** (0.078)
Age				0.025*** (0.005)	0.025*** (0.006)	0.026*** (0.005)
Observations	16,331	16,328	16,328	16,328	12,565	16,328
R^2	0.005	0.005	0.007	0.044	0.053	0.042
Adjusted R^2	0.005	0.005	0.007	0.043	0.052	0.042
Residual Std. Error	2.708 (df = 16328)	2.707 (df = 16324)	2.705 (df = 16322)	2.655 (df = 16317)	2.646 (df = 12554)	2.657 (df = 16319)
F Statistic	22.790*** (df = 2.0; 16328.0)	19.068*** (df = 3.0)	17.645*** (df = 5.0)	36.381*** (df = 10.0)	38.170*** (df = 10.0)	44.813*** (df = 8.0)

*p<0.1; **p<0.05; ***p<0.01

The teaching modalities seem to be overall highly significant with respect to the in-presence modality. The impact of the distance modality is significantly negative at the 1% level across the first three specifications. When the interaction terms with the covid dummy and controls are added to the specification, the distance modality dummy presents both positive (0.248) and negative (-0.063) impact on the grade level, although not significant. The change in the direction of the impact between specification 4 and 5 could also be influenced by the exclusion of period 9, which holds a relatively large identification of courses taught by distance. Furthermore, specification 6 was generated to see whether the interaction terms posed an issue. The result shows that students that have been taught under the distance modality obtain 0.25 points of a grade less than those in the in-person modality - significant at the 5% level.

On the contrary, the hybrid modality has a significantly positive impact on student performance across all specifications at the 1% level. Interestingly, the impact of hybrid modality was strongest under specification 5 where grades increased by just over an entire point (1.04 pt.) with respect to in-person instruction. This could be explained by the increase in the number of hybrid classes offered during the pandemic, even if period 9 is not included in the sample. Moreover, the students could have genuinely performed better due to the mix in instructional methods, thereby accommodating different types of learning styles.

The covid dummy is of particular importance as it only represents the covid shock in period 10. The results suggest the covid shock positively impacted the grade level, at the 1% significance level, across all specifications. The influence of covid seems to be least predominant in specification 6, where grades were only increased by 0.16 grade points compared to other periods. Moreover, when the interaction terms are added to specifications 3 and 4, the impact of covid increases by up to 0.70 and 0.63 points of a grade point, respectively. The aim of the interaction terms between modality and covid is to simply show how the impact of the alternative modalities changes when covid shock is present. Both interaction terms have a relatively strong negative impact on the grades, even reaching an entire point decrease in the grade level at the 1% significance level under specification 5. This means that

Table 2.13: Variance inflation factor (VIF) for pooled OLS

Variable	VIF Factor
Distance:Covid	7.79
Distance	6.55
Hybrid:Covid	5.26
Intercept	4.31
Hybrid	3.65
Covid	3.40
SCECO	1.16
LANGUAGE	1.16
Master2Level	1.05
SexM	1.02

during the crisis, the hybrid and distance teaching modalities became less effective. Due to the confounding impacts between modality and covid, it is not surprising that there could be some level of correlation between covid and the interaction terms.

In order to check for multicollinearity between all the independent variables, the variance inflation factor was computed (Table 2.13). Generally, a VIF that has a value larger than 4 is an indication that the variable is causing multicollinearity. It is therefore not surprising that the interaction terms are causing increases in the coefficients of all the other variables, as they have a VIF value of 7.79 and 5.26, respectively, indicating that multicollinearity might exist. Unfortunately, the distance dummy variable is also found to have a high VIF factor (6.55). In this regard, and in order to adjust for the multicollinearity, while maintaining the variables of interest, the interaction terms should be dropped from the model. Therefore the full model will be specification 6.

Lastly, the controls for the indicators of departments, master level and gender are added to provide further explanatory power to the model. Considering specification 6, student grades under the sciences and languages departments are estimated to be 0.62 and 0.61 of a grade point higher, respectively, compared to grades in the Engineering department. This provides an indication of the impact of different teaching modalities on certain types of courses found in each department. When looking at the master level dummy, holding all things equal, the M2 level performs 0.52 grade points better than the M1 level. This could be expected as the

students would have more experience with the study domain as they have built on their M1 experience. Finally, males seem to perform 0.59 grade points worse than female students.

Results: Impact of Teaching Modalities on Student Performance

The panel data regression was estimated for three different specifications; (1) pooled OLS, (2) fixed effects, and (3) random effects estimations (Table 2.14). Interestingly, the intercept under the pooled OLS specification, which represents a female M1 student from the IFIS department taught in the presence modality, would obtain a grade of 11.98 points. In the random effects specification, the student grade for the in-person modality is 13.78 points and equally significant at the 1% level. This large difference is justified as the random effects model implements an individual specific intercept. In general, the explanatory power is the highest for the random effects specification (0.279), while the R^2 is lowest for the fixed effects model (0.017). In this case, the adjusted R^2 may be more dependable as it corrects for goodness-of-fit of the model, without influencing the model accuracy from additional explanatory variables. Subsequently, the adjusted R^2 for the fixed effects model is large yet negative (-0.298). This confirms that the R^2 is small (0.017), and that the variation in the values around the predictions is greater than the total variance of the data around their mean. In other words, the fixed effect model does not seem to have much explanatory power. It can also be due to an insufficient sample size ($n = 1,667$ grades). In this regard, the random effects estimation provides the highest explanatory power ($R^2 = 0.279$) and model accuracy (adjusted $R^2 = 0.278$) among the three specifications.

In terms of modalities, the results seem to be in line with the hypothesis that the online modality has a negative impact on student performance. There is a strong significant negative impact of hybrid and distance modalities on student performances when compared to presence modality across all three specifications. The distance teaching modality seems to have the strongest negative impact compared to presence modality (approximately -0.70 points of a grade), keeping all things equal. This is to be expected as the pandemic was unforeseen,

and the university departments were not prepared to transition suddenly into fully digital instruction.

The impact of alternative modalities can therefore be interpreted as two-fold; the preparedness of the teachers to teach online and the students' ability to learn in a fully remote context. Teachers with previous experience in teaching online courses would have a steeper learning curve in using digital tools to teach in an online context. Students' ability to cope and learn during the pandemic could also influence student performance. Other factors such as self-motivation, self-control and maturity are highly-debated innate characteristics that are unobserved and could have a tremendous impact on student performance, especially during a pandemic semester. This is also supported by the stronger negative effect on student performance under the random effects estimation for distance modality (-0.782 grade points) when considering different kinds of unobserved heterogeneity beyond student unobserved effects on performance.

In the pooled OLS specification, in terms of the departments, it seems that student grades in both the Languages (LANGUAGE) and Sciences (SCECO) departments were better than student grades in the Engineering department (IFIS). The student performance from the Language department was a 0.441 increase in grade points compared to the Engineering department at the 10% level. This could be due to the overall underrepresentation of Language department grades in the dataset. Students from the Sciences department performed an entire 1.025 grade points better than the engineering department! This could be explained by the content of the courses; the courses from the science department may be more easily taught online due to the courses' pedagogy and/or typology. Alternatively, the engineering department could have more practical classes, requiring hands-on experience or more physical interaction, thereby limiting the ability of the students to apply their knowledge as they would in a traditional context.

In regards to the master level, the M2 group does better than the M1 group by 0.398 points of a grade. This could be due to the longer experience of the student with the material, providing the student a foundation from M1 to do better in M2. In addition there are many

internships in the M2 level, which could influence the grades, as it would require students to be present at work to be evaluated on their experience. Moreover, the age does not seem to have a significant effect on the grades of older students (0.05 point increase in their grade). Lastly, during the pandemic period, male students seem to have received relatively worse grades, approximately a decrease of 0.86 grade points, compared to their female counterparts across courses.

To verify which model is statistically better to use for the panel data regression, an F-test was run to compare pooled OLS and fixed effects specifications and their significance. The null hypothesis was rejected, confirming that the fixed effects was preferred to the pooled OLS (Figure 2.15). This is expected as the FE model controls for unobserved heterogeneity and course-invariant issues compared to pooled OLS.

Going further, the Hausman test is used to verify if there is a correlation between the unique errors and the regressors in the model. The test confirmed that the fixed effects specification was consistent and statistically better compared to the estimation of the random effects, due to correlation between the unique errors and the regressors (Figure 2.16). In other words, fixed effects estimator is consistent because there is some covariance between the unobservable and the explanatory variable. Even though the random effects model captures for the composite error the element of the unobserved heterogeneity within each student, i.e. intrinsic random effect such as individual abilities, the fixed effects over the control variables and the student unobserved heterogeneity have a stronger statistical explanatory power regarding the effect on student grades across courses. For example, fixed control variables, such as the department and the master level, affect students' performance more than the intrinsic student effects, such as innate abilities and experience. This echoes the need for further research on the impact of different types of courses (science/language/engineering) on student performance.

Table 2.14: Impact of modality on student performance across courses during the pandemic.

	<i>Dependent variable:</i>		
	Note.1		
	(1)	(2)	(3)
ModalityHybride	−0.260* (0.146)	−0.421*** (0.141)	−0.407*** (0.133)
ModalityDistanciel	−0.670*** (0.158)	−0.679*** (0.148)	−0.782*** (0.143)
DepartmentLANGUES	0.441* (0.227)		
DepartmentSCECO	1.025*** (0.135)		
Master.LevelM2	0.398*** (0.131)		
Age	0.050*** (0.013)		
SexM	−0.858*** (0.126)		
Constant	11.928*** (0.360)		13.778*** (0.118)
Observations	1,667	1,667	1,667
R ²	0.104	0.017	0.279
Adjusted R ²	0.100	−0.298	0.278
F Statistic	27.589*** (df = 7; 1659)	10.779*** (df = 2; 1262)	30.150***

*p<0.1; **p<0.05; ***p<0.01

Table 2.15: F test on pooled OLS versus fixed effects

Test Summary	F	df 1	df 2	p-value
Pooled OLS	2.3724	397	1262	2.20E-16

Table 2.16: Hausman Test

Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Cross-section radom	12.012	2	0.002464

Results: Least Square Dummy Variable Model

Using the LSDV within estimator, the results also confirm the hypothesis that covid did impact student performance. The impact on the student performance during period 10 resulted in a highly significant increase of 0.72 points of a grade for all the students, compared to the reference year, period 7. This means that students performed better during the covid period than they did during the first semester of M1, which was not under the covid context. Interestingly, during the second semester of the M1 the students performed worse (-0.18 grade points).

Table 2.17: LSDV model results

	<i>Dependent variable:</i>
	Note.1
as.factor(Period)8	-0.189** (0.092)
as.factor(Period)9	0.227** (0.092)
as.factor(Period)10	0.723*** (0.092)
Observations	1,400
R ²	0.094
Adjusted R ²	-0.210
F Statistic	36.333*** (df = 3; 1047)

*p<0.1; **p<0.05; ***p<0.01

The purpose of the LSDV model is similar to the fixed effects model as it controls for the student fixed effects across time periods. Luckily, it does not require adjustments to the standard errors. Similarly to fixed effects estimation, the LSDV exploits time-demeaning of grades across time. The LSDV model accounts for heterogeneity by allowing for different intercepts for each student. In this way, it also captures unique student characteristics. The fixed effect is time invariant. This is a one-way fixed effect, which captures the heterogeneity

across students. A two-way fixed effect would also capture the course variation but it was not applied to the study.

2.8 Conclusion

From the data and the models investigated, this chapter concludes that purely online instructional modality had an overall negative impact on student performances. Moreover, the pandemic had a positive effect on the grades. These findings are in line with previous research regarding the effects of online education on student performances, as the majority of the studies have found either negative or insignificant effects of the online modality in a traditional education context. The sample that was collected from the UGE administration and teacher survey provided a small, yet representative, data set to investigate and shed light on the impact of alternative modalities and covid on student grades. The sample descriptive statistics suggest that distance education has consistently had a much higher standard deviation around the mean compared to the other modalities. This variation in the grades suggest that there was a strong but varied impact on the student performances. This could be explained by student factors, such as motivation and learning difficulties, or teacher-related factors, such as teaching quality under different modalities and leniency in grading, especially during the crisis. The increase in the number of online-held courses is clearly visible in the period when the pandemic arrived.

In order to evaluate the impact of covid and the alternative education modalities separately, multiple regression models were estimated. The first model was a simple pooled OLS one which captured the combined impact of the modalities and the covid shock on student performance from September 2017 - June 2020. In terms of the impact from the modalities, and in line with previous research, the results suggest that distance modality had a significant negative impact on student performance, although once the controls were taken into account, the distance modality became insignificant. The reasons for this are trivial. It could suggest that student performance is not actually dependent on the modality when certain institu-

tional and student characteristics are considered in the model. On the other hand, the hybrid teaching modality, which combines both distance and in-person teaching modalities, has a consistent and significant positive impact on student performance. Moreover, and as seen in the literature, the hybrid model is a middle ground between returning to fully traditional or choosing fully remote education modalities.

In regards to the covid shock, the research in this chapter has found that it had a positive and significant impact on student performance. Moreover, the effects of the grades of different departments suggest that some departments, such as LANGUE and SCECO, performed better (0.5 points of a grade) better than IFIS in the same time period. And when all the departments are considered, the students in M2 would fare relatively better (0.60 points of a grade) than M1 students. This could suggest maturity and the habituation a M2 student can exhibit with the material, stress, workload and university lifestyle compared to an M1 student. It could also suggest that the students were able to cheat more easily, although there is no clear way to capture the extent of cheating. Moreover, although this effect would not apply to every student and program, the M2 student are usually working on an apprenticeship/internship while studying, which diversifies the academic pressure. Lastly, the male students are found to perform worse (0.59) compared to female students.

The second model involves an alternative approach to unbalanced panel data. Instead of regressing over time, the second model regressed across courses only in the period in which covid arrived (January-June 2020) as a way to isolate the impact of covid by ensuring that all stakeholders were impacted by the same external shock. The findings were surprising and in line with the observations in the descriptive statistics. Under the pooled OLS specification of this model, the distance and hybrid modalities were found to negatively and significantly impact the student performance. The impact regarding the online modality is consistent with the findings even from the first model. Conversely, the hybrid modality specifically during covid has a significantly negative impact on student performances, which is the opposite of what was found in the first model with pooled OLS panel data, when the covid period is considered as a separate variable (Table 2.12, specifications 1-3, and 6). Although,

when considering the interaction terms between hybrid teaching modality and covid, it is also significantly negative (Table 2.12, specifications 4-5). Even more interestingly, when the fixed and random effects are integrated to capture any unobserved heterogeneity, specifically pertaining to the students, the impact of both modalities only strengthens and at a higher significance level. Moreover, and with the ICC, the fixed effects model is found to be most which ultimately concludes that the impacts of both hybrid and online modalities were negative upon student performance during the covid semester.

As a way to investigate the isolated impact of the covid period on the student performance, the third model provides a simple least square dummy variable model which tracks the same cohort of students across four consecutive semesters. The findings suggest that the impact of covid on the last semester of this cohort was positive, and rather increased the grades by 0.72 points. Interestingly, there is a jump from 0.22 grade points in 2019 to 0.72 in 2020. Although this could suggest that there is an impact from covid, it is simply to suggest that the grades have increased, although the full reason behind this jump in the grade would need to be investigated further.

This chapter contributed to the literature on the covid crisis and its impact on students. As a majority of studies have focused on one, usually introductory, course, this study has taken into account 3 departments of different courses. The goal is not to evaluate the course but rather the teaching modality by evaluating across courses. In this way, the chapter contributes by shedding light on the different types of courses and departments before and during the pandemic.

Although this chapter is fruitful in trying to provide alternative modellings and views of teaching modalities, it does have its limitations. First and foremost, the survey was very brief as it was send out online in order to ensure that the response rate would be sufficient for the data collection. If the survey were longer, and thereby more detailed, then more information could have been collected from individual professors regarding their teaching modalities. Even though the modalities were defined in the survey, the definitions are very broad and therefore can be interpreted in different ways. For example, the extent to which

a course can be considered hybrid or distance is different for certain teachers compared to others. As there are no definitive criteria by which a course is defined as distance or hybrid, the decision of the modalities is solely left to the interpretation of the teacher that taught the courses themselves. This is a risk of not having a clear distinction in the hybrid and distance modalities, which could be a heavy limiting factor to the research.

Another limitation is the lack of available information regarding the students' grades. In other words, there is no information regarding the types of assessments used that comprise the final grade for a course in a semester. As a future improvement, it would be interesting to have information on the different types of assessments in order to evaluate appropriately the methods of assessment and whether these methods themselves were conducted online. It would provide a clear picture of the breakdown of the grade by type of assessment and all the evaluations that make up the final semester grade. Also, the marking criteria would be useful to monitor if the criteria has changed in time, and especially in the time of the crisis.

Moreover, there is no information on the teacher quality in the data collected. This can have a heavy impact on the course and the student performance, especially if the teacher quality is affected due to the change in the teaching modality. An alternative way to capture the teacher quality could be through taking the mean within a particular class and comparing it to other groups that the teacher is teaching the same class material, or comparing it to a similar class. Alternatively, the mean of the same course can be monitored over time to see if the grades change drastically for a particular teacher. From the perspective of the course, it would be interesting to evaluate different courses to see for which types of course alternative modalities can work and how it can be improve the courses in which online and hybrid education is currently difficult.

Annexes

2.A Survey Example

The modalities were defined as:

- Distance learning: the course was taught entirely online.
- Hybrid: the course was taught using both distance and face-to-face methods.
- Face-to-face: the course was taught entirely in class at the university.

These four questions were asked, including a list of subjects (courses) after each question for which the teacher had to identify the modality. If a teacher did not teach in a particular year, the question was eliminated from their survey.

Survey questions:

- ☐ What was the teaching method used for the following subjects in the 2019-2020 academic year?
- ☐ What was the teaching method used for the following subjects in the 2018-2019 academic year?
- ☐ What was the teaching method used for the following subjects in the 2017-2018 academic year?
- ☐ What teaching method was most used for subjects before the 2017 academic year?

2.B Robustness checks to define grade

There were three robustness checks that were carried out on the definition of a grade as a dependent variable based on the available data. The first check was based on defining the dependent variable as the original grade obtained by the student, without considering any adjustments to the grade if any make-up assessments were done. The second check considered the original grade, but if there were any adjustments to the grade, then the adjusted grade was considered instead. Lastly, the original grades were considered, and the adjusted grade was used to fulfill any missing original grades, in this way ensuring that there was a grade for all students.

2.C APOGEE descriptive data

Evolution of grades by period for academic years 2015 – 2020

Table 2.18: Evolution of grades by period for academic years 2015 – 2020

Period	Count	Mean	std	min	25%	50%	75%	max
1	15,195	12.68	2.67	0	11	13	14.50	20
2	13,125	12.94	2.70	0	11.40	13	14.83	20
3	15,306	12.74	2.73	0	11.15	13	14.50	20
4	12,963	12.88	2.87	0	11.15	13	14.97	20
5	15,205	12.85	2.81	0	11.23	13	14.80	20
6	12,503	13.05	2.88	0	11.50	13.32	15	20
7	15,168	13.19	2.53	0	11.75	13.50	15	20
8	12,229	13.17	2.70	0	11.50	13.50	15	20
9	14,586	13.14	2.69	0	11.60	13.50	15	20
10	11,792	13.34	2.77	0	11.93	13.50	15	20
Total	138,072							

Source: APOGEE

Evolution of grades by period and department for academic years 2015 – 2020

Table 2.19: Evolution of grades by period and department for academic years 2015 – 2020

Period	Department	Count	Mean	std	min	25%	50%	75%	max
1	IFIS	9,280	12.57	2.69	0	11.00	13.00	14.40	20
1	LANGUES	1,999	12.55	2.93	0	10.80	12.92	14.50	20
1	SCECO	3,916	13.02	2.46	0	11.50	13.02	14.63	20
2	IFIS	8,313	12.85	2.75	0	11.13	13.00	14.77	20
2	LANGUES	1,511	12.64	3.18	0	11.00	13.00	14.96	20
2	SCECO	3,301	13.32	2.28	3.00	12.00	13.50	14.98	20
3	IFIS	8,841	12.55	2.80	0	11.00	13.00	14.42	20
3	LANGUES	2,131	12.59	3.01	0	11.00	12.95	14.50	20
3	SCECO	4,334	13.18	2.34	0	12.00	13.27	14.67	20
4	IFIS	7,584	12.74	3.02	0	11.00	13.00	15.00	20
4	LANGUES	1,781	12.63	3.07	1.00	10.90	12.75	14.75	20
4	SCECO	3,598	13.30	2.38	0	12.00	13.50	14.92	20
5	IFIS	8,626	12.72	2.91	0	11.00	13.00	14.75	20
5	LANGUES	2,184	12.55	2.96	1.25	10.50	12.75	14.58	20
5	SCECO	4,395	13.28	2.46	0	11.97	13.40	14.94	20
6	IFIS	7,106	12.87	2.99	0	11.00	13.00	15.00	20
6	LANGUES	1,509	13.03	3.12	0	11.30	13.41	15.10	20
6	SCECO	3,888	13.40	2.51	0	12.00	13.67	15.00	20
7	IFIS	8,461	13.13	2.51	0	11.72	13.37	15.00	20
7	LANGUES	2,435	13.11	2.73	2.50	11.48	13.25	15.00	20
7	SCECO	4,272	13.35	2.43	0	12.00	13.61	14.94	20
8	IFIS	6,635	13.06	2.74	0	11.41	13.05	15.00	20
8	LANGUES	1,926	13.12	2.94	0.25	11.40	13.40	15.00	20
8	SCECO	3,668	13.41	2.46	0	12.00	13.71	15.00	20
9	IFIS	7,941	13.15	2.77	0	11.67	13.50	15.00	20
9	LANGUES	2,675	12.88	2.78	2.00	11.00	13.00	14.88	20
9	SCECO	3,970	13.30	2.43	0	12.00	13.50	15.00	20
10	IFIS	6,371	13.13	2.91	0	11.42	13.16	15.00	20
10	LANGUES	2,039	13.19	2.87	0.50	11.50	13.25	15.00	20
10	SCECO	3,382	13.83	2.33	0	12.50	14.00	15.40	20
Total		138,072							

Source: APOGEE

Evolution of grades by period and master level for academic years 2015 – 2020

Table 2.20: Evolution of grades by period and master level for academic years 2015 – 2020

Period	Master Level	Count	Mean	std	min	25%	50%	75%	max
1	M1	7,421	12.60	2.81	0	11.00	13.00	14.50	20
1	M2	7,774	12.76	2.54	0	11.07	13.00	14.50	20
2	M1	6,816	13.09	2.69	0	11.59	13.30	15.00	20
2	M2	6,309	12.79	2.70	0	11.00	13.00	14.50	20
3	M1	6,578	12.54	2.88	0	11.00	13.00	14.50	20
3	M2	8,728	12.89	2.59	0	11.40	13.00	14.50	20
4	M1	6,025	12.83	2.98	0	11.13	13.00	14.94	20
4	M2	6,938	12.93	2.77	0	11.19	13.00	15.00	20
5	M1	6,799	12.61	3.03	0	11.00	13.00	14.63	20
5	M2	8,406	13.05	2.60	0	11.50	13.28	14.98	20
6	M1	6,241	13.03	3.00	0	11.42	13.38	15.00	20
6	M2	6,262	13.08	2.75	0	11.50	13.25	15.00	20
7	M1	6,308	12.99	2.63	0	11.50	13.02	14.80	20
7	M2	8,860	13.33	2.44	0	12.00	13.56	15.00	20
8	M1	5,915	12.98	2.79	0	11.25	13.11	15.00	20
8	M2	6,314	13.35	2.59	0	12.00	13.50	15.00	20
9	M1	6,058	12.72	2.79	0	11.00	13.00	14.50	20
9	M2	8,528	13.44	2.57	0	12.00	13.95	15.00	20
10	M1	5,676	13.11	2.81	0	11.50	13.25	15.00	20
10	M2	6,116	13.56	2.71	0	12.00	13.96	15.44	20

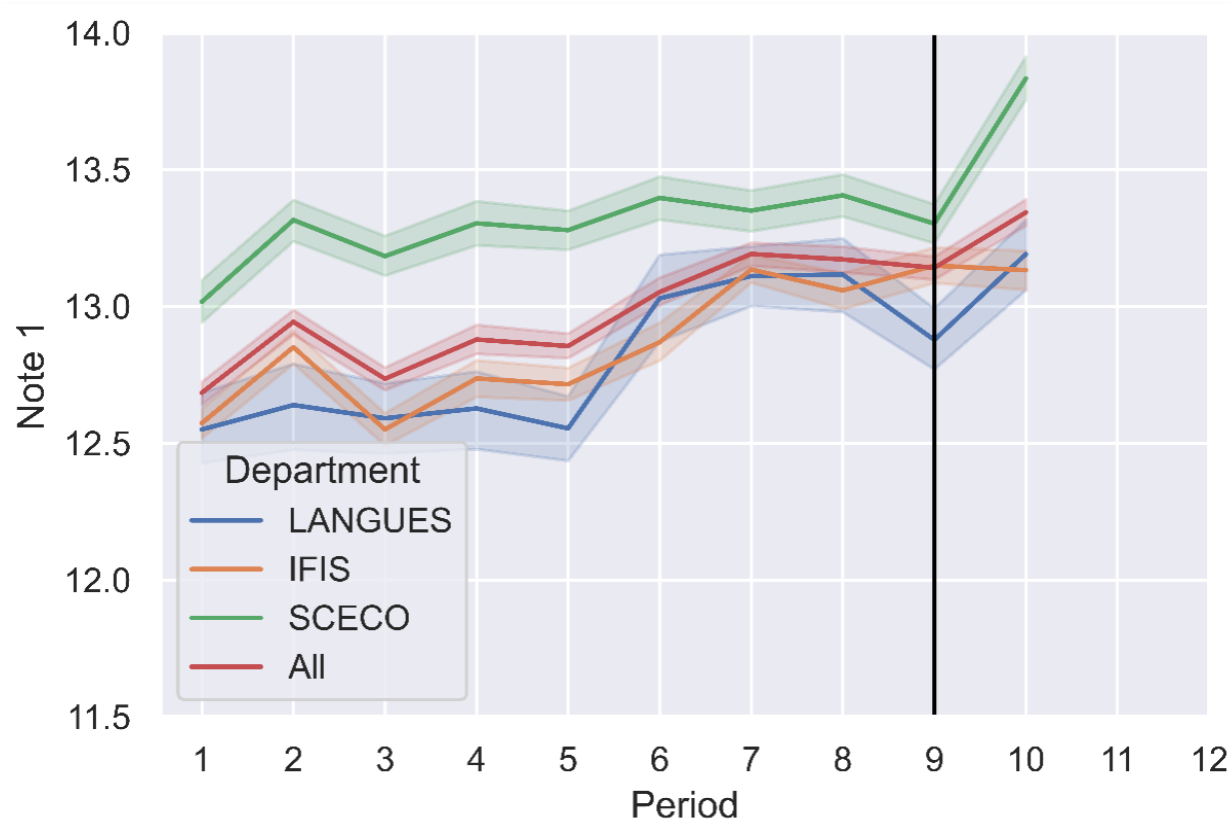
Total	138,072
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Source: APOGEE

2.D Evolution of average grades by department and period

With the evolution of the mean grades by department, it is observed that there is a common upward trend amongst all the departments represented by the red line. Interestingly, there is a break in the average student performance in each department when the pandemic starts, represented by the black horizontal line. At the point of the pandemic, the average student performance for both the Languages and the Sciences departments increases, while for the Engineering department the average performance decreases.

Figure 2.4: Evolution of average grades by department and period



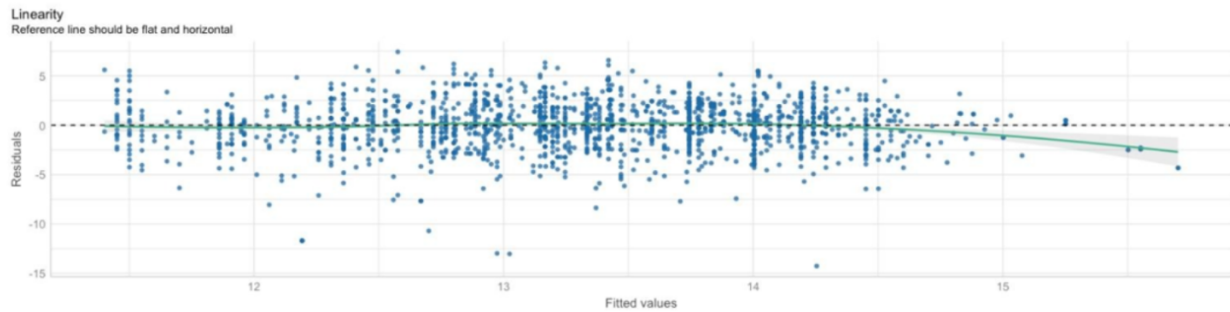
Notes: The three UGE departments Languages (LANGUE), Sciences (SCECO) and Engineering (IFIS) are represented by the average student performance ("Note 1") by period (semester). An average among the three departments is represented by the red line. Source: APOGEE

2.E Validating the fixed effects model assumptions

Multiple tools were used in order to validate the fixed effects assumptions.

To validate the linearity assumption, the residuals were plotted against the fitted values resulting in Figure 2.5. It is observed that the data set has a linear character as the variances of the error terms are plotted around the zero line. The reference line, in green, confirms the linearity. Although for fitted values greater than 15 the reference line deviates slightly downward from the zero line, which could suggest that there might be some outliers.

Figure 2.5: Linearity Assumption for Fixed Effects Model



In order to check for any influential observations, the standardized residuals were plotted against leverage (Figure 2.6). The leverage captures the level of influenced of each data point in the regression. The dashed green lines represent Cook's distance: in other words the extent to which the model will change if a data point was removed from the model. There are no data points outside of this bound, so it confirms that there is no strong influence of any data point in the data set.

In Figure 2.7, the normality assumption in the residuals is confirmed. Overall, the data falls along the normality line, or at least within the bounds. The lower quantiles seem to suggest that there could be outliers that could skew the data and the model fit. A posterior predictive check was conducted to visualized the predicted data against the observed data (Figure 2.8). It seems that the data were adequate enough to provide insight into the study.

The homogeneity of the variance in the residuals is also confirmed as the plot in Figure 2.9 shows a relatively even spread between data points. Moreover, the reference line represented

Figure 2.6: Standardized residuals against leverage

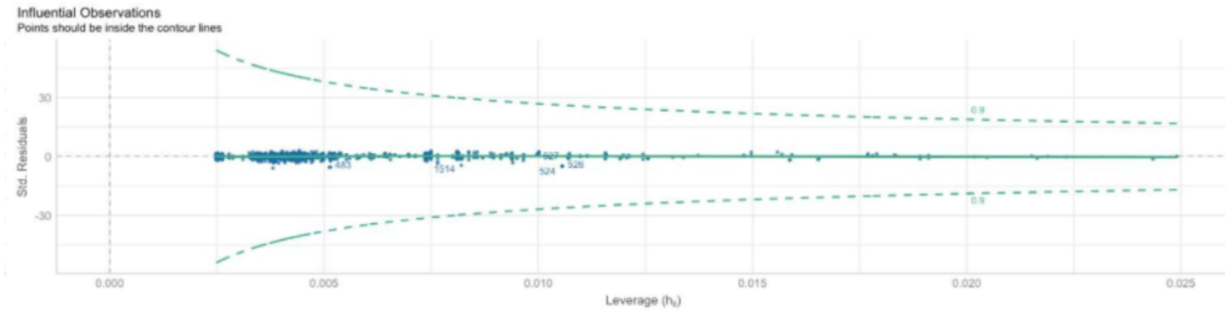


Figure 2.7: Normal distribution of residuals

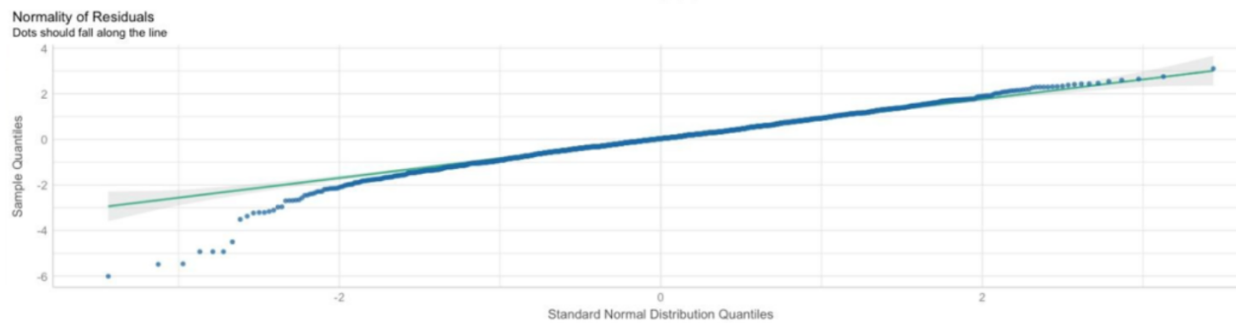
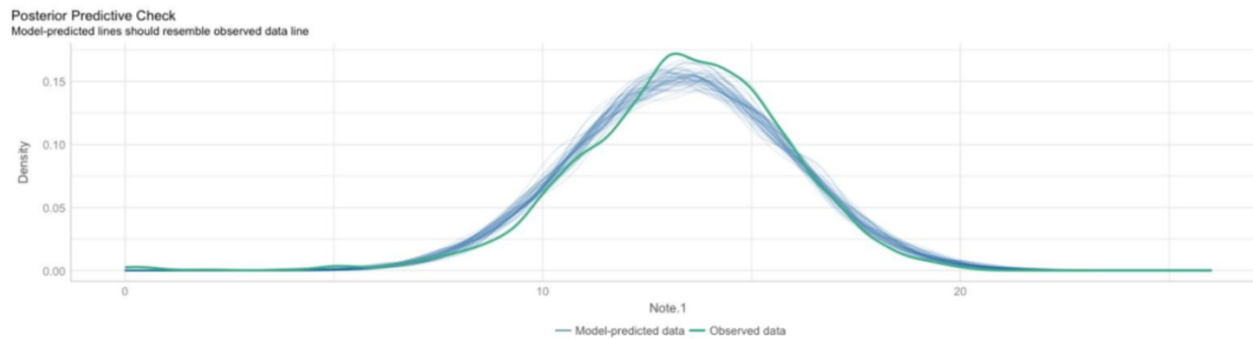


Figure 2.8: Posterior predictive check



in green is relatively flat which confirms homoscedasticity.

Lastly, Figure 2.10 presents the results of the variance inflation factor as a way to measure for multicollinearity in the regression. Values of VIF that are above 4 or below 0.25 suggest that multicollinearity might exist. For the model of this study, the VIF is low represented by the green dots.

Figure 2.9: Homogeneity in residuals

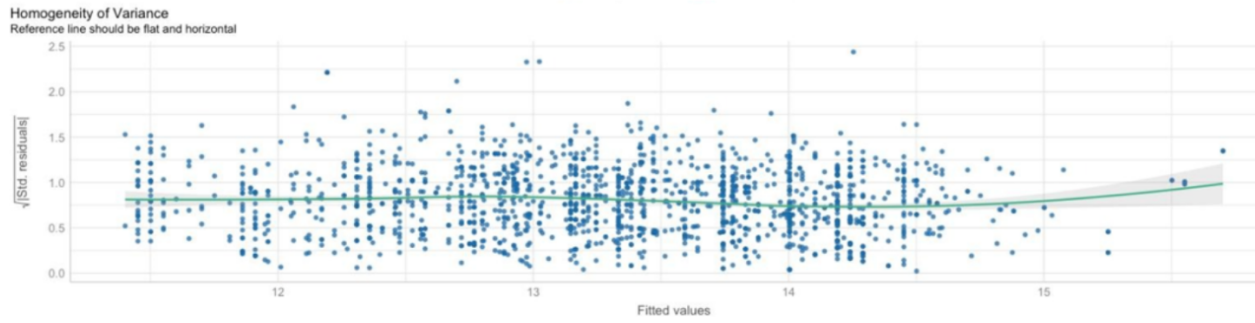


Figure 2.10: Variance inflation factor



Chapter 3

The Impact of Online Education Degrees on Employment

3.1 Introduction

Education is a powerful indicator for a recruiter regarding an applicants' preparedness to work. Although the usefulness of education in terms of accumulating human capital and increasing productivity has been widely discussed, the rise of online education alternatives has raised the question of whether it can provide equally positive signals on employment applications. In other words, is an online degree graduate necessarily better prepared for a job compared to a traditional university graduate? Research has shown that recruiting decisions rely heavily on the amount of education attained by prospective candidates as a way to ensure productivity and avoid high costs of retraining. The quantity of education is only one factor in evaluating the pertinence and quality of the candidates' potential skills. In terms of the quality of education, the method of instruction and learning has a direct effect on an individuals' learning, which will have a subsequent effect on their academic performance and thereby preparedness for work. In light of the influx of online education courses, programs, even university degrees, this study aims to evaluate if a recruiter is more likely to recruit candidates with an online or traditional educational background.

With the advance in technological development and the recent pandemic, online education is becoming widely used and accepted, even throughout universities. There are increasingly more universities that provide online courses and even full degrees done entirely online. In other words, the traditional academic environment is progressively becoming more technologically sophisticated, which does have benefits in terms of pedagogical and learning outcomes, especially for students that are unable to physically attend university. Moreover, there are private education companies that provide MOOCS at the course level and institutions that provide full online degrees with equivalent credentials to a traditional higher education degree. This type of educational offer has become popular among the learners.

The choice of taking a degree taught completely online compared to a traditional one could be due to many reasons, one of the major reasons being time. The flexibility in time can be used for further studying, reviewing, or even a side-job. Autonomous learning has not been given the same recognition as traditional education in regards to the skills curated through effective independent learning and ultimately obtaining similar, if not the same, learning outcomes as the aforementioned traditionally trained graduate. If the learners are highly accepting of the alternative modalities in education, are the employers following suit ? In this regard, this study will use a correspondence test (Fremigacci et al., 2013), across three French cities, to evaluate recruiter preferences on positions that are currently highly demanded due to the labor market context and for which learners are seeking more education.

The candidate profiles chosen were in the fields of data science with a masters level¹ education background and IT with a bachelor degree². Differing education levels were used in order to match the pedagogical curricula for the two professions, and hence the skills obtained, between the online and traditional institutions. The study used two French institutions that provide entirely online or traditional offline degrees. The online degree provider chosen was OpenClassrooms, which provides online bachelor and master degrees that are state-endorsed. The online education platform has a corporate priority to make education

¹This is equivalent to a bac+5 under the French education system

²This is equivalent to a bac+3 under the French education system

accessible and employable, providing 57 training programs resulting in accredited degrees. The most popular program is web development (45.9%), followed by data (16.5%) and systems and networks (11.4%) under which the master in data scientist and bachelor in IT are respectively found (OpenClassrooms, 2022). As a contrast, a French traditional university, Université Gustave Eiffel, was selected as it is traditional in-person degree provider. The university also has the master of data science and bachelor in IT programs providing similar training and learning experience to that of OpenClassrooms. The applications in both professions included one candidate with a traditional education background and another from an entirely online education background.

The correspondence test was conducted in Marseille, Lille and Lyon. The goal is to see whether there are different perspectives of online education from different labor market contexts. The choice of the city was made based on similar characteristics, such as large working populations and labor market compositions. The characteristics data were based on the most recent INSEE statistics as of 2019. As the fictitious applicants were 27 years old at the time of the test, the age group used to compare the demographic aspects of the labor markets across the three cities was 25 - 54 years old. This age group comprised 61.3%, 61.5% and 59.7%, of the population aged 15 - 64 years old for Marseille, Lyon and Lille, respectively (INSEE, 2022). Within the 25 - 54 age group, all three cities had relatively high employment rates at 72%, 81% and 80%, respectively (ibid). As the data scientist candidates have a masters education level, and the IT technicians have a bachelors level, it was important to verify the unemployment rates by the level of education received. In this regard, the unemployment rates for those with a bachelors education level were 9.5%, 8.7%, and 8.4% for Marseille, Lyon and Lille. As Marseille is much larger in population compared to Lille, it is not surprising that their unemployment level is a bit higher than that of Lille. For the master level category of education, the three cities have an unemployment rate of 7.8%, 7.2%, and 6.4%, respectively. Overall, the cities seem to be relatively similar in terms of employment and unemployment rates, especially on the education level achieved.

The contribution of this study is three-fold. Firstly, as there is a lack of literature on the

effectiveness of an online degree in obtaining a job, this study will contribute by shedding light on whether there is a greater preference for a certain type of education achieved. In terms of the methodology, correspondence testing has mainly been used in exposing discriminatory hiring behaviour. As there is no legally defining discrimination on the grounds of educational background, this study will use the method of correspondence testing to test whether there is differential, rather than pure discriminatory, behaviour based on the recruiter's responses. Lastly, the testing was conducted on data scientist and IT technician candidate profiles across three different cities in France, which will add to the labor market preferences based on those professions within the cities.

This chapter is organized in the following manner. Section 2 will provide insight on the existing, yet limited, empirical literature specifically on correspondence studies conducted in the domain of education and the meaning of discrimination in this regard. Section 3 will be dedicated to the overall research protocol, design and data collection methodology. Section 4 will provide results of the correspondence testing and the econometric analysis on the probability of obtaining a positive response with respect to having a fully online degree. Section 5 will conclude and provide recommendations for further research work.

3.2 Literature Review

Correspondence studies have become a popular method in detecting discriminatory behaviour in access to employment, housing market and consumer goods and services (Riach and Rich, 2002; Rooth, 2014; Zschirnt and Ruedin, 2016; Bertrand and Duflo, 2017; Quilian and al., 2017; Baert, 2018; Neumark, 2018). In terms of education, both taste-based and statistical discrimination have been tested using correspondence studies. As per Becker's (1957) theory, taste-based discrimination arises from employer dislikes or prejudice against applicant characteristics. By contrast, due to the imperfect information provided by the applicants, statistical discrimination arises from the employers' perception of applicants' average attributes and inferred productivity. Even if the recruiter is rational and not prejudiced, according to

the statistical discrimination model, the recruiter will unknowingly categorize the applicant based on individual innate characteristics and average characteristic information of groups that have similar attributes to the applicant (Arrow, 1971; Phelps, 1972). Furthermore, differential treatment is applied based on differences in the signaling effect, arising from the information provided to recruiters, between applicants regarding their productivity and abilities. In other words, the less information the recruiter has about a specific applicant, the more likely the recruiter will be prone to use statistical discrimination in the recruitment decision process.

The literature on potential discrimination of education modalities specifically is highly limited. Two studies were found that have attempted to test the employability of candidates based on educational modalities. Lennon (2020) conducted a correspondence study based on 1,891 applications using 100 fictitious candidates with a bachelors degree in engineering, IT, business and medical professions, and found that traditional degree holders received approximately twice as many callbacks compared to the candidates that held an online degree. Although the paper only focuses on identifying employer responses based on education modality, more research is necessary to identify the reasons why employers preferences lean more towards traditional education. Similarly, Deming et al. (2016) used an audit study in five metropolitan cities³ in the United States to test employers' perceptions regarding for-profit online institutions at the undergraduate level. Their findings suggest that applicants with online degrees in business had 2 percentage points less probability of receiving a callback compared to applicants with the same degree from public universities. Even when comparing online versus traditional degrees within for-profit institutions, the probability of equal callback rates is significant only at the 10% level.

As with every correspondence study, there were some caveats. The institutions that they used in the resumes were not fully online institutions; rather they contained predominantly online degrees. Moreover, they did not explicitly specify whether the degree was online or not on the applicants' resumes, but rather relied on the employers' general knowledge and

³These are Los Angeles, Miami, Chicago, San Francisco and New York.

cross-checking. The authors argued, however, that employers would nonetheless be aware of the institutions' online degrees simply due to the institutions' names and recent institutional changes. This is based on the fact that the majority of the universities contained in the sample do not offer any in-person degrees, and from those that have physical campuses have experienced a decline in their in-person enrolment as enrolment in online campuses has risen. All in all, recruiters seem to consider online degrees as a negative signal due to the perception of online education quality, and thereby of acquired human capital. In this regard, statistical discrimination can arise and be practiced on the basis of these general perceptions of subsequent productivity and of unobserved applicant characteristics, such as motivation.

Usually the differentiation in education has been evaluated through institutional characteristics, such as accessibility, quality and learning outcomes, on the basis of classification factors such as gender, ethnicity, origin, or age (Fremigacci et al., 2013, Baert et al, 2016; Aleksynska and Tritah, 2013). In terms of discrimination in the accessibility to education, Brodaty, du Parquet, and Petit (2014) use a correspondence study to find discriminatory behaviour in the access to education on the basis of student ethnic origins for private colleges in France. On the contrary, Chiswick (1988) finds strong evidence that these differences in access to education are due to self-selection rather than discrimination for the USA.

The quality of the institution also plays a key role in explaining the inequality in access to education and hence the potential discrimination that different ethnic groups must endure as a result of the institution quality. In the literature, university quality has been investigated based on the university characteristics, such as selectivity and student performance. Using a nationally representative data set, Dale and Krueger (2011) find that when considering observable student characteristics, such as their grades, there is a significantly positive return of university selectivity. Even well into the students' career, the return of university selectivity persists. But, when the unobserved student characteristics are considered, such as motivation and family education background, the returns to university selectivity is almost zero. In other words, having more information on the student and their abilities would deplete the signal effect of a more selective university. Moreover, black and Hispanic groups have higher

returns of university selectivity. This could be explained through the valuable networking opportunities that are provided to black and Hispanic groups. Overall, the student attributes that are valued in selective universities may also be valued by future recruiters. In this regard, using a correspondence test, Gaddis (2015) finds evidence that bachelor level graduates from an elite university in the United States receive higher positive response rates. This suggests that university selectivity does impact the employers' perception of the future candidates' and their inferred group membership by university type.

On the contrary, Bardón and Braga (2020) test the employers' statistical discrimination against students who are not applying from prestigious universities. Their main hypothesis is to show that employers' decisions about unobserved worker ability could be rendered through the university reputation, but that this type of discrimination decreases with the accumulation of work experience attained by the applicant. The reasoning is that employers use information of new graduates, such as their education, as a variable that could correlate to their actual productivity. Therefore the choice of education, and thereby university, is of importance for signalling ability. Using a regression discontinuity design, Bardón and Braga (2020) use the earning premium to find that for students in their first year of employment, the wage premium could reach up to 13% for students that are just above the university admissions threshold compared to students just below the threshold. This premium is estimated to decrease to 4% for admitted students that have more than 6 years of work experience which suggest that the importance of the university reputation for the recruiter decreases with the exposure to work and thereby the revealing of worker productivity.

In addition to university selectivity, student performance and specific skills sets have also been evaluated as informational signals towards recruiters. The signals have mostly been measured in terms of future earnings. Hansen et al. (2021) used a grade-scale reform in 2006 in Denmark to evaluate the impact of grades on labor market outcomes. The grade-reform induced almost one full standard deviation difference between pre- and post- grade reform for students. This increase in the GPA was found to consequently increase the students' earnings only for the first two years of employment. Beyond that the effect of student performance

diminishes entirely as the employers would learn enough to predict the productivity of the worker. This is also reflected in the decrease in the premium wage about three years into the job experience straight after graduation.

These findings confirm that when hiring employers want to ensure the potential value, in terms of productivity, of a future employee. In order to do so, and as initially they have very limited information regarding the applicant, their decision relies on observable information such as student performance indicated on resumes or skill verification through recommendation letters. Although more information can be gathered with subsequent interviews, the true productivity of a worker can only be learnt with time and experience on the job. Altonji and Pierret (2001) called this the statistical discrimination with employer learning model (EL-SD). Furthermore, they used panel data to evaluate whether observable education characteristics, such as quantity and quality of education, have an impact on earnings. Based on the information initially available to employers, Altonji and Pierret (2001) empirically confirm the existence of statistical discrimination as the wage effect of education decreases with time the more employers learn about the productivity of the worker through experience. Many studies have proven the quick rate at which employers learn about the productivity of workers from educational credentials to having concrete experience with the worker (Araki et al., 2016, Aryal, Bhuller and Lange, 2022). Other studies have been conducted to capture the signalling effect of grades on the likelihood of obtaining a job interview (Koedel and Tyhurst, 2012; Piopiunik et al., 2020).

On the other hand, skill sets are not usually directly observed by employers, hence why workers try to send signals based on different skills. Skills can be cognitive or non-cognitive, both shedding light on the applicant. Piopiunik et al (2018) test the signalling effect of three skill domains - cognitive skills, social skills and maturity - on 579 German human resource managers through a correspondence study. For college graduates, they find that these skill domains have a significant impact on the probability of getting a job interview. Moreover, they find that human resource heterogeneity tends to be significant in the choice of providing a job interview. Older recruiters seem to value more non-cognitive abilities, such as

social skills and maturity, while younger recruiters would prefer to base their decision on the applicants' cognitive skills, such as grades. Although recruiters from larger firms would focus more on the grades potentially due to the standardization of candidate selection. Therefore different categories of skills are prioritized based on recruiter characteristics and company size. Moreover, the type of skills depend on the relevancy to the job vacancy.

Knowing that technology has made an impact on education, especially through education modality and hence learning outcomes, employers could have alternative views on the actual preparedness of graduates. As education background does not provide full information on the capacity and abilities of the candidate, the employer is bound to have imperfect information regarding the candidates' capacities, and more importantly, their productivity. As per Spence's (1973) signaling theory, the ability of individuals is unobservable to the employer and differs across individuals regardless of the education achieved. The potential changes in human capital formation as a result of the impact in differing education modalities can enhance the unobserved effect further. As productivity is unobservable, the education achieved acts as a signal to the employer of the candidate's ability. This is based on the premise that more educated individuals will invest more in education, and hence be more productive. The decision of individuals investing in education is derived by the human capital theory, suggesting that investing in education would increase future gains. In that case, even if the employer is being rational and non-prejudiced, the employer could use statistical information regarding the educational qualification to ensure the credibility of the candidates' skills. In other words, this type of statistical discrimination arises when the employer uses statistical information regarding the candidates' characteristic, in this case it would be the modality in which the education was received to infer candidates' productivity. As higher education is becoming more common, employers need to look beyond simply the degree and search other ways to distinguish worker productivity and ability.

Overall, previous research on education and discrimination has largely focused on discrimination within the academic environment and specifically on institutional characteristics which could induce discriminatory behaviour on labor market outcomes. Tannock (2008) dis-

agrees with this approach in evaluating educational discrimination ⁴. Instead he argues that education-based discrimination is used as a proxy that overlaps with the usual classifications of discrimination. In his view, education-based discrimination exists as the differentiation on the basis of credentials, meaning the qualifications achieved, and meritocracy, demonstrated through personal ability, of individuals. Thereby, education based discrimination could exist through the differences in how credentials are perceived and the extent to which ones' demonstrated ability is necessarily better when comparing education backgrounds of individuals. Although these can be theoretically valid discriminatory factors in education, Wasserman (1998) acknowledges that it is unclear to what extent qualification and merit can be used as benchmarks to measure discrimination. Therefore, it is not socially accepted that discrimination exists on the basis of education differences, as there is also no law against such differentiation to be discriminatory. On the contrary, social acceptance of specific observable characteristics, i.e. educational background, play a key role in the information available to employers and the category in which they would be inferred to belong. In this regard, the employers would have incomplete information on the candidates' productivity and would base themselves on the statistical information available regarding this type of qualification. With the up and rising volume of online education programs, there is skepticism around online education. In lieu of such inferences, the main hypothesis of this study aims to determine whether online degrees are more acceptable by the labor market compared to the same degree taken in traditional format.

3.3 Experiment Protocol and Data Collection

The correspondence testing method has been used in France for two decades to identify the existence of discrimination in hiring (du Parquet et al, 2014). The principle of this approach is to construct applications of fictitious candidates, similar in all aspects, except for the characteristic being examined that could have an effect on the probability of obtaining a

⁴These include discrimination on the grounds of race, ethnicity, gender, and age.

job. Since the field of research is new, very little empirical research has been done on the comparison between online and traditional education in terms of employer acceptance.

The aim of this study's protocol is to evaluate whether there is discrimination⁵ in hiring candidates on the basis of their educational background. There are two professions for the fictitious candidates, data scientist and IT. The characteristic of interest is the modality in which the education was received by the candidates. This was clearly identified through using a traditional French university, University Gustave Eiffel, and an online education school, OpenClassrooms, that both provide similar degrees in both professions. The industries to which the candidacies were sent were pre-identified using the NAF/CPF Nomenclatures database. The fictitious applications are sent in response to available job offers to companies within the identified industries. As the job applications are spontaneous, they could also be sent to companies that are not actively hiring. In this regard, as this is the candidate's initiative, it is critical that the potential job offers and/or company mission correspond to the profiles constructed. Moreover, the testing must be conducted carefully so that the recruiters do not detect that they are the subject of an experiment, thereby giving each applicant fair judgement. The comparison of the responses received by the fictitious candidates allows the study to highlight the existence of discrimination in access to job interviews, based on the characteristic examined.

Choice of Profession

The two professions chosen for this experiment were data scientist and IT profiles. The data scientist profession consists of optimizing company production and increasing performance. It is a profession that requires candidates to have knowledge in statistical tools and programming skills, especially in machine learning algorithms that are used for optimization. Due to the relatively new position on the labor market, it is also interchangeably used between positions for data analysts and data engineers. The IT profile mainly contains skills and

⁵Throughout the thesis, discrimination will be used to refer to the difference in preferred preference of one type of degree over another, unless it is explicitly described otherwise.

responsibilities in the maintenance of hardware and software, such as computer component functionalities, network security and data privacy. It is a customer service position that provides technical support.

These professions are highly sought after in the current market place due to the technological progress and the recent crisis that increased the volume of work conducted at a distance. With the increase in the demand for such professions, this limits the probability of detections or rejections of the spontaneous applications by the recruiters, regardless of the recruiters' response. The only limitation regarding a highly demanded profession is that recruiters will be less selective and thereby difference in access to a job interview would be more difficult to observe.

Fictitious Candidate Profiles

There were two fictitious profiles created for each profession. Each candidate had a resume that was attached to their email stipulating their identities, educational background, previous experience and technical competencies, among other additional background information. The resumes were drafted similar in terms of graphic design, using a simple curriculum vitae template but with different colors and fonts for each candidate (example of resumes in Annex 3A). Personal interests were also similar between candidates in order not to stand out.

The identities of the candidates were created using census data and addresses within the city in which the candidate applied (Table 3.1). The birth year was standardized across all candidates⁶, allowing for work experience to have accumulated and to absorb the time during the pandemic. The most common first and last names for the regions within the particular birth year were chosen using census data. As the testing was executed across three different cities, the addresses for each candidate were based within a neighborhood in each city. The neighborhood was chosen based on similar median disposable income per consumption in 2019 among all neighborhoods using data provided by INSEE⁷. In this way, all applicants

⁶All candidates were 27 years old.

⁷Territory comparator tool. Source: Insee-DGFIP-Cnaf-Cnav-Ccmsa, Fichier localisé social et fiscal en

Table 3.1: Identity of the candidates

Department	Data Scientist	IT Technician	Candidates Address
Lyon (69)	Léa Petit Marine Dubois	Thomas Lefebvre Maxime Moreau	12 Rue de la Platière 69001 Lyon
			57 Rue de l'Abondance, 69003 Lyon
			31 Rue Francois Génin 69005 Lyon
			60 rue de Gerland, 69007 Lyon
Lille (59)	Léa Petit Marine Dubois	Thomas Lefebvre Maxime Moreau	29 rue de la Paix d'Utrecht, 59000 Lille
			45 Rue Edouard Vaillant, 59800 Lille
			7 Rue Mermoz, 59000 Lille
			10B Rue des Archers, 59800 Lille
Marseille (13)	Léa Petit Marine Dubois	Thomas Lefebvre Maxime Moreau	4 Rue Poucel, 13004 Marseille
			12 Bd Dr David Olmer, 13005 Marseille
			43 Bd Larrat, 13010 Marseille
			6 Bd Luc, 13013 Marseille

came from similar places of residency.

In order to capture statistical discrimination in the education acquired, both degrees from OpenClassrooms and UGE in both professions must be comparable in terms of curricula and capacities taught. A comparison study was executed to ensure that the capacities were similar from both online and traditional degrees. For the data scientist candidacies, a degree in data science at the masters 2 level was used for both profiles. The degree is similar between both education institutions, especially in the acquired skills such as data preparation, programming skills, and communication (Annex 3B). Moreover, both programs also incorporate experience through an apprenticeship during the training, allowing for student exposure to the labour market from both the traditional and the online university. For the IT candidacies, the degrees used were in the field of informatics at the bachelor level, specifically Bac+2 level

géographie au 01/01/2021.

Table 3.2: Distribution of message pairs sent to the tested companies

Profile	Candidates	Education	Number of Firms
Data Scientist	Léa PETIT	Online	756
	Marine DUBOIS	Traditional	
IT Technician	Thomas LEFEBVRE	Online	998
	Maxime MONREAU	Traditional	
Total			1,754

in France. In both degrees, computer science and technical skills were targeted, such as computer system and network use, security management, problem solving and technical assistance (Annex 3C). Both education institutions confirm in their programs that these are the relevant skills for a job as an IT technician.

In order to isolate the effect of the pandemic, all candidates obtained their degrees prior to the crisis and have similar professional experiences compared to their pair. For example, the data scientist profile has employment experience in the energy and automobile industry, executing similar tasks and responsibilities. The IT candidates' professional backgrounds are based in industries of consulting and telecommunications. The technical competencies in each pair of profiles was also similar in order to avoid any capacity advantage.

The correspondence testing was conducted over four weeks. There were 756 companies contacted for the data scientist profession and 998 company addresses for the IT profession (Table 3.2). For each profession a list of company email addresses was identified and randomly split into two equally weighted groups. The list of companies and the order of sending applications to the companies was randomized between each candidate of the two professions. Companies were only contacted once by each fictitious candidate. In order to avoid detection of similarity between candidates, a window of some days length was given between each batch of applications sent to companies.

Candidate Messages

The messages sent on behalf of the candidates consisted of a simple message of interest in a position of the same domain of expertise as the candidates' profile. It also explicitly stated the educational institution and whether it was online or traditionally attained. A resume was attached to the application.

Message 1:

Bonjour,

Je souhaite postuler auprès de votre entreprise pour un poste de Technicien Informatique. Je pense que je suis un bon candidat pour ce poste car j'ai obtenu un diplôme en ligne d'OpenClassrooms et j'ai une expérience variée dans le domaine.

Ci-joint, veuillez trouver mon CV.

Je vous remercie.

Cordialement,

Thomas LEFEBVRE

Message 2:

Bonjour,

Je recherche actuellement un emploi de Data Scientist. Diplômée de l'Université Gustave Eiffel, je suis certaine de pouvoir répondre aux exigences du poste.

Veuillez trouver ci-joint mon CV. Je vous remercie pour votre considération.

Table 3.3: Number of candidacies sent by department

Profession	Candidate Name	Lille (59)	Lyon (69)	Marseille (13)	Total
Data scientist	Léa Petit	262	302	192	756
Data scientist	Marine Dubois	262	302	192	756
IT technician	Thomas Lefebvre	295	440	263	998
IT technician	Maxime Moreau	295	440	263	998
Total		1,114	1,484	910	3,508

Cordialement,

Marine DUBOIS

Selection of Job Postings and Responses

The correspondence testing was done across three cities in France; Lille, Lyon and Marseille. The number of tests was not a variable that was controlled for in the experiment. Instead, the number of tests was maximized during the collection period, in order to ensure an overall greater sample size for both professions and to analyse the difference in the responses in different major cities. There are more companies identified for Lyon in comparison to Lille, or even Marseille for both professions (Table 3.3). But it seems to be a sufficient sample size compared to other sample sizes used in previous studies, such as Duguet et al. (2010) who test 140 accountants' offers, Adida, Laitin and Valfort (2010), who respond to just over 130 job offers, or L'Horty et al. (2011) who test 307 IT jobs. Ultimately, a total of 1,754 unique companies were tested with two different candidate profiles sent out each time, which resulted in a total of 3,508 observations.

The industries from which the companies were sourced was the official French activity nomenclatures (INSEE, 2021). They were based on the previous experience of the candidates, and industries in which their experience would be recognized (Annex 3D). For the data scientist applicants, their experience was in the energy and automobile industry, but additional industries through which firm data were sourced were the financial and transportation sec-

tor. Similarly, additional sectors, such as information and communications, were added to the industries in which the IT technician candidates had experience.

Due to the large set of email addresses sourced, there were different employer characteristics to which the applications were sent (Table 3.4). This was based on the contact information that was available for each firm. The following types of professional roles were contacted: assistants, collaborators, directors, managers, leaders, and agents. Predominantly collaborators (26%) and leaders (42%) were the contact points within the companies. In terms of company size, half of the sample is composed of small to medium enterprises (50%), followed by micro-enterprises comprising 30% of the sample. The size ranges were determined according to the number of employees defined by INSEE (2022). The majority of the companies are joint stock companies, 59% (*sociétés anonymes par actions*), or limited liability companies, 35% (*SARL*). This is expected as the sample is composed mainly of very small to medium sized companies, which usually opt for a limited or joint legal structure. Lastly, more companies responded from Lyon (42%) and Lille (32%) compared to Marseille (26%).

The responses that were valid were only considered for the results of the experiment. In other words, all responses for which there was an error, i.e. a delivery failure, were not counted. The recipient was only contacted once by each candidate. The responses to the candidacies were considered as non-negative if there was acknowledgement of receipt, the mail was transferred to the correct department for further consideration, or if a call or supplementary information was requested. On the other hand, a negative response was considered if the correspondent asks how their email was obtained without further follow-up, if the correspondent is no longer in charge of the position, out of office, left the company, or if it is a clear rejection to the candidacy due to no current need for the application.

Table 3.4: Characteristics of tested companies

Turnover	Count	Share	Mean
Lille (59)			8,245,676
Lyon (69)			8,531,871
Marseille(13)			4,921,540
Legal Form			
Sole proprietorships	22	0.01	
Social and solidarity companies (ESS)	54	0.03	
Joint stock companies (Action)	1041	0.59	
Limited liability companies (SARL)	621	0.35	
Holding company (Groupement)	9	0.01	
Public companies	6	0.00	
Number of Employees			
Microenterprise (1 - 10 employees)	528	0.30	
Small - Medium enterprises (11 - 250 employees)	884	0.50	
Intermediate-sized enterprises (251 - 4,999 employees)	60	0.03	
Large enterprises (5,000 or more employees)	5	0.003	
Not provided	277	0.16	
Number of Companies per Department			
Lille (59)	557	0.32	
Lyon (69)	742	0.42	
Marseille (13)	455	0.26	
Recruiter Profiles			
Assistant	53	0.03	
Collaborators (Collaborateurs)	457	0.26	
Directors (Directerus/Dirigeants/Gerants)	125	0.13	
Leaders (Mandataire)	729	0.42	
Managers (Responsable)	244	0.14	
Not provided	40	0.02	

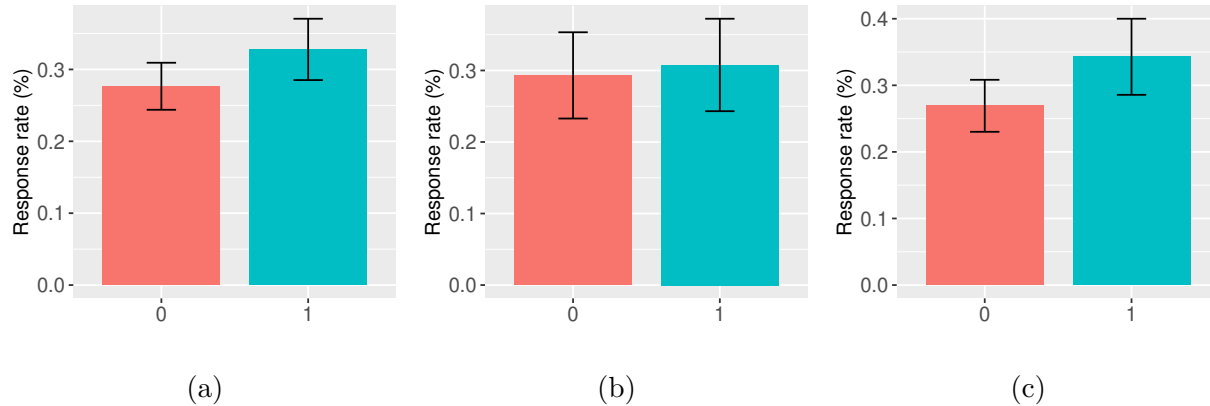
3.4 Empirical Findings

Gross Results

As all applicants from each profession applied to the same recruiter, the order in which the candidates were sent was randomized for each mailing. This allowed for each type of candidate an equal opportunity to be sent first to a recruiter. There were 1,754 unique companies contacted, out of which 238 companies returned a response resulting in a 13.5% overall company response rate. A total of 310 responses were received as some companies responded to both candidates that applied to the same company. From the 310 responses received, there are approximately 33% that responded positively and 28% negatively to the candidates overall (Figure 3.1a). It is likely that the period in which the test was conducted was influenced by strong recession and residual impact of the covid pandemic on the labor market, which is not conducive to obtaining large favorable responses rates from companies. Moreover, the behaviour towards responses may vary from one company to another. The non-responses could be negative responses as some firms do not bother to respond unless they are sure to positively respond to a candidate. In addition, although very unlikely, a non-response can also happen due to human error which is simply a mistake in the treatment of the candidacy by the firm. Unfortunately, the study cannot ensure the action taken by the firm once the candidacies were sent out, as the testing only counts the responses that were received.

When considering the responses by profession, there were 110 responses on the data scientist profiles, and 200 responses to the IT technician profiles. Both professions received more responses for the online degree candidate, about 34% for the IT and 31% for data scientist, compared to the traditional candidacies. Although, for the data scientists, the response rate between the online and traditional candidates is quite similar with 28% for the traditional data scientist candidate (Figure 3.1b). This difference is larger for the IT technician (Figure 3.1c), where the online IT technician candidate seems to be much more

Figure 3.1: Positive response rates (online = 1, traditional = 0) for (a) all candidates (b) Data Scientists (c) IT Candidates



Source: TEPP Correspondence Test

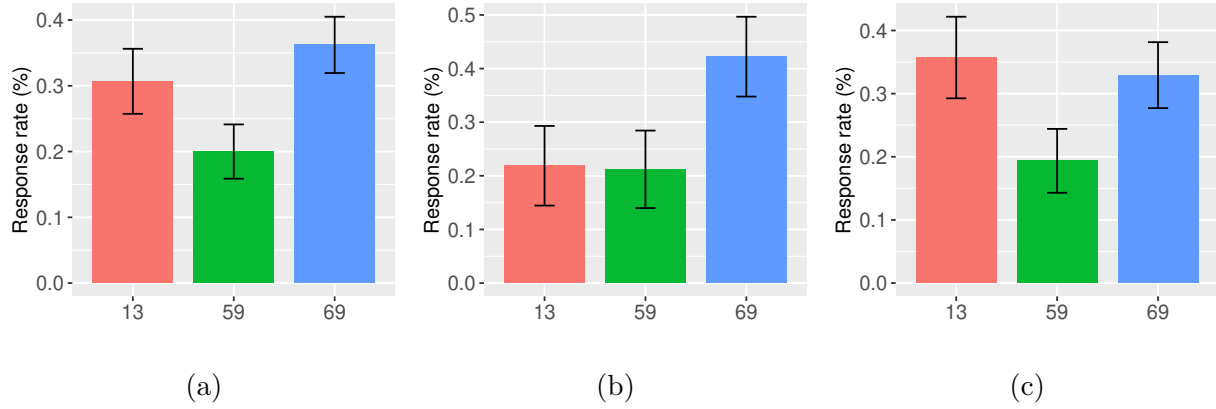
preferred compared to the traditionally educated candidate (26%).

The positive response rates largely differ across the three cities. The highest positive response rate was received from Lyon (36%) followed by 31% for Marseille and 20% for Lille (Figure 3.2a). This is interesting considering that the total candidacies sent out were the highest for Lyon (1,114 candidacies), followed by Lille (1,484 candidacies) and lastly Marseille (910 candidacies), as reported in Table 3.3. When broken down by profession (Figure 3.2c), the IT technician has the highest positive response rate in Marseille (35%) with the lowest positive response rate in Lyon (19%). For the data scientist, the positive response rate in Lyon (43%) largely surpasses that of Marseille (22%) and Lille (21%), which are both similarly quite low (Figure 3.2b).

Econometric analysis

In the experiment, the candidates have similar profiles except in regards to the education received whether that was fully online or in a traditional setting. Within each profession, candidates applied to the same employers with the aim to see if there is recruiter preference over one applicant compared to the other. Nonetheless, there could still be some heterogeneity in the applications sent to the recruiters, such as the language used in the email and resumes.

Figure 3.2: Positive response rate by department (Marseille 13, Lyon 69, Lille 59) for **(a)** all candidates **(b)** Data Scientists **(c)** IT Candidates



Source: TEPP Correspondence Test

The econometric specification used is a linear probability model, such that

$$Pr(Y_{ir} = 1) = \alpha + \gamma C_i + \theta Marseille_{ir} + \eta Lille_{ir} + \sum_j \beta_j \lambda_{ir} + \epsilon_{ir} \quad (3.1)$$

where the probability of each candidate i obtaining a positive response from the recruiter r is represented by Y_{ir} . The type of candidate is denoted by C_i , which refer to either a traditional or online educational background candidate. The departments that were tested are variable dummies $Marseille_{ir}$ and $Lille_{ir}$, with Lyon as the reference category. A set of controls variables are represented by λ_{ir} for the candidates and the recruiters, including the residual ϵ_{ir} .

There are four explanatory variables included as controls to the experiment. The first is the order of the mailing for each pair of candidates to companies. In other words, an investigation of the variables verified that there is no effect of the application order on the probability of a positive response. The next three variables are related to the recruiter and the company characteristics, such as the gender of the recruiter, the company size and the legal form of the company, for example limited liability, corporation, or social economy enterprise.

All regressions are estimated separately for the data scientist and the IT technicians. The linear probability model is estimated first, followed by probit and logit as the recruiter response is a binary variable. The results show the coefficients of the linear probability

model and the marginal effects for the probit and logit models. The standard errors are clustered at the company level, as there are two applications sent to each firm. It should be noted, however, that in the responses received not all companies responded to both of the candidacies sent to each firm.

For the data scientist candidates, the regression results are presented in Table 3.5 with specifications 1-3 being estimated by an OLS linear probability model, specifications 4-6 being estimated by a probit model, and specifications 7-9 are represented by a logit model. The total number of observations is 110, although once the controls are added the observations drop to 79, due to missing values for company sizes. In the OLS specifications, the second and third specifications containing the controls have the highest R^2 . The third specification contains the interaction terms between online education and the city to capture the probability of response based on education background and city. In the probit and logit models, the AIC is lowest for the second specification in both models, which may suggest that the interaction terms are not well suited for the model overall.

Overall, online education appears to negatively impact the probability of obtaining a response from recruiters, although it is not significant when the controls are taken into consideration. Without the controls, the probability that a candidate with an online education background will receive a response is positive (3%), but still not significant. These results suggest that an online education background does not necessarily impact the probability of receiving a response from recruiters.

The departments in specifications 1, 4 and 7 appear to have a negative impact on the probability of obtaining a response. The probability is about 20% across all three specifications, which means that a candidate with a data scientist profile in Marseille and Lille would have approximately 20% less probability, compared to Lyon, of obtaining a positive response from a recruiter. These results are significant at the 10% level.

Regarding the controls, companies that are of medium size seem to have a higher probability (68%) of responding positively to candidates compared to large companies (reference category), and are highly significant at the 1% level.

Table 3.5: Probability estimates on responses for data scientist candidates

	OLS			probit			logit		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	0.41*** (0.08)	0.56 (0.38)	0.54 (0.40)						
online	0.03 (0.09)	−0.00 (0.11)	−0.03 (0.16)	0.03 (0.07)	−0.01 (0.08)	−0.04 (0.12)	0.03 (0.07)	−0.00 (0.08)	−0.03 (0.12)
dept13	−0.21* (0.11)	0.02 (0.13)	−0.05 (0.18)	−0.18* (0.11)	0.01 (0.16)	−0.06 (0.17)	−0.18* (0.11)	0.02 (0.16)	−0.05 (0.17)
dept59	−0.21** (0.10)	−0.10 (0.14)	−0.08 (0.19)	−0.19* (0.10)	−0.10 (0.18)	−0.08 (0.21)	−0.19* (0.10)	−0.10 (0.19)	−0.07 (0.21)
order		0.01 (0.11)	−0.00 (0.11)		0.01 (0.09)	−0.01 (0.09)		0.00 (0.09)	−0.01 (0.09)
civiliteMonsieur		0.08 (0.14)	0.08 (0.14)		0.06 (0.19)	0.07 (0.20)		0.07 (0.20)	0.07 (0.21)
company_sizeM		0.48 (0.63)	0.55 (0.66)		0.68*** (0.06)	0.68*** (0.06)		0.68*** (0.06)	0.68*** (0.06)
company_sizeS		−0.09 (0.36)	−0.05 (0.37)		−0.08 (0.27)	−0.05 (0.31)		−0.08 (0.24)	−0.05 (0.29)
company_sizeXS		−0.41 (0.36)	−0.37 (0.38)		−0.40 (0.31)	−0.37 (0.35)		−0.41 (0.30)	−0.37 (0.34)
company_classificationESS		0.06 (0.25)	0.07 (0.25)		0.07 (0.37)	0.09 (0.39)		0.06 (0.39)	0.07 (0.41)
company_classificationSARL		0.02 (0.12)	0.02 (0.12)		0.02 (0.13)	0.01 (0.13)		0.03 (0.13)	0.02 (0.13)
online:dept13			0.13 (0.26)			0.14 (0.17)			0.14 (0.17)
online:dept59			−0.05 (0.29)			−0.06 (0.27)			−0.08 (0.28)
R ²	0.05	0.15	0.15						
Adj. R ²	0.02	0.02	−0.00						
Num. obs.	110	79	79	110	79	79	110	79	79
AIC				136.89	110.45	113.91	136.88	110.27	113.70

Note: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$ Source: TEPP Correspondence Test

Table 3.6: Probability estimates on responses for IT candidates

	OLS			probit			logit		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	0.31*** (0.05)	0.99*** (0.33)	1.00*** (0.33)						
online	0.06 (0.07)	0.06 (0.07)	0.05 (0.11)	0.06 (0.06)	0.06 (0.06)	0.05 (0.09)	0.06 (0.06)	0.05 (0.06)	0.05 (0.09)
dept13	0.02 (0.08)	0.04 (0.08)	0.03 (0.10)	0.02 (0.09)	0.03 (0.09)	0.03 (0.10)	0.02 (0.09)	0.03 (0.09)	0.03 (0.10)
dept59	-0.14* (0.08)	-0.16** (0.08)	-0.17* (0.10)	-0.14* (0.08)	-0.16** (0.08)	-0.17** (0.08)	-0.14* (0.08)	-0.16** (0.08)	-0.16* (0.08)
order		-0.10 (0.07)	-0.10 (0.07)		-0.10* (0.05)	-0.10* (0.05)		-0.09* (0.05)	-0.09* (0.05)
civiliteMonsieur		0.02 (0.07)	0.02 (0.07)		0.02 (0.08)	0.02 (0.08)		0.02 (0.08)	0.02 (0.08)
company_sizeM		-0.40 (0.35)	-0.40 (0.36)		-0.29*** (0.04)	-0.29*** (0.04)		-0.29*** (0.04)	-0.29*** (0.04)
company_sizeS		-0.63* (0.32)	-0.64* (0.33)		-0.54*** (0.04)	-0.54*** (0.04)		-0.54*** (0.04)	-0.54*** (0.04)
company_sizeXS		-0.73** (0.32)	-0.73** (0.33)		-0.46*** (0.04)	-0.46*** (0.04)		-0.46*** (0.04)	-0.46*** (0.04)
company_classificationESS		0.65 (0.45)	0.66 (0.46)		0.71*** (0.04)	0.71*** (0.04)		0.71*** (0.04)	0.71*** (0.04)
company_classificationSARL		-0.00 (0.07)	-0.00 (0.07)		-0.01 (0.08)	-0.01 (0.08)		-0.01 (0.08)	-0.01 (0.08)
online:dept13			0.01 (0.16)			-0.00 (0.12)			0.00 (0.12)
online:dept59			0.02 (0.17)			0.03 (0.15)			0.02 (0.16)
R ²	0.03	0.09	0.09						
Adj. R ²	0.01	0.05	0.04						
Num. obs.	200	200	200	200	200	200	200	200	200
AIC				244.99	244.99	248.95	244.97	245.35	249.32

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$ Source: TEPP Correspondence Test

For the IT technicians candidates, the results from the linear probability, probit and logit models are shown in Table 3.6. Online education seems to provide a positive probability (approximately 6%) in callbacks to the IT technician candidates, although the results are not significant. Interestingly, the results for the online education variable are similar across all three model types.

Regarding the departments, in Marseille, compared to Lyon, an IT technician candidate seems to have an increase in probability of getting a positive response, although the results are not significant. On the contrary, in Lille an IT technician has approximately 16% less probability of obtaining a callback, at the 10% significance level, compared to in Lyon.

The company size is very significant for the IT technician profession. Under the linear probability model, micro-companies (XS) and small companies (S) would respond negatively to the IT technician with a probability of 73%, at the 5% significance level, and 63%, at the 10% significance level, respectively.

3.5 Conclusion

The education received acts as a signal towards future employers. There has been a rise in the demand for online education due to many reasons from the students' perspective, such as constraints of physical distance or time. As the method of attaining online education is different to that of the traditional methodology, the perspective of the employers is crucial. In other words, as the recruitment decision is made out of educational signals and previous experience in order to judge skills and productivity, the applicants' education background could have an impact in the hiring decision. Moreover, it could lead to employer statistical discrimination through presumed productivity and categorizing students based on their educational background.

The literature has focused predominantly on subsequent discrimination in the workforce, represented in socio-economic factors such as income differentials, that can arise from inequality in access to education. The university prestige is found to have a large impact on

the initial hiring process, including the level of income received. This shows a clear sign that employers rely heavily on the educational background to predict the productivity and skills of a university graduate. This is due to the imperfect information that the employer would initially have when hiring. Studies have shown that the effect of university reputation decreases the longer the student has worked, as this on the job experience would provide additional information to the employers regarding the students' experience. Lastly, the heterogeneity in the human resources staff at firms can also influence the hiring decision. Overall, there is very little literature that has assessed the perception of employers regarding online versus traditional higher level education degrees. The few studies that have attempted to test this impact have found that traditional education background candidates seem to receive higher callbacks compared to candidates with online education background.

This study used a correspondence test across three French cities in France, contacting 1,754 unique companies, based on two professions, data scientists and IT technicians. Both candidacy profiles have some years of experience in the field in which the applications were sent. The response rate was 13.5%. Out of the total responses received (310), the data scientist received more response rates (33%) compared to the IT technician (28%). Both candidate profiles received more responses if they had online education as their educational background.

For the data scientist, the results suggest that online education has a positive impact on the probability of obtaining a positive callback (3%), although this impact is not significant. The departments have a significant effect at the 10% level. There is a lower probability of obtaining a positive callback in Marseille (18%) and Lille (19%) compared to Lyon. When the controls are added, however, the direction of the effect remains the same for the department, but the impact is insignificant. Interestingly, company sizes, particularly medium-sized firms, seem to have a highly significant (1% level) and large probability of giving a positive response (68%). This is not the case for small firms and micro-enterprises, where the results are negative and insignificant. This provides an indication of which companies would be most interested in the candidates with an online degree in data science.

For the IT technician, having an online degree has a positive (6%), yet insignificant impact on the probability of receiving a positive callback. On the contrary, the results suggest that IT candidates in Marseille received a lower probability of callbacks (16%) compared to Lyon. When looking at firms' characteristics, it seems that the estimates of the micro-enterprises (46%), small firms (54%) and medium sized firms (29%) are highly significant and have a much lower probability of providing a call back to an IT technician candidate, compared to large companies.

All in all, the results from both professional profiles seem to suggest that having an online education background seems to have a positive impact on the probability of getting a positive callback, although it is not significant. Due to the not significant character of the results, it cannot be proved that the recruiters have a preference for one education background compared to another. This is in some way a good result, as it confirms that there is no differentiation made by the recruiter responses to candidates from either online or traditional education background. The probability of obtaining a callback based on the department, specifically Marseille, is lower for both types of candidates if they have an online degree background, compared to the Lyon.

The contribution of this study was to test whether the education background type could impact the probability of obtaining a positive response from recruiters. Although the results are not significant across many variables, it does provide intuition regarding the direction of the impact. Moreover, the findings contribute to the lack of literature in the field of online education research. In terms of methodology, the study uses a correspondence test to evaluate recruiters' perception of online education, and if there is a differential in the choices made between candidates, where all other characteristics and experiences are similar. Lastly, the study sheds light on the recruiter preferences in three metropolitan cities in France.

The study can be improved in many ways. Firstly, the study only measures the first response to the candidates, without considering how the candidacy could result if additional steps, such as responding to the recruiter, thereby taking the experiment further. Moreover, the duration of the testing could have been longer, allowing for potentially more responses

to be received. The number of companies and industries chosen could have been increased in order to enlarge the pool of potential recruiters. The testing was conducted during the month of July 2022, which is when companies could be hiring less. The economic context due to the current high inflation, recessionary pressures and the residual impact of the covid pandemic could add to the slowdown of the recruitment and hence the response rates. Moreover, the professions tested were only for data scientists and IT technicians. Other professions could have alternative results, depending on how open the recruiters are to alternative methods of education and training. Lastly, only three French cities were considered. The results could differ if the same study was conducted in different cities and countries. In this regard, repeating this type of study for different professions, in different cities, and extend it to incorporate other discriminatory criteria such as origin and gender of the candidate/applicant would enrich the results and the field of research.

Annex

3.A Example curriculum vitae

Below, examples of four CVs are presented that have been used to apply for jobs as data scientist and IT technician. Each pair of candidates was sent out in Lille, Lyon and Marseille. The data scientist candidates were female, and the IT technicians were male. The applications were standardized to correspond to the French labor market. Table 3.7 summarizes the identities of the fictitious candidates and their educational background, as the variable that is being differentiated.

Table 3.7: Identity of fictitious candidates

Profession	Candidate Name	Differentiated Education	Gender
Data scientist	Léa Petit	Online	Female
Data scientist	Marine Dubois	Traditional	Female
IT technician	Thomas Lefebvre	Online	Male
IT technician	Maxime Moreau	Traditional	Male

Maxime MOREAU

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Technicien Informatique

OBJECTIF

J'ai exercé pendant 2 ans le métier de technicien informatique dans des entreprises différentes, ce qui m'a permis de développer mes compétences et de cerner les besoins des clients.

FORMATION

2020 : Technicien Informatique
Université Gustave Eiffel – niveau 5

EXPERIENCES

Janvier 2021 –Avril 2022

Technicien informatique chez **GroupAgora**

- Mettre en service et paramétrer les matériels et solutions informatiques
- Assister techniquement les utilisateurs sur site ou à distance
- Rédiger les rapports d'intervention et les communiquer à la hiérarchie
- Conseiller les utilisateurs sur les mises à jour nécessaires / sur le renouvellement du matériel
- Gestion du parc informatique
- Gérer le flux de matériel (réception-expéditions) dans la gestion de stock

Juin 2020 – Janvier 2021

Technicien Soutien Informatique à **Orange**

- Gérer l'installation et la maintenance des postes de travail, des moyens d'impression, des postes téléphoniques et équipements télécoms internes.
- Assurer le soutien et l'accompagnement auprès des utilisateurs
- Faire le diagnostic et la résolution de problèmes
- Suivi du system de ticketing et effectuer le reporting d'activités

COMPETENCES TECHNIQUES

- Effectuer une assistance informatique
- Monter un poste de travail répondant aux besoins de l'utilisateur
- Maîtrise de la configuration, du diagnostic et de la maintenance des réseaux.
- Gérer les droits d'accès aux données dans le respect de la stratégie de sécurité
- Décrire et utiliser systèmes et réseaux informatiques

SOFT SKILLS

Rigueur, Réactivité, Autonomie

LANGUES

EN – TOEIC C1

CENTRES D'INTERET

Yoga
Tennis
Danse salsa

Marine DUBOIS

6 Bd Luc

13013 Marseille

06 41 47 67 58

marineddubois@gmail.com

Née en 1995 à Meaux (77)

Data Scientist

Compétences informatiques

TABLEAU
SAS
STATA
VBA
R
PYTHON
NOSQL
SQL
AGILE
MICROSOFT POWER BI

Outils Machine Learning

NUMPY
PANDAS
PLOTLY
TENSORFLOW
SCIKIT-LEARN
SEABORN

Langues

Anglais – courant

Hobbies

Cinéma
Football
Séjours touristiques à l'étranger

Diplômes

2019-2020

Master Data Science et Société Numerique (D2SN) – Université Gustave Eiffel

2018

Licence MASS – Université de Clermont-Auvergne

Compétences professionnelles

Développement, fusion et gestion de bases de données multi sources, fiabilisation de la qualité de la donnée, nettoyage des données.

Développer des algorithmes pour résoudre des problèmes de situation complexes et générer des analyses. Capacité à gérer des données structurées et non structurées.

Maîtrise des méthodes de data science machine learning, analyse de réseaux et analyse textuelle.

Production et optimisation de la modélisation statistique et de l'analyse des données. Générer des prédictions sur les tendances futures des performances et interpréter les résultats.

Expériences

2020 – 2022

Data Scientist chez Renault Group à Guyancourt (78)

Collecter, nettoyer et traiter le big data et les appliquer dans le contexte de l'entreprise; développer les applications de machine learning; analyser les données à l'aide d'outils statistiques; optimiser et contrôler les plans d'expérience afin d'améliorer l'efficacité des simulations.

2019

Alternance Data Scientist chez Engie à Saint-Ouen (93)

Optimiser les mesures de performance dans le suivi de l'activité des clients, développer de modèles de machine learning avec les bases de données des clients.

Vérification de la qualité des données, nettoyage et analyse des données, analyse de l'impact des campagnes marketing sur la transformation des prospects en clients, recommandations.

Léa PETIT

29 rue de la paix d'utrech
59000 Lille

06 41 94 82 02
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27 ans

Data Scientist

FORMATION

2020 : Master en Data Science
OpenClassrooms, 10 Quai de la Charente, 75019, Paris
[100% à distance – titre RNCP niveau 7 – partenariat CentraleSupélec]

2018 : Licence en Sciences, Vie et Santé
UFR Sciences, 28 av. Valrose, 06034, Nice

2015 : Baccalauréat série S

EXPERIENCES

Septembre 2020 – Mars 2022

Data Scientist chez EDF

- Construire et nettoyer de grandes bases de données
- Analyser les données pour construire une vision des processus et des activités réelles, en déduire des améliorations puis mettre en œuvre des solutions de suivi et de remédiation.
- Développer des applications de machine learning à partir de données d'affaires
- Utiliser une approche agile pour la création d'indicateurs, le reporting et le suivi de la performance des activités des clients.

Mars – Septembre 2019

Apprentie Data Scientist chez PSA Peugeot-Citroën

- Développer des outils de mesure pour identifier les leviers d'amélioration de l'activité.
- Analyser des ensembles de données provenant de sources multiples pour diagnostiquer des processus complexes à optimiser et suggérer des améliorations sur les activités de performance,
- Réaliser des prédictions pour améliorer les ventes de l'entreprise

COMPETENCES PROFESSIONNELLES

- Collecter, nettoyer et préparer les données pour l'analyse.
- Développer des algorithmes de Machine Learning pour analyser, optimiser et prédire les tendances.
- Solides connaissances en outils statistiques pour la production d'analyses.
- Gestion des données structurées/non structurées

COMPETENCES TECHNIQUES

Tableau, SQL, NoSQL, Python, R, Stata, SAS, VBA, Microsoft Power BI, Agile

AUTRES

Pandas, Numpy, Scikit-learn, Pytorch, Seaborn, Matplotlib

LANGUES

EN – TOEIC C1

CENTRES D'INTERET

Cinéma
Rugby
Musique

Thomas LEFEBVRE

Technicien Informatique

Ayant toujours été passionné par l'informatique, je dispose de 2 ans d'expérience. Les formations dispensées par OpenClassrooms m'ont permis d'acquérir les compétences nécessaires et appris l'autonomie et la rigueur.



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LANGUES

Anglais: courant

CENTRES D'INTERET

Voyager / Art / Musique

ATOUTS

Autonome / Curieux /
Méthodique

FORMATION

2020

Technicien Informatique • **OpenClassrooms (Distanciel)** • Niveau 5

EXPERIENCE

2021

Technicien Informatique à **Michael Page**

- Diagnostic à distance des dysfonctionnements informatiques (matériel et logiciel),
- Accompagnement de l'utilisateur pour résoudre le dysfonctionnement ou prise en main du système à distance pour effectuer la résolution,
- Gestion de la maintenance matérielle,
- Configuration des postes de travail, PC, imprimante, téléphone et dispositif mobile éventuel, aux besoins de l'utilisateur et réalisation des tests de fonctionnement,
- Gestion du Parc Informatique et des dispositifs connectés

2020

Technicien Support Informatique à **Groupe Mobile**

- Accueillir les utilisateurs
- Établir un diagnostic et identifier les pannes
- Conseiller, former et assister les utilisateurs
- Traiter le Backlog des incidents, demandes et emails en assurant un bon suivi.

COMPETENCES TECHNIQUES

- Installer et intégrer le matériel dans l'environnement
- Réaliser la maintenance de matériel informatique
- Excellentes compétences en matière de diagnostic et de résolution de problèmes
- Compréhension approfondie de divers systèmes et réseaux informatiques
- Bonne connaissance des principes de sécurité sur Internet et de confidentialité des données

3.B Comparing UGE versus OC Master in Data Science

The programs of the data scientist degree (Table 3.8) is compared between the offer from UGE and OC. The level of education is at the master level. It can be seen that it is comparable between the two institutions in terms of education level, degree level, length of study, and training format. Moreover, both institutions also collaborate with other traditional-based partnerships. The main difference is in the learning modality, where UGE teaches in traditional format, with the guidance of a teacher, while OC uses online modality with the support of a mentor throughout the learning journey.

Table 3.8: Comparing UGE versus OC Master in Data Science

Category	Master Science and Digital Society	Master Data Science
Education Level	M2	M2
Diploma Level	Niveau 7	Niveau 7
Time	9 months	9 months
Learning Modality	Presence	Online
Guidance	Teacher	Mentor
Program Partnerships	ESIEE and LISIS	CentraleSupélec
Training Format	Initial Training Continuing education VAE Work-study training	Initial Training Continuing education VAE Work-Study training

Source: UGE and OC Master level catalogues

3.C Comparing UGE versus OC Master in Information Technician

The IT technician program is the second profession that had a comparable program between the two institutions (Table 3.9). On the other hand, it is at the bachelor level (*Licence* in French). It is also similar at the education and diploma level, and provides the very similar future employment prospects for potential jobs for graduates. The difference between the

two programs remains in the modality, where UGE is traditional based while OC provides their program entirely online.

Table 3.9: Comparing UGE versus OC Bachelor in Information Technician

Category	UGE : Informatics	OC : Information Technician
Education Level	L2 and/or L3	Licence
Diploma Level	Bac+2 and/or Bac+3	Bac+2
Potential Future Jobs	Computer technician Fuctions of developer	Computer technician IT Support Technician (HelpDesk) Computer maintenance technician Systems and Networks Technician

Source: UGE and OC Bachelor level catalogues

3.D Nomenclatures of French activities for Data Science Candidates

The nomenclatures of the French industries are sourced from the French national Institute of statistics (*L’Institut national de la statistique et des études économiques* in French). Under each nomenclature category, a specific sub-cateogry is chosen to source the companies to which the data scientist candidacies were sent out (Table 3.10).

Table 3.10: Nomenclatures of French activities for Data Science Candidates

NAF Category	Category sub-title
Industrie manufacturière	Fabrication de carrosseries et remorques Fabrication d'équipements électriques Fabrication d'autres équipements automobiles Fabrication de motocycles
Production d'électricité/gaz/vapeur et d'air conditionnée	Transport d'électricité Distribution d'électricité Commerce de combustibles gazeux Production et distribution de vapeur/d'air conditionné
Recherche-développement en sciences humaines et sociales	R&D en sciences humaines et sociales
Études de marché et sondages	Études de marché et sondages
Commerce; Reparation d'auto et de moto	Commerce de voitures Commerce de détail d'équipements automobiles
Transport et entreposage	Transports par conduites
Activites financieres et d'assurance	Activités de banque centrale Autres intermédiations monétaires Fonds de placement et entités financières similaires Autres assurances Caisses de retraite Administration de marchés financiers Courtage de valeurs mobilières et marchandises Gestion de fonds

3.E Nomenclatures of French activities for IT Candidates

The nomenclatures of the French industries are sourced from the French national Institute of statistics (*L’Institut national de la statistique et des études économiques* in French). Under each nomenclature category, a specific sub-cateogry is chosen to source the companies to which the IT technicians candidacies were sent out (Table 3.11).

Table 3.11: Nomenclatures of French activities for IT Candidates

NAF Category	Category sub-title
Information and Communications	Télécommunications filaires
	Télécommunications sans fil
	Autres activités de télécommunication
	Programmation informatique
	Conseil en systèmes et logiciels informatiques
	Tierce maintenance de systèmes et d'applications informatiques
	Gestion d'installations informatiques
	Autres activités informatiques
Activites de services administratifs et de soutien	Traitement de données, hébergement et activités connexes
	Activités des agences de placement de main-d'œuvre
	Activités des agences de travail temporaire
	Autre mise à disposition de ressources humaines
	Services administratifs combinés de bureau

General Conclusion

Contributions

New perspectives and evidence is provided in this thesis in regards to alternative education modalities, their impact on student performance, and labor market prospects. As a result of the recent pandemic, and the exposure to the alternative education modalities and use of technological tools, changes in the pedagogy and the methods of teaching and learning are bound to evolve. In this light, the results of this thesis provide insight into the impact of the pandemic on higher education, the impact of alternative modalities on student performance, and the signal effect of such education in the French labor market.

In this regard, the first chapter provided the foundation of the thesis, as it focused on identifying the factors that consist of an effective and equitable higher education offer, and more importantly how these factors were impacted by the pandemic. The chapter uses the USA context due to large availability of national data and surveys at the state and national level, including differing university structure types, i.e. community colleges, private, and public. More specifically, the equity of education due to the use of alternative education modalities is analysed through the factors of access to education and the home environment, which can be an impediment to distance learning. The findings suggest that if the access to technological materials, such as computers and a stable internet connection, are not linked to the student circumstances but are rather supported at the institutional level, then adopting distance education can have positive effects on the access to higher education. In other words, with distance education more students who are equipped will be able to connect, use online

learning materials and interact through learning management platforms without experiencing any educational disruptions or delays. Moreover, education access through online means can also increase the accessibility at scale. On the other hand, if each student is left to ensure their own equipment or rely on the family and home environment, this would induce another layer of inequality on the basis of family income and capacity to ensure appropriate tools to study and a home environment from which to study. As a result, the repercussions of the inequality in online education access would only increase the digital divide, learning losses, and the skills gaps that are associated to the use of online education and tools.

On the other hand, the effectiveness of online education is analysed through student performance based on assessments, class interactivity and the readiness to work. In terms of student performance, the difficulty, especially during the pandemic, was in the assessments conducted and the management of cheating. Examinations were either delayed or cancelled, calling for alternative assessments such as homework, class exercises and case studies. Moreover, as it was difficult to ensure attendance through communication tools, such as Google Classrooms. Interactivity in online classes was initially found to be limiting as the learning management systems were new to students and teachers alike. Nonetheless, the research found that students and teachers are willing to integrate more of the technological tools and distance modalities in the curriculum. Surveys have found that even though there is a learning curve in using the technology, the stakeholders are willing to adapt and see the potential of effective learning in alternative modalities that can be used to aid the traditional education context and methods rather than replace them. Moreover, and as in the aftermath of the pandemic looms an economic recession, the development of digital skills for students and the increase in their cognitive skills, such as self-motivation and self-confidence, will equip them with the necessary skills to remain agile and adaptable.

In light of contributing to the research on the effectiveness of online education, the second chapter focused on the impact of alternative education modalities on three departments at the masters level of the Université Gustave Eiffel in France. The study used three empirical models in order to capture three alternative cases. The first model used a pooled panel

data, estimated via OLS, to capture the impact of both covid and the alternative modalities on student performances. The findings suggest that distance modality has a significant negative impact on student performances compared to the in-person modality. Alternatively, the hybrid modality has a significantly positive impact of student grades compared to in-person modality. Evidence is also found that for courses under departments of linguistics and economic sciences students performed significantly better compared to courses from the engineering department. The results also suggest that students studying in their second year of masters (M2 in France) will do better earning more than half a grade point compared to the first year of the masters. Moreover, male students are found to receive at least half a point of a grade worse compared to female students. The second model uses a panel data regression across courses, rather than time, that are all subjected to the pandemic. Therefore the courses considered are only those that happened in the period January - June 2020. In this way, the shock of the pandemic is experienced by all courses and students. Under this model, the hybrid and distance modalities are found to have significantly negative impacts on student performances compared to traditional in-person modality. Moreover, the distance modality have a higher negative impact compared to hybrid modality. The last model simply tried to capture the impact of the pandemic, without education modality, on the student performances. The results show that the period in which the pandemic began, the student grades increased by 0.72 points of a grade, which is higher compared to previous periods, suggesting that the pandemic had pushed upwards the grades independently of the modality of the courses.

In the third chapter, the focus was to investigate the probability of obtaining a positive response from recruiters, and if there is differential treatment towards candidates on the basis of education background - more specifically whether the candidate had graduated from a traditional university or a fully online degree granting institution. In this regard, UGE and OC were used as the two institutions that are comparable in the masters degree of data science and bachelors degree of IT technician. The education modality is the only difference, where UGE is the traditional education institution, while OC is the online education provider. A

spontaneous correspondence test for the data science and IT technician professions was used in three French cities; Lille, Lyon and Marseille. For the case of the data scientist, the study finds that having an online education background in the CV has a negative impact on the probability of obtaining a positive response from recruiters, when the control variables are considered. Without the control variables, the probability of the receiving a positive callback for candidates with online degree background is 3% although it is not significant. This suggests that there is no differentiation made by the recruiters on the basis of the online education background. Evidence is found that the size of the recruiters' company, specifically medium-sized firms, have a significantly positive impact on the probability of positive response to the candidate compared to large firms. In terms of the different cities, there is less probability (20%) for a data scientist's profile to receive a positive callback compared to the case of Lyon. For the case of the IT technician, online education background does have positive coefficients, but none are significant. In other words, there is no significant evidence, similar to the case of data scientist profession, that there is an impact of the online education background on the probability of obtaining a positive response from recruiters. There is strong significant evidence that the company size plays an important role in the probability of obtaining a positive response. Companies particularly of micro-enterprise structures, small firms, and medium firms have a significantly negative impact on the probability of positive recruiter response.

Limitations and Recommendations

The chapters of the thesis contain conclusions that are specific to the data collected and empirical methods used. The results of chapter two and three cannot be generalized. Chapter two has data that were collected from the teaching staff of the French university UGE and the university administrative database, therefore the results pertain only to the case of that university and its students. The results are therefore specific and case based. For the case of chapter three, the data are collected using spontaneous correspondence test method, which is

not representative of the whole labor market (Heckman, 1998). This is because the firms were sourced specifically for Lille, Lyon and Marseille, with two precise professions and within a specific time frame. These results are therefore partial and localized, but provide merit and shed light on the first step of the recruitment process. Alternatively, the analysis of the first chapter is applicable and can be generalized, as it summarizes the alternative approaches to effectiveness and equity in education. It is therefore interesting to expand on the approaches to evaluate the effectiveness and equity of online education and other alternative modalities as the education technology expands, and especially with the rise in available data and tools after the pandemic.

Furthermore, the effectiveness of higher education was tested using student performance as an the indicator. There are other factors, such as level of student attendance, teacher quality, institutional funding, that constitute the level of educational effectiveness which remain to be tested and investigated through the use of alternative education modalities. Moreover, the digital tools that were used were not considered but can have profound impact on the education delivery and accessibility. These are avenues of factors that require more research in order to acquire a better understanding of the extent to which alternative modalities can be effective in the higher education context.

In terms of access to employment, and as a result of studying under a certain modality, the thesis aimed to evaluate if there was any differentiated treatment and preference between graduates of fully online versus traditional higher education background. Future research that adopts similar approach to testing could ensure a much larger sample and for more professions. Moreover, the testing period should be conducted over a longer time frame. As the experiment was done through spontaneous correspondence testing, the results could differ if the applications were sent to positions that were vacant rather than spontaneously contacting companies that might not be hiring at the time.

The country of focus was the USA for chapter one and France for chapters two and three, which are both high income countries. The impact of the pandemic on their education systems would be different compared to middle and lower income countries. Moreover, higher income

countries will have an easier transition into alternative education modalities. Lessons can be learnt from different types of countries in regards to their experience with the pandemic and the transition into providing effective higher education through alternative modalities.

Lastly, it would be interesting to replicate the same empirical methodologies to assess whether the situation has changed for higher education now that some time has passed after the pandemic, and whether the teachers and students have adopted higher levels of alternative education modalities. As more data become available, a stronger counterfactual and control groups can be created for further research, and at a much more granulate level to evaluate the impact of alternative education modalities in the aftermath of the pandemic.

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