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Influence of political movement on fields of study: Evidence from Hong Kong☆

Yonghong Zhou

Faculty of Finance, City University of Macau, Taipa, Macao SAR

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ABSTRACT

Exposure to political movements may influence individuals' behavior, such as decisions on fields of study. On the basis of the Hong Kong Population Census 2011 and 2016, this paper investigates the difference in fields of study between two cohorts, one exposed to the Occupy Central movement in 2014, by applying the cohort difference-in-differences approach. As a global business center, business-related fields of study have been popular among students in Hong Kong. However, the political movement triggered the interests of young people to study several nonbusiness-related fields, such as humanities, social and behavioral sciences, life sciences, health, and law. Significant differences in the effect exist across language speaking, household income, and gender. The study shows that political movement may affect education by triggering public awareness of related knowledge, but it varies by human capital, identity, and family background.

1. Introduction

Special experience in life may have significant effects on an individual's later outcome (Akresh and de Walque, 2008; Lee, 2014; Akbulut-Yuksel, 2017). In particular, exposure to major events in early life has a negative influence on education (Ichino and Winter-Ebmer, 2004; Shemyakina, 2011; Chamarbagwala and Morán, 2011; Akbulut-Yuksel, 2014; Utsumi, 2022). The literature claims that the shock of major events reduces the resources available to individuals, and thus changes the outcome later. In other words, the change in an individual's behavior is caused passively by external constraints. However, teenage years are a special period of physical development when an individual's beliefs, values, and commitments take shape (Flanagan and Sherrod, 1998; Caro and Schulz, 2012; Manganelli et al., 2012; Blaskó et al., 2019). Exposure to major public events during this stage of life may leave a deep impression on youth and cause individuals to actively, rather than passively, change their behavior. To the best of my knowledge, there is limited research on the effect of external shock from the perspective of active change in behavior. This paper fills the gap by investigating the influence of exposure to political movements on decision on fields of study. Moreover, current studies believe that the major choice for study is mainly determined by expected income, industry development, individual preference, and ability (Montmarquette et al., 2002; Arcidiacono et al., 2012; Brodaty et al., 2014; Patnaik et al., 2022). However, this study provides another explanation for fields of study — the trigger of major events on young people's awareness of related knowledge.

This work investigates the effect of the Occupy Central (hereinafter referred to as "OC") movement in 2014 on fields of study by applying cohort difference-in-differences (DID) approach. OC movement was one of the largest political movements in

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E-mail address: yhzhou@cityu.mo.

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Hong Kong, and young people were its main participants. For an international financial center, fields related to business, such as accountancy, business administration, financial management, and studies in secretarial skills, have a large demand in the Hong Kong educational market. However, the Hong Kong Population Census (2011 and 2016) shows that more young people chose to study in some nonbusiness-related fields, including humanities, social and behavioral sciences, life sciences, health, and law, after the OC movement. We claim that exposure to the OC movement changes the youth's behavior, leading to the choice of studying in fields inspired by their experiences in this political movement. In heterogeneity analysis, we find that the effects are mainly from people with bilingual competence (Mandarin and English), but an inverse effect could be observed among people who spoke Mandarin. The effect was also stronger among people with low household income and females. The result shows that political movement may affect education by triggering public awareness of related knowledge, but it varies by human capital, identity, and family background.

This paper contributes to the study of two fields — the effects of special life experience on education, and the determinants of major choice or fields of study. Exposure to negative events may lead to a loss of resources, resulting in poor outcomes, such as the educational loss caused by World War II (Ichino and Winter-Ebmer, 2004; Akbulut-Yuksel, 2014) and the drop in educational achievement for children exposed to the Rwandan Genocide (Akresh and de Walque, 2008). Similarly, Shemyakina (2011) found evidence of the lesser probability for girls exposed to the conflict in Tajikistan to complete their mandatory schooling. Other evidence includes a strong negative effect of Guatemala's Civil War on the education of rural Mayans (Chamarbagwala and Morán, 2011). Utsumi (2022) investigated the spillovers of conflict on education and showed that conflict in Afghanistan has a negative effect on the school enrollment rate not only in areas where actual conflict occurs but also in areas with no conflict. As mentioned earlier, the literature claims that the shock of major events reduces the resources available to individuals and thus changes the educational outcome later. Different from these studies, this paper focuses on active change in later behavior rather than passive change due to the limited resource that the individual can use.

In another field to which this paper contributes, the determinants of major choice or fields of study have always been a concern of education economists. Studies have provided evidence for the determinants of major choice, including gender, college grade, abilities, preference, and gaining parents' approval (Arcidiacono et al., 2012; Bartolj and Polanec, 2012; Zafar, 2013; Astorne-Figari and Speer, 2019; Bordón et al., 2020). However, expected income plays a crucial role in the choice of college major (Montmarquette et al., 2002). Freeman and Hirsch (2008) found that the choice of college major is responsive to changes in the knowledge composition of jobs and the wage returns to types of knowledge. Similarly, Long et al. (2015) found that college majors are most strongly related to wages observed three years earlier. Xia (2016) showed that the effect of wage plays the role through family background — the family member's wage at the time the major choice is made. However, Wiswall and Zafar (2015) criticized that analyses that ignore the correlation in tastes with earnings expectations inflate the role of earnings in college major choices. Determining the fields of study according to the expected income means that this decision must be carried out according to a cost–benefit analysis. Risk is another important factor in the cost–benefit analysis of major choices. Brodaty et al. (2014) took future wage risk into account and treated the direct and opportunity costs of education as additional sources of risk, showing that the risks affecting time-to-degree and future wages play a role in their choice of educational investment. Through an experiment, Ruder and Noy (2017) also claimed that expectations of earnings risk matter in major choice. Considering the heterogeneity in risk aversion and time discounting, Patnaik et al. (2022) claimed that current models without this heterogeneity overstate the importance of earnings to major choice. However, when an individual is exposed to an external shock, his utility function may change. Thus, the decision may not be made in terms of cost–benefit analysis based on the development of the existing market. Different from these studies, this paper investigates how the political shock triggers the awareness of related knowledge, and thus leads to a decision on fields of study.

The studies closest to this paper are the influences of changes in macro or micro environment, external shock, and individual's experience on major choice or fields of study. Exposure to an academic field has impacts on major choice (Fricke et al., 2018). However, in most cases, individuals obtain relevant knowledge indirectly through environmental change. Orrenius and Zavodny (2015) investigated the spillovers of immigrants on fields of study among US natives. They found that the higher the immigrant share in their college cohort, the less likely are women to major in science and engineering. Similar evidence comes from Ransom and Winters (2020), who found that the US Immigration Act of 1990 changed natives' skill investment and studies in STEM majors.[1] Business cycles and development in certain industries may also affect people's learning of related knowledge. The Great Recession increased the frequency of STEM majors but decreased the frequency of business majors in college major decisions (Liu et al., 2019). Han and Winters (2020) showed that the energy boom made two energy-related majors more popular. For studies related to Hong Kong, Kutnick et al. (2020) found that students perform strongly on international science and mathematics assessments, although its economy is reliant on a dwindling number of engineers. Using student interviews, they showed that students' aspirations in STEM were largely supported at a personal level via experiences offered by family and friends in Hong Kong. Different from these studies, I provide another explanation of the decision on fields of study — the trigger of political movement on relevant knowledge, which has a guiding effect on young people's decision in terms of fields of study.

The rest of this paper is organized as follows. Section 2 presents background information on the OC movement and introduces a simple mechanism of the effects of exposure to this political event on fields of study. Section 3 presents our data, variables, and empirical methodology in detail. Section 4 presents the empirical results which include basic estimates, parallel trend tests, robustness checks, and heterogeneity analysis. Section 5 concludes the paper.

[1] STEM refers to science, technology, engineering, and mathematics.

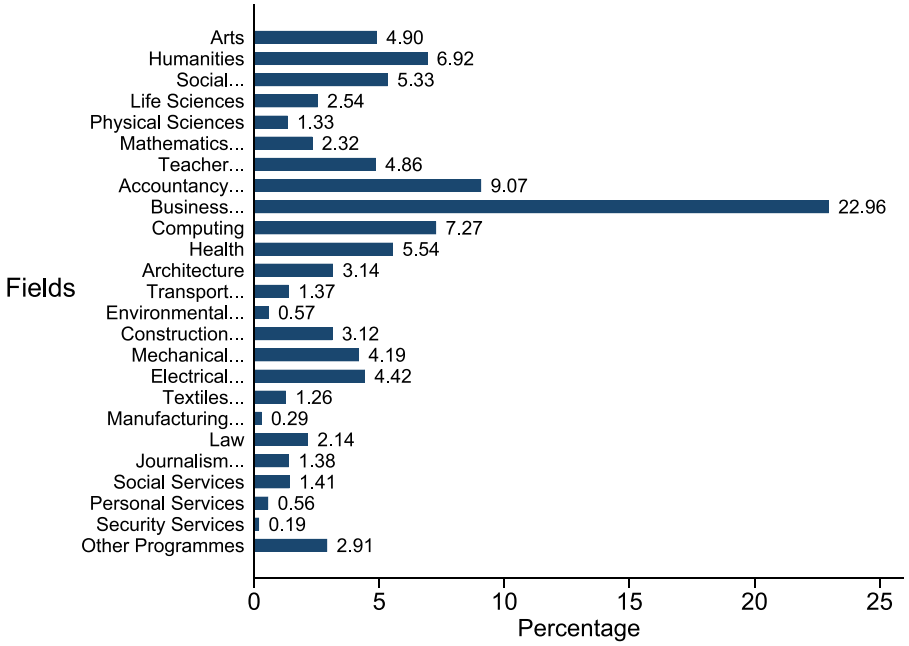


Fig. 1. Highest field of education attended.
Note: The data are collected from the Hong Kong Population Census (2016). The labels on the vertical axis are incomplete.[3]

2. Background

2.1. Fields of study and the OC movement

Over the past decades, the Hong Kong government has attached great importance to promoting quality post-secondary education by welcoming talent, upholding academic freedom, respecting institutional autonomy, fostering collaboration and promoting academic exchanges. Currently, there are 9 publicly-funded and 13 self-financing universities in Hong Kong, offering a wide array of program from sub-degree to doctoral levels. The institutions in Hong Kong enjoy a high degree of autonomy in the admission of students and thus make admission decisions primarily based on the merits of individual applications.[2] Hong Kong is one of the major financial centers in the world and has led to a great demand in finance, business, and related services. To meet market demand, Hong Kong residents usually choose related fields to study. Fig. 1 shows that accountancy and studies in secretarial skills, business administration and financial management, and computing are the three most popular fields for students, accounting for 9.07%, 22.96%, and 7.27% in the proportion of the highest field of education attended, respectively. Thus, the knowledge of human capital in Hong Kong is dominated by business-related fields.

However, major external shocks may influence such inertia thinking in fields of study. The OC movement in 2014 was one of the largest political conflicts between the Hong Kong government and opposition since its return to China in 1997. The conflict originated from the dispute on the Chief Executive election scheme of Hong Kong. In the dispute, the protesters opposed the reform approved by the central government and requested that the government restart political reform, but the government refused. The main protests began in late September 2014 and later led to violence on the streets. People from different cultural backgrounds had different attitudes toward this movement, and sharp conflicts arose between them. During the conflict, protesters gathered in the central business district and clashed with police, which led to disruption of normal traffic and business and closure of some shops and schools. Several countries, such as the United States, Australia, Singapore, and Italy, issued travel warnings to their citizens. The conflict ended in December 2014 with police clearance and the failure of the occupiers. In the 30 years before the OC movement, there had been many demonstrations and protests in Hong Kong, but the Occupy Central movement caused fierce conflicts between demonstrators and police, and ended with police clearance for the first time. The previous protests began and ended peacefully,

[2] For more information, please refer to the website: StudyinHK [https://www.studyinhongkong.edu.hk/en/].

[3] The fields, from top to bottom in the vertical axis, are Arts, Humanities, Social and Behavioral Sciences, Life Sciences, Physical Sciences, Mathematics and Statistics, Teacher Training and Education Science, Accountancy and Studies in Secretarial Skills, Business Administration and Financial Management, Computing, Health, Architecture, Transport and Logistics Services, Environmental Protection, Construction, Civil and Structural Engineering, Mechanical and Marine Engineering, Production and Industrial Engineering, Chemical Engineering, Biotechnology, Electrical and Electronic Engineering, Textiles and Clothing Technology, Manufacturing and Processing, Law, Journalism and Information, Social Services, Personal Services, Security Services, and Other Program.

lasting for a relative short time, but the Occupy Central movement lasted for several months and, as a result, the influence of the movement on participants was the largest in the past 30 years.

2.2. The trigger of political movement on relevant knowledge

Many of the participants in the OC movement were young people, including students who had just completed their high-school studies. Adolescence is a developmental period when civic beliefs, citizenship, values and commitments take shape (Flanagan and Sherrod, 1998; Caro and Schulz, 2012; Manganelli et al., 2012; Blaskó et al., 2019). During the period in which values are formed, major public events may leave a deep impression on youth and can, in turn, change their thinking and sense of worth.[4] Therefore, the experience of major public events during this stage of life may lead these young people to actively change their behavior.[5] With the highly developed social media and internet, personal social networks have greatly expanded. Peer behaviors and attitudes affect individual political participation (Tufekci and Wilson, 2012; Reuter and Szakonyi, 2015; Larson et al., 2019; Enikolopov et al., 2020; Manacorda and Tesei, 2020; González, 2020).[6] As a result, social media accelerates the spread of protests (Gaby and Caren, 2012; Park et al., 2015; Acemoglu et al., 2018).[7] Therefore, highly developed internet and social network together accelerate the triggering of awareness of related knowledge among the cohort. As the influence of the OC movement on participants may be the largest in the past 30 years, it left a deep impression on youth and may change their behavior. One of the major decisions for youth is the choice of fields to study after the triggering of related knowledge of OC movement. To understand this change in educational behavior, let us focus on the cohort aged 18 to 19 years. Most of the youths aged 18 and 19 years are in the first or second year of their university education, and thus, such a cohort in the 2016 census may have made their decisions on fields of study after the OC movement in 2014. Compared with 2011, Fig. 2 shows that some fields were more favored in 2016 among youth aged 18 and 19 years, such as Humanities, Social and Behavioral Sciences, Life Sciences, Health, and Law. However, some other fields were less favored, especially those related to business such as Accountancy and Studies in Secretarial Skills, Business Administration and Financial Management, and Computing.[8]

In the financial center, Hong Kong, learning business-related knowledge always has a high expected return. However, exposure to the OC movement triggered the youth to think about some issues that are not closely related to business. First, the organizers claimed that the basis for launching the OC movement is "civil disobedience",[9] which led to a large number of issues about legitimacy and rationality. This proposition triggered the learning and understanding of knowledge related to citizens and laws among those who experienced the event. Second, the conflict in the event resulted in serious casualties. In some scenes, first aid was needed, and the participants also learned how to protect their personal safety. This experience triggered people's attention to health and life sciences knowledge. Third, after Hong Kong's return to China in 1997, personnel exchanges between mainland China and Hong Kong have become increasingly frequent, which has also caused conflicts in culture, language and behavioral habits between these two groups. For example, Mandarin and simplified Chinese have become symbols of the culture and politics of the Chinese mainland, which has been rejected by those with a strong local identity who only use Cantonese and traditional Chinese (Lai, 2001, 2011; Cheung and Sung, 2020; Liu and Zhong, 2020; Zheng and Zhou, 2021). Due to the general support of the mainland Chinese for the government in the OC movement, the conflict between the mainland Chinese and Hong Kong natives erupted in the event (Luo and Zhai, 2017). These cultural and political conflicts also aroused people's reflection on the relationship between diversity and social integration, civilization and conflict, etiquette and social care, etc. All the humanities, sociology, and political knowledge mentioned above cannot be obtained in learning in business-, science-, and engineering- related majors. Thus, the instant expansion of vision made young people not only consider the major choice from the perspective of cost–benefit analysis in a traditional business society but also from the perspective of considering a new utility function of career life. In such a new utility function, some new elements, such as the overall development of individuals and their contributions to society, became important factors. Fig. 3 shows the mechanism in which the political movement triggered people's awareness of related knowledge.

Table 1 classifies the fields into different categories according to our basic assumption. Accountancy and Studies in Secretarial Skills, Business Administration and Financial Management, and Computing are defined as business-related fields. Humanities, Social and Behavioral Sciences, Life Sciences, Health, and Law are defined as OC-related fields.[10] Other disciplines involved in the database

[4] Summarizing earlier studies on aging and attitude change in social psychology, Krosnick and Alwin (1989) claimed that the socializing influences individuals experience when they are young have a profound impact on their thinking throughout their lives. In addition, individuals are eminently flexible and responsive to social circumstances when they are young, but as they age, their flexibility decreases gradually. Recent studies have expanded the research on adolescent characteristics, such as Vecchio et al. (2007), Flanagan and Stout (2010), and Ma et al. (2022).

[5] For some empirical supports, please refer to the attitude of young during presidential election campaign (Krosnick and Alwin, 1989), the effect of experience in "impressionable years" on preference (Giuliano and Spilimbergo, 2014), the impact of exposure to Cultural Revolution (1966–1976) in China during adolescence (Bai and Wu, 2020; Cheng et al., 2023), and the effect of exposure to Chinese land reform (1978–1985) before turning 18 (Chen et al., 2023).

[6] The evidences include the effects of social media on the protests in Egypt in 2011 (Tufekci and Wilson, 2012, 2011) Russian parliamentary elections (Reuter and Szakonyi, 2015; Enikolopov et al., 2020), 2015 Charlie Hebdo protest in Paris (Larson et al., 2019), the spillovers of the coverage of mobile phone signal in Africa between 1998 and 2012 (Manacorda and Tesei, 2020), and student network in the 2011 student movement in Chile (González, 2020).

[7] Please refer to Gaby and Caren (2012), Park et al. (2015), Acemoglu et al. (2018) for the studies on the effects of Facebook, Twitter and Youtube in political movements.

[8] As supplementary quantitative support for Fig. 2, Fig. A.1 in the Appendix depicts the coefficients indicating the change in majors from 2011 to 2016.

[9] The OC movement was generally regarded as a large-scale show of "civil disobedience", see *South China Morning Post* [https://www.scmp.com/topics/occupy-central].

[10] "OC" refers to OC movement.

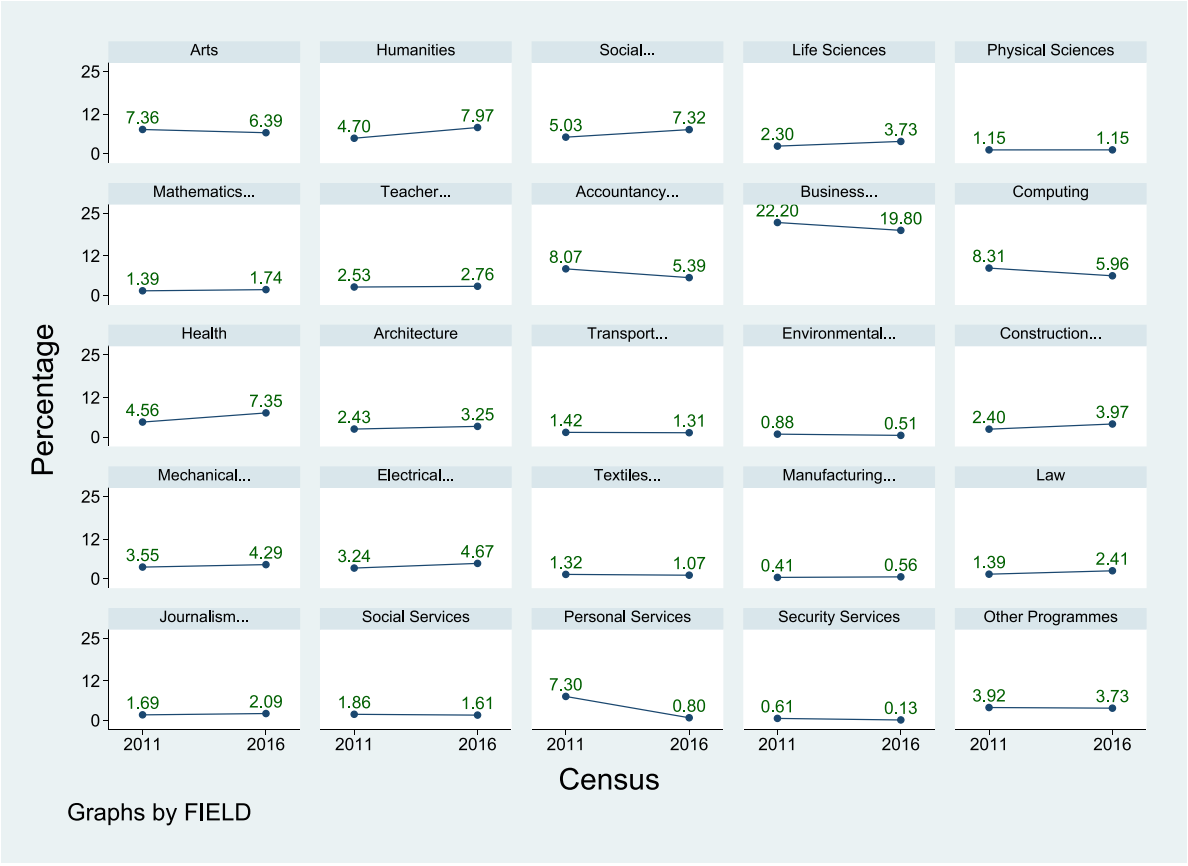


Fig. 2. Change of highest field of education attended.
Note: Data are collected from the Hong Kong Population Census (2016 and 2011). Only observations aged 18 and 19 years are included. For the titles of the sub graph, please refer to the footnote to Fig. 1.

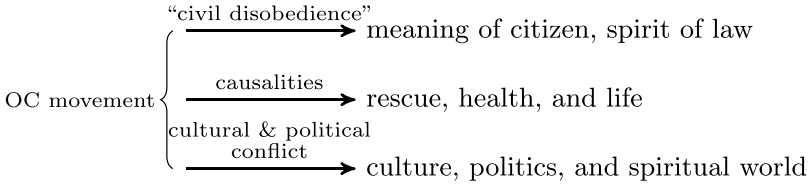


Fig. 3. OC movement and related knowledge.

are classified as "others." In the following quantitative analysis, we will prove whether the OC movement reduced the learning willingness of business-related fields and improved that of OC-related fields.

3. Data and method

3.1. Hong Kong population census

The data used in this study were obtained from the Hong Kong 2016 and 2011 Population Census 5% Sample Data Set by the Census and Statistics Department of Hong Kong. The 2016 Population By census was conducted over a 34-day period from 30 June to 2 August 2016. The 2011 Population Census was conducted over a 34-day period from 30 June to 2 August 2011. It was a sample enquiry on a broad range of demographic and socio-economic characteristics of the population. Approximately one-tenth of all quarters in Hong Kong were sampled, and all households therein were included in the enquiry.

The Population Census was a simple enumeration of nine-tenths of households to provide basic information regarding household members together with a detailed investigation of the remaining one-tenth on a broad range of demographic and socio-economic characteristics of household members. The sample data set used in this study was taken from the detailed enquiry of one-tenth of the population. These censuses covered the Hong Kong Resident Population, which included Usual Residents (Hong Kong Permanent

Table 1
Changes in fields of study.

	Highest field of education attended
OC-related	Humanities, Social and Behavioral Sciences, Life Sciences, Health, Law
business-related	Accountancy and Studies in Secretarial Skills, Business Administration and Financial Management, Computing
Others	Arts, Physical Sciences, Mathematics and Statistics, Teacher Training and Education Science, Architecture, Transport and Logistics Services, Environmental Protection, Construction, civil and Structural Engineering, Mechanical and Marine Engineering, Production and Industrial Engineering, Chemical Engineering, Biotechnology, Electrical and Electronic Engineering, Textiles and Clothing Technology, Manufacturing and Processing, Journalism and Information, Social Services, Personal Services, Security Services, Other Program

Note: The name of highest field of education attended is defined by the Hong Kong Population Census.

Residents who have been staying in Hong Kong for at least three months during the six months before or for at least three months during the six months after a reference date, regardless of whether they were in Hong Kong on the reference date and Hong Kong Non-permanent Residents who were in Hong Kong on the reference date) and Mobile Residents (Hong Kong Permanent Residents who have stayed in Hong Kong for at least one month, but less than three months during the previous six months, or for at least one month, but less than three months during the six months after the reference date, regardless of whether they were in Hong Kong on the reference date).[11]

3.2. Variables

Our dependent variable is a dummy indicating the category of an individual's fields of study. Using the census and age information, we can define the cohort that experienced OC movement before they decided to study in certain fields. We also control other factors that may influence the fields of individuals' study, including family background and individual demographic characteristics. Some indicators that measure the heterogeneity of the effect are also applied. The details of the definition of the main variables are as follows.

As the dependent variable, $Fields_{OC}$ is the indicator of the field choice of an individual. It is equal to 1 if an individual's field belongs to one of the following fields that are more favored in 2016: Humanities, Social and behavioral sciences, Life sciences, Health, Law; and 0 otherwise. In further discussion, we also use another dummy, $Fields_{Business}$, which equals to 1 for fields less favored in 2016, including Accountancy and studies in secretarial skills, Business administration and financial management, Computing, Personal services, and Security services. To identify the effect of the OC movement, I must define the cohort. Most of the youths aged 18 and 19 years are in the first or second year of their university education, and thus, such a cohort in the 2016 census may have made their decisions on fields of study after the OC movement in 2014. To identify the cohort effects, we used two dummy variables to define the cohort, $Cohort_{18-19}$ and $Census_{2016}$. $Cohort_{18-19}$ equals 1 for an individual aged 18 or 19 years, and 0 otherwise. $Census_{2016}$ equals 1 if the observation is collected from 2016 census, and 0 otherwise. In Section 3.4, I go further in detail on the definition of different cohorts. I also control for other factors in the regressions. To capture the influence of parents' field, I denote $Fields_{increase}^{Parent}$ as the field choice of an individual's parent. Similar to $Fields_{OC}$, it equals 1 if one of his/her parents' field belongs to one of the following fields more favored in 2016: Humanities, Social and Behavioral Sciences, Life Sciences, Health, and Law; it equals 0 for fields less favored in 2016, including Accountancy and Studies in Secretarial Skills, Business Administration and Financial Management, Computing, Personal Services, and Security Services. In heterogeneity analysis, I consider the effects of language, household income and gender. First, Cantonese, Mandarin, and English are the main languages used by Hong Kong people in daily life. $Language_{Bilingual}$ equals 1 if an individual declares that he/she speaks both Mandarin and English, and 0 otherwise.[12] $Language_{Mandarin}$ equals 1 if an individual declares that he/she speaks Mandarin but does not speak English, and 0 otherwise. $Language_{English}$ equals 1 if an individual declares that he/she speaks English but does not speak Mandarin, and 0 otherwise. Second, $Income_{45}$ is applied to indicate the level of household income. In the main analysis, $Income_{45}$ equals 1 if the monthly household income is greater than or equal to 45,000 Hong Kong dollars. For supplementary analysis, $Income_{40}$ and $Income_{50}$ are also applied in regressions. $Income_{40}$ equals to 1 if the monthly household income is greater than or equal to 40,000 Hong Kong dollars, and $Income_{50}$ equals 1 if the monthly household income is greater than or equal to 50,000 Hong Kong dollars. Finally, $Male$ equals 1 if an individual is male and 0 for female.

[11] For more information, please refer to the User Guide of Hong Kong 2016 and 2011 Population Census 5% Sample Data Set.

[12] The census discloses information on the usual language spoken at home and three to four other languages spoken by an individual. When an individual reports a language in the above questions, I define that he/she speaks the language.

Table 2
Descriptive statistics in main estimates.
Source: Hong Kong Population Census (2016 and 2011).

Variable	N	Mean	SD	N	Mean	SD	T-test
	Cohort = 1			Cohort = 0			
	2011 Census						
$Fields_{OC}$	2,075	0.34	0.47	4,457	0.40	0.49	−5.20***
$Fields_{OC}^{Parent}$	2,075	0.08	0.28	4,457	0.07	0.26	1.15
$Language_{Bilingual}$	2,075	0.64	0.48	4,457	0.69	0.46	−4.33***
$Language_{Mandarin}$	2,075	0.06	0.24	4,457	0.05	0.23	1.55
$Language_{English}$	2,075	0.15	0.36	4,457	0.15	0.36	−0.05
$Income_{45}$	2,075	0.21	0.41	4,457	0.22	0.41	−1.15
$Income_{50}$	2,075	0.25	0.43	4,457	0.27	0.44	−2.10**
$Income_{50}$	2,075	0.18	0.39	4,457	0.18	0.39	−0.12
Male	2,075	0.49	0.50	4,457	0.49	0.50	−0.16
	2016 Census						
$Fields_{OC}$	2,591	0.54	0.50	4,382	0.50	0.50	3.49***
$Fields_{OC}^{Parent}$	2,591	0.10	0.30	4,382	0.78	0.27	3.59***
$Language_{Bilingual}$	2,591	0.69	0.46	4,382	0.69	0.46	−0.03
$Language_{Mandarin}$	2,591	0.02	0.14	4,382	0.03	0.16	−1.73*
$Language_{English}$	2,591	0.25	0.43	4,382	0.20	0.40	4.57
$Income_{45}$	2,591	0.31	0.46	4,382	0.31	0.46	0.02
$Income_{40}$	2,591	0.37	0.48	4,382	0.38	0.48	−0.22
$Income_{50}$	2,591	0.27	0.45	4,382	0.27	0.44	0.57
Male	2,591	0.48	0.50	4,382	0.48	0.50	0.06

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

3.3. Descriptive statistics

In the main analysis, I only consider the observations with a field belonging to OC-related or business-related fields. That is, the field must belong to one of the following fields: Humanities, Social and Behavioral Sciences, Life Sciences, Health, Law, Secretarial Skills, Business Administration and Financial management, Computing, Personal Services, and Security Services. In the main identification, individuals aged 18, 19, 21, or 22 years are considered. In the 2016 census, the cohort aged 18 to 19 years was 16 to 17 years old in 2014, when the OC movement occurred, and thus, they are considered to have made the decision of the field choice after the political movement. Based on the same assumption, the cohort aged 21 and 22 years is considered to have made the decision before the political movement. For the individuals aged 20 years in the 2016 census, they were 18 years old in 2014. Thus, it is difficult to judge whether they made decision in the fields of study before or after the OC movement. Therefore, I do not consider the observations aged 20 years, and apply the cohort aged 21 to 22 years as the control group. In Hong Kong, the craft level (including apprenticeship) is the lowest level that offers different fields to study. Thus, only observations with the highest level attended equal to or higher than the craft level (including apprenticeship) are included.[13] In this manner, those who only completed secondary education without continuing to choose certain fields to study for further education were excluded.

A total of 13,505 observations are applied, including 2,591 and 4,382 observations from cohorts aged 18 to 19 and 21 to 22 years in the 2016 census, respectively, and 2,075 and 4,457 observations from cohorts aged 18 to 19 and 21 to 22 years in 2011 census, respectively. The samples cover 15 ethnicities, 20 nationalities, 28 districts, 10 industries of parents, and 10 occupations of parents. For the 2016 census, the value of the T test of $Fields_{OC}$ is 3.49, which is significant at the 1% level, showing that the mean of $Fields_{OC}$ for the cohort aged 18 to 19 years after the OC movement is significantly larger than that for the cohort aged 21 to 22 years. However, the opposite is observed for census 2011, the year before the political shock. This is exactly the basic phenomenon we want to investigate further in this paper. In terms of the main control variable, $Fields_{OC}^{Parent}$, the T test is insignificant for the 2011 census and satisfies the parallel trend assumption.[14] See Table 2 for detailed descriptive statistics.

3.4. The cohort

I use the cross term, $Cohort_{18-19} \times Census_{2016}$, to measure the influence of OC movement on fields of study. $Cohort_{18-19}$ equals 1 for individuals aged 18 or 19 years, and $Census_{2016}$ equals 1 if the observation is collected from the 2016 census. Therefore, the

[13] According to the census, the data on fields of study are unavailable for individuals with the highest level attended lower than the craft level (including apprenticeship). Fig. A.2 in the Appendix reports the proportion of samples with and without information on the highest field of education completed among different samples by age.

[14] However, the T test is significant for the 2016 census. To eliminate the worries about the possible imbalance between treatment and control groups, I conduct a triple differences approach to test the effect of parents' field on the basic estimates. The results are reported in Table A.1 of Appendix. Fortunately, the key coefficients, $Cohort_{18-19} \times Census_{2016} \times Fields_{OC}^{Parent}$, are insignificant, showing that parents' field has no effect on the estimates.

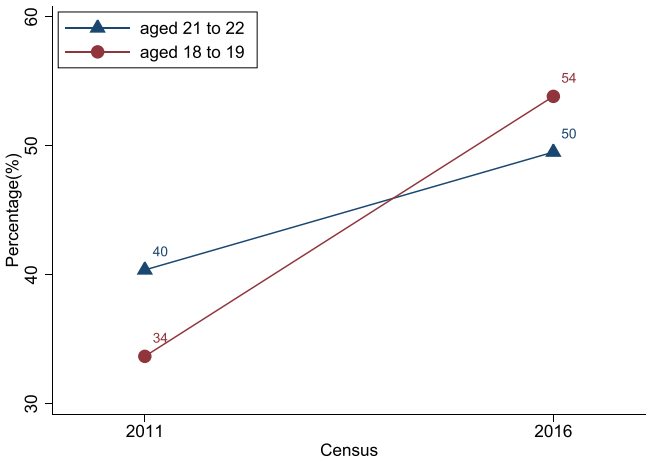


Fig. 4. Percentage for choosing OC-related fields among cohorts.
Note: The data are collected from the Hong Kong Population Census. Only observations with the highest level attended equals to or higher than the craft level (including apprenticeship) are included.

value of 1 for the cross term $Cohort_{18-19} \times Census_{2016}$ indicates the cohort that experienced the OC movement before the decision to choose a field to study. Fig. 4 depicts the change in percentages of individuals who chose OC-related fields between the two cohorts. In 2011, the year before the OC movement, the percentage of choosing OC-related fields was higher for the cohort aged 21 to 22 years. For these two cohorts, the percentages increased from the 2011 to 2016 census, but that of the cohort aged 18 to 19 years increased more significantly (from 34% to 54%) than that of the cohort aged 21 to 22 years (40% to 50%). Whether in the 2011 or 2016 census, the cohort aged 21 to 22 years made their decision on fields of study without experiencing the OC movement. In the 2011 census, the cohort aged 18 to 19 years made their decisions without experiencing the political movement, but in the 2016 census, this cohort made their decisions after experiencing the OC movement. Intuitively, after the political movement in 2014, more youths preferred to study one of the following OC-related fields: Humanities, Social and Behavioral Sciences, Life Sciences, Health, or Law. We will investigate the effects empirically later.

3.5. Strategy of identification

3.5.1. Main identification

Cohort difference in differences is applied to estimate the effects of the political movement on fields of study and identify the growth effect and reduction effect. The main strategy of the identification is shown below:

$$\begin{aligned} Fields_{OC,imnt} = \alpha &+ \beta Cohort_{18-19,n} \times Census_{2016,t} \\ &+ \gamma Z_i + \tau_m^{Age} + \eta Census_{2016,t} + \epsilon_{imnt}, \end{aligned} \tag{1}$$

where the dummy, $Fields_{OC,imnt}$, is an indicator of studying in OC-related fields of individual i aged m years in cohort n and census t. $Census_{2016,t}$ equals 1 if t is 2016 and 0 otherwise. Z_i is a set of personal characteristics of individual i, including $Fields_{OC}^{Parent}$ and those captured by ethnicity, nationality, parents' industry, and parents' occupation fixed effects. τ_m^{Age} refers to age fixed effects. ϵ_{imnt} is the error term. From a social-spatial perspective, people's attitudinal impact of the OC movement varied according to their spatial proximity to the protest sites (Xu and Guo, 2023). Thus, standard errors clustered at the district level are applied. As we mentioned before, we focus on the coefficient of $Cohort_{18-19,n} \times Census_{2016,t}$. A significantly positive β suggests the effect of OC movement on promoting the study of OC-related fields.

3.5.2. Heterogeneity analysis

In heterogeneity analysis, we focus on the difference in the effect among individuals with heterogeneity in language speaking, household income, and gender. A triple differences (DDD) model is applied as follows:

$$\begin{aligned} Fields_{OC,imnlt} = \alpha &+ \beta_1 Cohort_{18-19,n} \times Census_{2016,t} \times Heterogeneity_l \\ &+ \beta_2 Cohort_{18-19,n} \times Census_{2016,t} \\ &+ \beta_3 Census_{2016,t} \times Heterogeneity_l \\ &+ \beta_4 Cohort_{18-19,n} \times Heterogeneity_l \\ &+ \gamma Z_i + \tau_m^{Age} + \eta_1 Heterogeneity_l + \eta_2 Census_{2016,t} + \epsilon_{imnlt}, \end{aligned} \tag{2}$$

where $Heterogeneity_l$ denotes an indicator of heterogeneity classified in category l. Specifically, $Heterogeneity$ includes $Language_{Bilingual}$, $Income_{45}$, and $Male$ to measure the heterogeneity in language speaking (with bilingual skills), household income

Table 3
Main results.

	$Fields_{OC}$		
	(1) OLS	(2) OLS	(3) OLS
$Cohort_{18-19} \times Census_{2016}$	0.109***	0.122***	0.123***
	(0.018)	(0.019)	(0.019)
$Fields_{OC}^{Parent}$		√	√
Ethnic fixed effects		√	√
Nationality fixed effects		√	√
Father's industry fixed effects		√	√
Mother's industry fixed effects		√	√
Father's occupation fixed effects		√	√
Mother's occupation fixed effects		√	√
District fixed effects		√	√
Age fixed effects	√	√	√
$Census_{2016}$	√	√	√
Adjusted R^2	0.019	0.034	0.033
Observations	13,505	10,132	9,976
Sample	All	All	Subsample

Note: Standard errors clustered at the district level are reported in parentheses. The subsample excludes observations with special educational institutions related to nursing and health.
*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

(whether the monthly household income is greater than or equal to 45,000 Hong Kong dollars),[15] and gender (whether the individual is male), respectively. For supplementary analysis in the Appendix, $Language_{Mandarin}$ (with Mandarin skill or not), $Language_{English}$ (with English skill or not), $Income_{40}$ (whether the monthly household income is greater than or equal to 40,000 Hong Kong dollars), and $Income_{50}$ (whether the monthly household income is greater than or equal to 50,000 Hong Kong dollars) are also applied.

4. Empirical results

4.1. Main results

The result of the cohort DID is reported in Table 3. Column (1) does not control any variables except for the necessary terms of cohort DID strategy, age fixed effects, and $Census_{2016}$. Column (2) controls for personal and family background factors, and district fixed effects. Column (3) uses only the subsample that excludes the observations with special educational institutions related to nursing and health. In such institutions, all the majors are related to health, which belongs to OC-related fields. The cross term, $Cohort_{18-19} \times Census_{2016}$, in all columns is positively significant at the 1% level. According to the results, we can conclude that OC movement had an influence on the choice of fields to study among young people. We can observe that such fields, including Humanities, Social and Behavioral Sciences, Life Sciences, Health, and Law, are most related to the legitimacy of political movements and their effects on human behavior and society.[16] The results imply that political movements trigger the public's awareness of related knowledge.

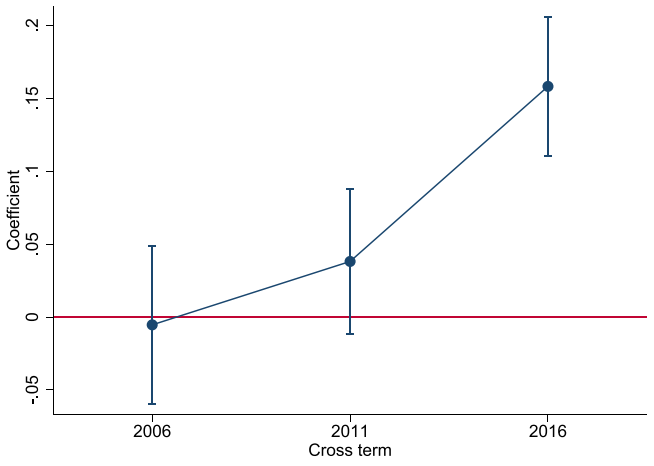
4.2. Parallel trend test

An important prerequisite of the strategy of the DID approach is the parallel-trend assumption. In this part, we further conduct a quantitative test of the parallel-trend assumption in detail. The regression models are modified on the main identification Eq. (1), in which the terms $Cohort_{18-19} \times Census_{2006}$ and $Cohort_{18-19} \times Census_{2011}$ are included and data are extended to Hong Kong Population Census 2001 and 2006. See Eq. (3):

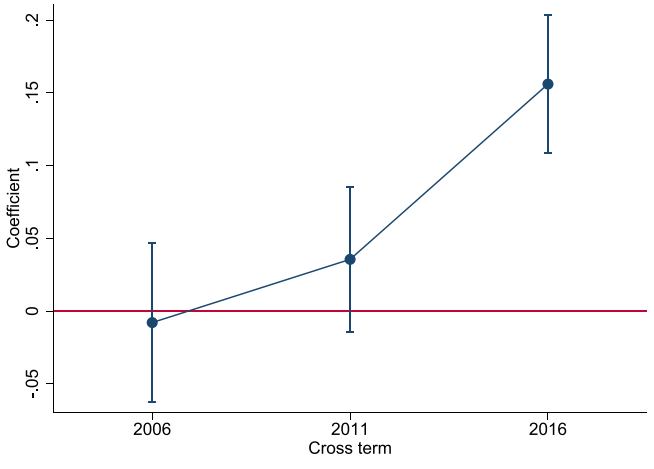
$$Fields_{OC,imnt} = \alpha + \sum_t \beta_t Cohort_{18-19,n} \times Census_{y,t} + \gamma Z_i + \tau_m^{Age} + \tau_t^{Census} + \epsilon_{imnt}, \quad (3)$$

[15] According to the median monthly wage of employees (May–June 2014), released by the Census and Statistics Department, Hong Kong government (Please visit the website [https://www.censtatd.gov.hk]), the median monthly wages for cohorts aged 15 to 24, 35 to 44, and 45 to 54 years old are 10,700, 17,200, and 15,000 Hong Kong dollars, respectively. Thus, for a family with parents aged 35 to 44 years old and a child aged 15 to 24 years old, the median monthly household income is 45,100 Hong Kong dollars. For a family with parents aged 45 to 54 years old and a child aged 15 to 24 years old, the median monthly household income is 40,700 Hong Kong dollars. Therefore, the threshold value of 45,000 Hong Kong dollars roughly measures the level of this median income.

[16] For technical complementation, the Appendix provides a decomposition of the effects by comparing with other fields of study. See A.3 for the basic theory and the results.



(a) All samples



(b) Subsamples

Fig. 5. Parallel trend test.
Note: The coefficients of $Cohort_{18-19} \times Census_{2006}$, $Cohort_{18-19} \times Census_{2011}$, and $Cohort_{18-19} \times Census_{2016}$ are denoted by "2006," "2011," and "2016" in the horizontal axis, respectively. The 95% confidence intervals are reported as well.

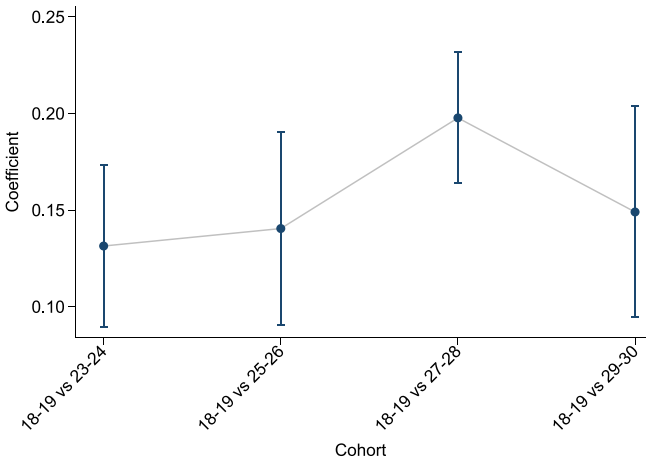
where t takes the value of 2006, 2011, and 2016, and τ_t^{Census} denotes the census fixed effects. Fig. 5 depicts the coefficients of $Cohort_{18-19} \times Census_{2006}$, $Cohort_{18-19} \times Census_{2011}$, and $Cohort_{18-19} \times Census_{2016}$, and the 95% confidence intervals. Consistent with columns (2) and (3) in Table 3, (a) uses the full sample and (b) uses the subsample. Evidently, the coefficients of $Cohort_{18-19} \times Census_{2016}$ are positively significant, while the coefficients of $Cohort_{18-19} \times Census_{2006}$ and $Cohort_{18-19} \times Census_{2011}$ are insignificant. In essence, the cohorts aged 18 to 19 and 21 to 22 years share a parallel trend before the political shock, which satisfies the assumption of the DID approach.

4.3. Robustness checks

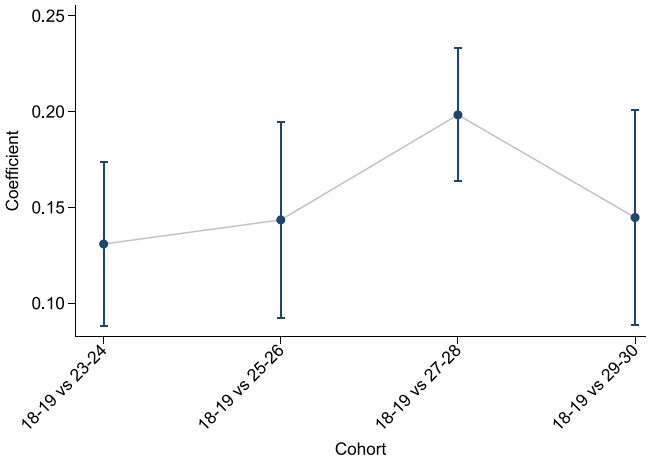
To confirm the robustness of our basic conclusion in the previous part, we carry out several robustness checks, including Probit estimates, excluding new immigrants, and placebo tests.

4.3.1. Using other control groups

I change the control group to be the cohorts aged 23 to 24, 25 to 26, 27 to 28, and 29 to 30 years, and re-estimate the effects by Eq. (1). Fig. 6 depicts the results of the regressions, consistent with columns (2) and (3) in Eq. (1). Evidently, all the coefficients of $Cohort_{18-19} \times Census_{2016}$ are positively significant. Thus, the robustness of our basic conclusion has been improved.



(a) All samples



(b) Subsamples

Fig. 6. Robustness check: using other control groups.
The coefficients of $Cohort_{18-19} \times Census_{2016}$ and the 95% confidence intervals are depicted. The label "#1-#2 vs #3-#4" on the horizontal axis denotes the estimate using the cohort aged #1 to #2 years as the treatment group and the cohort aged #3 to #4 years as the control group.

4.3.2. Probit estimates

As the dependent variable, $Fields_{OC}$, is a dummy variable with values of 1 and 0, we carry out discrete regressions for supplementary analysis. Similar to the basic structure shown in Table 3, Table 4 reports the results of Probit estimates. Moreover, as all the coefficients of $Cohort_{18-19} \times Census_{2016}$ remain positively significant at the 1% level, the robustness of our basic conclusion has been confirmed.

4.3.3. Excluding new immigrants

New immigrants may have a different understanding of Hong Kong's political environment, and thus, we exclude such samples. Specifically, we define new immigrants as the observations that an individual was born out of Hong Kong and the duration of residence in Hong Kong is less than 5 years. The results are reported in Table 5. All coefficients of $Cohort_{18-19} \times Census_{2016}$ remain positively significant at the 1% level, and thus, the robustness of our basic conclusion has been confirmed.

4.3.4. Placebo test

To rule out the contingency of our results brought by unobserved factors, we carry out a placebo test by considering alternative cohorts. We regress the model modified from Eq. (1). Specifically, we replace $Cohort_{18-19}$ with false cohorts indicated by $Cohort_{false}$, including cohorts aged 23 to 24 and 25 to 26 years, and re-estimate. We also compare the difference in effects between cohorts aged 23 to 24 and 25 to 26 years. In the same way as column (3) in Table 3, we control for personal and family background factors and district fixed effects and use only subsample that excludes the observations with special educational institutions related to nursing and health. The results are depicted in Fig. 7. The labels on the horizontal axis indicate the treatment and control groups used in

Table 4
Robustness check: Probit estimates.

	$Fields_{OC}$		
	(1) Probit	(2) Probit	(3) Probit
$Cohort_{18-19} \times Census_{2016}$	0.282***	0.326***	0.327***
	(0.046)	(0.049)	(0.049)
$Fields_{OC}^{Parent}$		√	√
Ethnic fixed effects		√	√
Nationality fixed effects		√	√
Father's industry fixed effects		√	√
Mother's industry fixed effects		√	√
Father's occupation fixed effects		√	√
Mother's occupation fixed effects		√	√
District fixed effects		√	√
Age fixed effects	√	√	√
$Census_{2016}$	√	√	√
Pseudo R^2	0.014	0.031	0.030
Observations	13,505	10,126	9,970
Sample	All	All	Subsample

Note: Standard errors clustered at the district level are reported in parentheses. The subsample excludes observations with special educational institutions related to nursing and health.
*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Table 5
Robustness check: excluding new immigrants.

	$Fields_{OC}$		
	(1) OLS	(2) OLS	(3) OLS
$Cohort_{18-19} \times Census_{2016}$	0.108***	0.122***	0.123***
	(0.017)	(0.018)	(0.018)
$Fields_{OC}^{Parent}$		√	√
Ethnic fixed effects		√	√
Nationality fixed effects		√	√
Father's industry fixed effects		√	√
Mother's industry fixed effects		√	√
Father's occupation fixed effects		√	√
Mother's occupation fixed effects		√	√
District fixed effects		√	√
Age fixed effects	√	√	√
$Census_{2016}$	√	√	√
Adjusted R^2	0.020	0.033	0.032
Observations	13,163	10,039	9,886
Sample	All	All	Subsample

Note: Standard errors clustered at the district level are reported in parentheses. The subsample excludes observations with special educational institutions related to nursing and health.
*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

the regression. For example, "23-24 vs 21-22" denotes that the treatment and control groups are the cohorts aged 23 to 24 and 21 to 22 years, respectively. Evidently, the coefficients of $Cohort_{false} \times Census_{2016}$ are all insignificant. Therefore, the contingency of our results is ruled out to some extent.

To further strengthen the credibility of the conclusion, an alternative placebo test is conducted by considering the randomly generated treatment group, following La Ferrara et al. (2012). Eq. (1) is regressed again 500 times, in which each has a random treatment group generated. Similarly, all regressions control for personal and family background factors and district fixed effects, and use only the subsample that excludes observations with special educational institutions related to nursing and health. Figs. 8 depicts the density of the estimates. Evidently, all the estimates are lower than the true value in Table 3, 0.109 to 0.123. Overall, the results of placebo tests increase the reliability of previous findings.

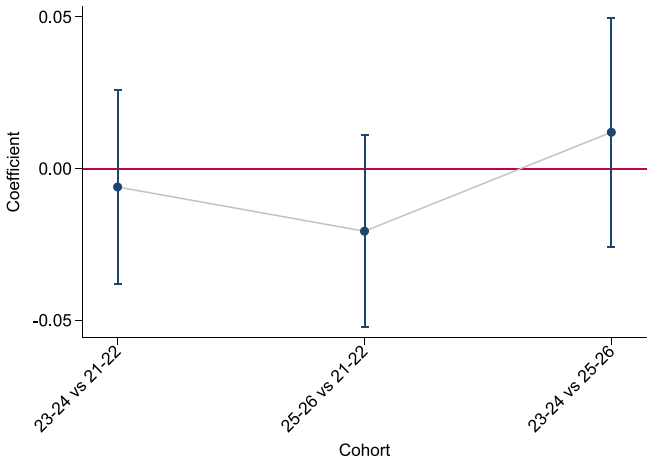


Fig. 7. Placebo test: false cohorts.
Note: The coefficients of $Cohort_{false} \times Census_{2016}$ and the 95% confidence intervals are depicted. The label "#1-#2 vs #3-#4" on the horizontal axis denotes the estimate using the cohort aged #1 to #2 years as the treatment group and cohort aged #3 to #4 years as the control group.

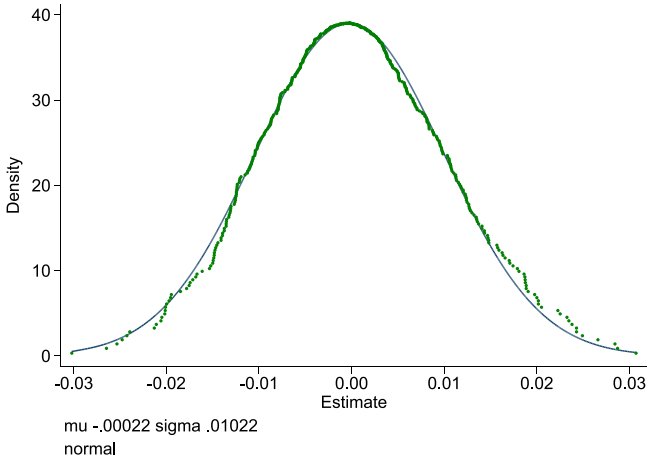


Fig. 8. Placebo test: random treatment group.

4.4. Other robustness discussion

4.4.1. Reallocation of educational resources

The reallocation of educational resources may affect the quota of enrollment, thereby limiting the field of choice of young people. Whether the decline in student enrollment in business-related programs of is due to the reduction in educational resources in these fields needs to be explored. The University Grants Committee of Hong Kong (UGC) calculates the student-teacher ratio by department every academic year.[17] The ratio of the Business & Management department is available in the statistics. As the teacher is the most important human capital in educational institutions, other educational resources may be adjusted by the number of teachers available. Therefore, the ratio of the Business & Management department can be used to analyze the change in educational resources in business-related fields. Fig. 9 depicts the student-teacher ratio from academic year 2011–2012 to 2016–2017. Supposing that the decline in the number of teachers leads to a decline in educational resources and the enrollment quotas, then the decline in the

[17] The universities funded by UGC include eight major universities in Hong Kong, including the City University of Hong Kong, Hong Kong Baptist University, Lingnan University, The Education University of Hong Kong, The Hong Kong Polytechnic University, Hong Kong University of Science and Technology, and Hong Kong University. The student-teacher ratio refers to the ratio of the number of students enrolled in UGC-funded programmes to the number of academic staff of academic departments with salaries wholly funded by General Funds. The numbers of student and departmental academic staff used in the compilation of the ratios are in full-time equivalents. In addition to Business & Management, UGC also calculates the student-teacher ratio in other departments such as Medicine, Dentistry & Health, Sciences, Engineering & Technology, Social Sciences, Arts & Humanities, and Education. For details, please refer to the website of The University Grants Committee [https://cdcf.ugc.edu.hk/cdcf/statSiteIndex.action].

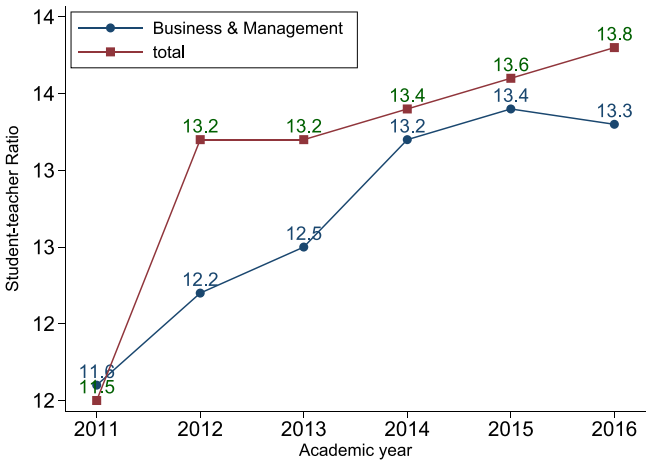


Fig. 9. Student-teacher ratio.
Note: Data are collected from the Student-teacher Ratio of UGC-funded Programmes by University and Departmental Cost Centre Group, University Grants Committee of Hong Kong (https://cdcf.ugc.edu.hk/cdcf/statSiteIndex.action). "2011" on the horizontal axis denotes the academic year 2011–2012, and the others are similar.

number of business and management students may keep the trend of the student-teacher ratio stable or at least keep it from falling too sharply. However, Fig. 9 shows a slowdown in the student-teacher ratio after the academic years 2014–2015 compared with the trend before 2014, which is unlikely to be caused by a decline in teachers. Compared with the stable total student-teacher ratio, we believe that fewer students choose to study business-related fields with an unchanged trend of educational resources allocated in these fields.

4.4.2. Employment opportunities

Studies show that the fields of study are affected by industry development, such as Han and Winters (2020). A boom in a certain industry may encourage young people to enter this industry and thus encourage them to choose a related major. Thus, the question becomes, did the young people in Hong Kong choose their fields according to the economic environment such as employment? The Census and Statistics Department of Hong Kong calculates unemployment by industry. Fig. 10 depicts the total unemployment rate and that of financing, insurance, real estate, professional and business services.[18] From 2012 to 2014, that is, before the OC movement, the unemployment rates in financing, insurance, real estate, professional and business services remained stable (at 1.5% and 0.6%) compared with the average rates in all industries. Thus, young people were unlikely to avoid choosing business-related majors because of the rise of unemployment in business-related industries.

4.4.3. Industry income

Expected income and wages observed are regarded as important determinants in the choice of college major (Montmarquette et al., 2002; Freeman and Hirsch, 2008; Long et al., 2015; Ruder and Noy, 2017). In this part, I plan to test whether the wage observed had an impact on the study in corresponding fields. The data are collected from the real and nominal indices (quarterly) of payroll per person engaged by industry section (the first quarter of 1999 = 100), released by the Census and Statistics Department, government of Hong Kong government.[19] Eleven industries are selected in the data: Manufacturing; Sewerage, waste management and remediation activities; Import/export and wholesale trades; Retail trade; Transportation, storage, postal and courier services; Accommodation and food service activities; Information and communications; Financial and insurance activities; Real estate activities; Professional and business services; Social and personal services. Among all these industries, Financial and insurance activities, Real estate activities, or Professional and business services are supposed to be the business-related industries. For a preliminary understanding, I average the quarterly indices as the annual one. Fig. 11 depicts the indices of supposed business-related industries and those of all selected industries. Through a preliminary observation, we cannot find a significant decline in wages in business-related industries, implying that the change in fields of study may not be due to the expected return or wage observed for working in these industries.

For a quantitative analysis, Table 6 reports the results of the regression of quarterly indices of wages by the DID approach, where $Industry_{Business}$ equals 1 if the industry belongs to Financial and insurance activities, Real estate activities, or Professional and business services. $Post_{2014q4}$ equals to 1 after the fourth quarter of 2014. The cross term $Industry_{Business} \times Post_{2014q4}$ is

[18] In addition to financing, insurance, real estate, professional and business services, the unemployment rate is also calculated in other industries such as manufacturing, construction, import/export trade and wholesale, retail, accommodation and food services, transportation, storage, postal and courier services, information and communications, public administration, social and personal services, and other industries.

[19] Please visit the website [https://www.censtatd.gov.hk].

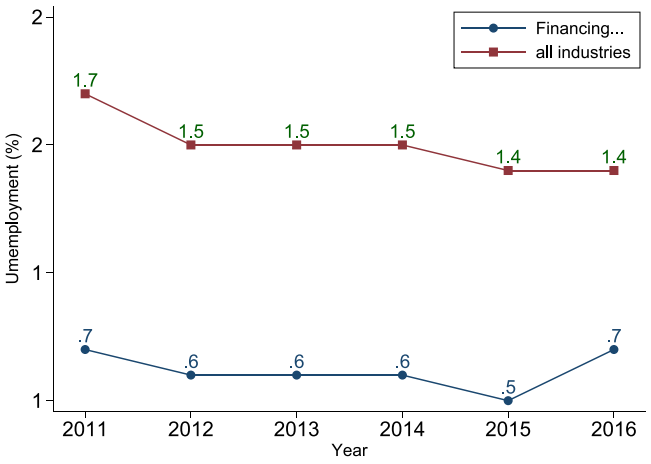
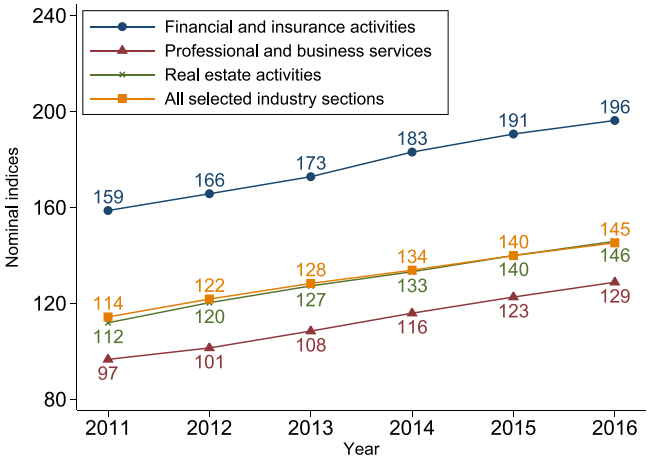
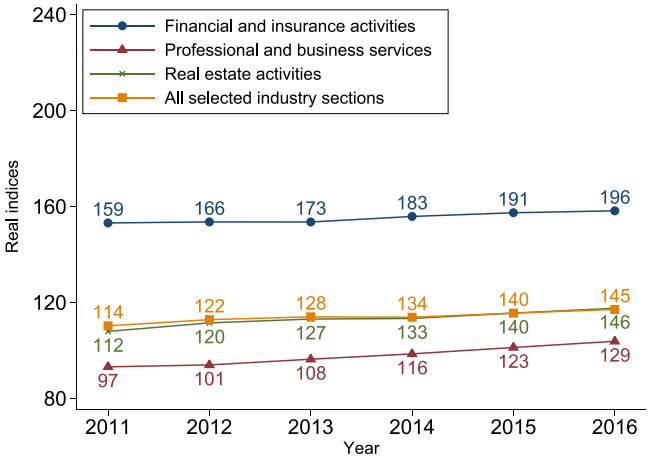


Fig. 10. Unemployment rate.
Note: Data are collected from Census and Statistics Department, Hong Kong (https://www.censtatd.gov.hk/en/). "Financing..." in legend denotes "Financing, insurance, real estate, professional and business services".



(a) Nominal indices



(b) Real indices

Fig. 11. Indices of wage.

Table 6
Indices of Wage.

	Nominal indices		Real indices	
	(1)	(2)	(3)	(4)
$Industry_{Business} \times Post_{2014q4}$	4.212**	4.212*	1.938	1.938
	(1.861)	(1.921)	(1.496)	(1.545)
$Industry_{Business}$	√		√	
$Post_{2014}$	√		√	
Industry fixed effects		√		√
Year fixed effects		√		√
Quarter fixed effects		√		√
Adjusted R^2	0.169	0.916	0.078	0.905
Observations	264	264	264	264

Note: The dependent variables are quarterly indices of payroll per person engaged by industry section (the 1st quarter of 1999 = 100), nominal and real. Standard errors clustered at the industry level are reported in parentheses.
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

positively significant or insignificant in the regressions of nominal and real indices of wage, showing that the income of business-related industries did not decline after 2014. Therefore, the change in fields of study may not be due to the expected return of business-related industries.

4.5. Heterogeneity analysis

Heterogeneity analysis helps identify the mechanisms by which the political movement affects fields of study. Through the DDD strategy, we carry out three heterogeneity analyses on areas of interest, including language speaking, household income and gender.

4.5.1. Language

In fields of study or major choice, current studies usually found evidence of heterogeneity in race or ethnicity (Liu et al., 2019). I used language as an agent variable to carry out heterogeneity analysis in this part. In addition to human capital, language is also a symbol of culture and identity (Bisin et al., 2008; Falck et al., 2012; Desmet et al., 2017). Hong Kong is a unique biliteracy and trilingualism region in the world. Mandarin, Cantonese, and English are related to the PRC national, local, and colonial or international identity, respectively.[20] Occupy central movement is a political movement. The participant's cultural and political identity affected the extent to which he was affected by the movement. In Eq. (2), we use $Language_{Bilingual}$ as the indicator of $Heterogeneity$ to measure the heterogeneity in individuals with Mandarin-English bilingual skills.

The coefficient $Cohort_{18-19} \times Census_{2016} \times Language_{Bilingual}$ in Table 7 remains positively significant in all columns. This scenario shows that individuals with bilingual skills are more likely to be affected by the OC movement. We believe that bilingual skills represent a high ability in study, and thus, those with bilingual skills pay more attention to the role of major learning in career development. This result is consistent with that of Arcidiacono et al. (2012), who showed that students' abilities in different majors are an important determinant of major choice. Next, we also report the heterogeneity in individuals with Mandarin skill (by $Language_{Mandarin}$ as the indicator of $Heterogeneity$) and English skill ($Language_{Mandarin}$ as the indicator of $Heterogeneity$) in Table 8. The coefficients of $Cohort_{18-19} \times Census_{2016} \times Language_{Mandarin}$ are negatively significant, but those of $Cohort_{18-19} \times Census_{2016} \times Language_{English}$ are insignificant. The difference in the key DDD coefficient indicates that the effect is less significant on individuals who speak Mandarin. Given that Mandarin speaking indicates national identity, we believe that these people were unlikely to support the OC movement, which opposes the political reforms approved by the central government. Therefore, the political shock did not have the same effect on the values of individuals with national identity, compared with those with local or international identity.

4.5.2. Household income

Household income is a core indicator of family background, and thus may affect the extent to which the youths participated in or were influenced by the political movement. We try different values of household income as the threshold to distinguish high and low income and find that approximately 45,000 Hong Kong dollars is a significant threshold. In Eq. (2), we use $Income_{45}$ as the indicator of $Heterogeneity$ to measure the heterogeneity across cohorts with different family backgrounds.[21] The percentage of the observations with a household income equal to or greater than 45,000 Hong Kong dollars is 25.69% of the total 13,339 observations. $Income_{45}$ equals 1 if household income equal to or greater than 45,000 Hong Kong dollars. The coefficients of $Cohort_{18-19} \times Census_{2016} \times Income_{45}$ are all negatively significant in Table 9. The results show that individuals with lower family income are more likely to be influenced by OC movement on the decision of field choice. In addition, for a robustness check, we change the indicator of $Income_{45}$ to $Income_{40}$ and $Income_{50}$, which indicate whether the monthly household income is equal to or greater than 40,000 and 50,000 Hong Kong dollars, respectively. The results are reported in Tables A.3 and A.4 of Appendix. The

[20] From some surveys (Lai, 2001, 2011), "Hongkongers" demonstrate the strongest integrative inclination toward Cantonese and English, whereas that toward Mandarin is comparatively weak, suggesting that Hong Kong maintains a stronger local identity than the PRC national identity.

[21] In the 2016 census, for the answer of monthly household income, 45,000 denotes a range from 44,950 to 45,050 Hong Kong dollars. In the 2011 census, 45,000 for monthly domestic household income denotes exactly 45,000 Hong Kong dollars. Although there are differences between these two statistical metrics, the indicator $Income_{45}$ can still distinguish different populations by income. Fig. A.4 depicts the distribution of household income.

Table 7
Heterogeneity: bilingual.

	$Fields_{OC}$		
	(1) OLS	(2) OLS	(3) OLS
$Cohort_{18-19} \times Census_{2016} \times Language_{Bilingual}$	0.102**	0.087*	0.091*
	(0.043)	(0.046)	(0.044)
$Cohort_{18-19} \times Census_{2016}$	0.039	0.062*	0.060
	(0.034)	(0.036)	(0.036)
$Census_{2016} \times Language_{Bilingual}$	−0.095***	−0.091***	−0.092***
	(0.019)	(0.025)	(0.025)
$Cohort_{18-19} \times Language_{Bilingual}$	−0.042	−0.041	−0.042
	(0.036)	(0.038)	(0.037)
$Fields_{OC}^{Parent}$		√	√
Ethnic fixed effects		√	√
Nationality fixed effects		√	√
Father's industry fixed effects		√	√
Mother's industry fixed effects		√	√
Father's occupation fixed effects		√	√
Mother's occupation fixed effects		√	√
District fixed effects		√	√
Age fixed effects	√	√	√
$Language_{Bilingual}$	√	√	√
$Census_{2016}$	√	√	√
Adjusted R^2	0.020	0.034	0.033
Observations	13,505	10,132	9,976
Sample	All	All	Subsample

Note: Standard errors clustered at the district level are reported in parentheses. The subsample excludes observations with special educational institutions related to nursing and health.
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 8
Heterogeneity: Mandarin and English.

	$Fields_{OC}$					
	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) OLS
$Cohort_{18-19} \times Census_{2016} \times Language_{Mandarin}$	−0.313*	−0.320**	−0.311*			
	(0.156)	(0.150)	(0.159)			
$Census_{2016} \times Language_{Mandarin}$	0.200***	0.233***	0.244***			
	(0.064)	(0.067)	(0.068)			
$Cohort_{18-19} \times Language_{Mandarin}$	0.038	0.076	0.071			
	(0.058)	(0.072)	(0.073)			
$Cohort_{18-19} \times Census_{2016} \times Language_{English}$				−0.079	−0.032	−0.035
				(0.058)	(0.053)	(0.050)
$Census_{2016} \times Language_{English}$				0.033	0.021	0.020
				(0.028)	(0.028)	(0.029)
$Cohort_{18-19} \times Language_{English}$				0.073	0.040	0.040
				(0.047)	(0.043)	(0.042)
$Cohort_{18-19} \times Census_{2016}$	0.117***	0.131***	0.131***	0.119***	0.124***	0.125***
	(0.018)	(0.018)	(0.018)	(0.020)	(0.022)	(0.021)
$Fields_{OC}^{Parent}$		√	√		√	√
Ethnic fixed effects		√	√		√	√
Nationality fixed effects		√	√		√	√
Father's industry fixed effects		√	√		√	√
Mother's industry fixed effects		√	√		√	√
Father's occupation fixed effects		√	√		√	√
Mother's occupation fixed effects		√	√		√	√
District fixed effects		√	√		√	√
Age fixed effects	√	√	√	√	√	√
$Language_{Mandarin}$	√	√	√			
$Language_{English}$				√	√	√
$Census_{2016}$	√	√	√	√	√	√
Adjusted R^2	0.020	0.034	0.034	0.021	0.035	0.034
Observations	13,505	10,132	9,976	13,505	10,132	9,976
Sample	All	All	Subsample	All	All	Subsample

Note: Standard errors clustered at the district level are reported in parentheses. The subsample excludes observations with special educational institutions related to nursing and health.
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 9
Heterogeneity: household income.

	$Fields_{OC}$		
	(1) OLS	(2) OLS	(3) OLS
$Cohort_{18-19} \times Census_{2016} \times Income_{45}$	−0.077**	−0.108**	−0.116***
	(0.037)	(0.039)	(0.041)
$Cohort_{18-19} \times Census_{2016}$	0.126***	0.149***	0.152***
	(0.025)	(0.029)	(0.030)
$Census_{2016} \times Income_{45}$	−0.026	−0.020	−0.017
	(0.028)	(0.030)	(0.030)
$Cohort_{18-19} \times Income_{45}$	0.065**	0.088***	0.093***
	(0.027)	(0.024)	(0.023)
$Fields_{OC}^{Parent}$		√	√
Ethnic fixed effects		√	√
Nationality fixed effects		√	√
Father's industry fixed effects		√	√
Mother's industry fixed effects		√	√
Father's occupation fixed effects		√	√
Mother's occupation fixed effects		√	√
District fixed effects		√	√
Age fixed effects	√	√	√
$Income_{45}$	√	√	√
$Census_{2016}$	√	√	√
Adjusted R^2	0.021	0.034	0.033
Observations	13,339	10,122	9,966
Sample	All	All	Subsample

Note: Standard errors clustered at the district level are reported in parentheses. The subsample excludes observations with special educational institutions related to nursing and health.
*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

results are almost similar. We believe that children from low-income families are more eager to succeed in their career development, and so they may pay more attention to the learning of knowledge in different fields. Thus, the experience of the political movement was more likely to influence their choice in fields of study.

4.5.3. Gender

Current studies focus on gender differences in fields of study or major choice (Montmarquette et al., 2002; Zafar, 2013; Astorne-Figari and Speer, 2019; Liu et al., 2019; Bordón et al., 2020; Kugler et al., 2021). Similar to the analysis in the previous part, we investigate heterogeneity in gender by applying the DDD approach based on Eq. (2), with $Male$ as the indicator of $Heterogeneity$. The coefficients of $Cohort_{18-19} \times Census_{2016} \times Male$ are all significantly negative, indicating that females are more likely to be influenced by the movement (see Table 10). I presume that in Eastern society, women do not have much bargaining power in the labor market, and thus, they are more sensitive to decisions on fields of study.

5. Conclusion

Major political movements affect peoples' behavior, including educational decisions. The OC movement in 2014 was the largest political movement in Hong Kong in the 30 years before that. The movement triggered the young Hong Kong people to think about the legitimacy of the movement, culture, politics, and the effects on human behavior and society. Based on the Hong Kong Population Census 2011 and 2016, this paper finds that more young people who experienced the OC movement chose to study humanities, social and behavioral sciences, life sciences, health, and law after completing secondary education. The conclusion is robust after the author uses different control groups, applies Probit estimates, excludes new immigrants, carries out placebo tests, and considers the influence of educational resources reallocation and industrial development. Through heterogeneity analysis, this paper finds that the effects are mainly from people with bilingual competence (Mandarin and English), but an inverse effect exists among Mandarin-speaking people. The effect is also stronger among people with low household income and females. Several reasons can explain the results. First, people with bilingual skills have higher human capital and are more capable of changing majors. Second, being able to speak Mandarin indicates individuals' national identity, and these people were unlikely to support the OC movement and less influenced by the political shock. Third, young people from low-income families are more dissatisfied with the political situation, more eager to succeed in career development, and thus are most affected by the movement. Finally, in Eastern society, women do not have much bargaining power in the labor market, so they are more sensitive to decisions on fields of study.

Table 10
Heterogeneity: gender.

	$Fields_{OC}$		
	(1) OLS	(2) OLS	(3) OLS
$Cohort_{18-19} \times Census_{2016} \times Male$	−0.124**	−0.125**	−0.143**
	(0.046)	(0.054)	(0.055)
$Cohort_{18-19} \times Census_{2016}$	0.169***	0.182***	0.192***
	(0.028)	(0.031)	(0.031)
$Census_{2016} \times Male$	0.046	0.066*	0.073*
	(0.034)	(0.037)	(0.038)
$Cohort_{18-19} \times Male$	0.077**	0.065**	0.080**
	(0.028)	(0.030)	(0.033)
$Fields_{OC}^{Parent}$		√	√
Ethnic fixed effects		√	√
Nationality fixed effects		√	√
Father's industry fixed effects		√	√
Mother's industry fixed effects		√	√
Father's occupation fixed effects		√	√
Mother's occupation fixed effects		√	√
District fixed effects		√	√
Age fixed effects	√	√	√
Male	√	√	√
$Census_{2016}$	√	√	√
Adjusted R^2	0.021	0.035	0.034
Observations	13,505	10,132	9,976
Sample	All	All	Subsample

Note: Standard errors clustered at the district level are reported in parentheses. The subsample excludes observations with special educational institutions related to nursing and health.
*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

This work has several contributions. First, the literature claims that the shock of major events reduces the resources available to individuals and thus changes the educational outcome later. Different from these studies, this paper focuses on active change in later behavior rather than passive change due to the limited resource that individuals can use. Second, current studies show that the decision on fields of study may be influenced by the expectation of income, the development of the labor market, and business cycles in industries. For supplementary evidence, this study shows that political movements may affect individuals' decisions on fields of study by triggering public awareness of related knowledge. From the perspective of behavioral economics, they may not follow the traditional method of cost–benefit analysis in major choices because the utility function changes rapidly after the political shock. The heterogeneity analyses show that the effect of political movement on educational decisions varies by human capital, identity, and family background. The results imply that the growth background of young people affects their attitude toward political movements, resulting in different sensitivities to political shocks. This issue has not been investigated in the current literature. The findings also shed light on other nations' contexts. The main participants in such large-scale protest events are usually young people. Therefore, when it is extended to other countries, any public political event dominated by young people would have a deep imprint on their life experience, thus affecting their behavior. In addition to major choices in study, it may also include career choices, education for the next generation, etc.

Declaration of competing interest

I declare that I do not have any commercial or associative interest that represents a conflict of interest in connection with the work submitted.

Data availability

The author does not have permission to share data.

Appendix

A.1. Change in highest field of education attended

See Fig. A.1.

A.2. Information on the highest field of education completed

See Fig. A.2.

A.3. Test of the effect of parents' field

See Table A.1.

A.4. Decomposition

The growth effect is defined as the effect that more students choose certain fields to study compared with the trend before the political shock. By contrast, the reduction effect is defined as fewer students choosing to study certain fields compared with the trend before the political shock. If a growth effect in OC-related fields and reduction effects in business-related fields are present, β_1 in Eq. (1) measures $GE_{OC} + RE_{business}$, as shown in (a) of Fig. A.3, where GE_{OC} denotes the growth effect in OC-related fields, and $GE_{business}$ denotes a reduction effect in business-related fields. However, if only growth effects in both groups of fields exist, β_1 measures $GE_{OC} - RE_{business}$, shown in (b) of Fig. A.3.

For quantitative analysis, we run the regressions Eq. (1) with samples choosing OC-related and other fields, and a modified one where the dependent variable $Fields_{OC,imnt}$ is replaced by $Fields_{Business,imnt}$, which indicates whether the business-related fields are chosen by individual i aged m years in cohort n and census t. Table A.2 reports the results. Columns (1) to (3) regress $Fields_{OC}$ with samples choosing OC-related and other fields,[22] and columns (4) to (6) regress $Fields_{\text{Business}}$ with samples choosing business-related and other fields. Thus, the coefficients of $Cohort_{18-19} \times Census_{2016}$ indicate the change in fields of OC-related and business-related majors, compared with other fields. The coefficients in columns (1) to (3) are positively significant at the 1% level. Although the coefficients in columns (4) to (6) are insignificant, they are negatively in columns (5) and (6). We conclude that a strong growth effect in studying OC-related fields and a weak reduction effect in studying business-related fields are found after the event.

A.5. Distribution of household income

See Fig. A.4.

A.6. Other heterogeneity analysis on household income

See Tables A.3 and A.4.

[22] Please refer to Table 1 for other fields of study.

Table A.1
Test of the effect of parents' field.

	$\text{Fields}_{\text{OC}}$		
	(1) OLS	(2) OLS	(3) OLS
$\text{Cohort}_{18-19} \times \text{Census}_{2016} \times \text{Fields}_{\text{OC}}^{\text{Parent}}$	−0.008	−0.039	−0.029
	(0.055)	(0.062)	(0.066)
$\text{Cohort}_{18-19} \times \text{Census}_{2016}$	0.107***	0.126***	0.126***
	(0.020)	(0.022)	(0.022)
$\text{Census}_{2016} \times \text{Fields}_{\text{OC}}^{\text{Parent}}$	−0.017	−0.006	−0.002
	(0.042)	(0.039)	(0.041)
$\text{Cohort}_{18-19} \times \text{Fields}_{\text{OC}}^{\text{Parent}}$	0.036	0.050	0.040
	(0.051)	(0.057)	(0.059)
Ethnic fixed effects		√	√
Nationality fixed effects		√	√
Father's industry fixed effects		√	√
Mother's industry fixed effects		√	√
Father's occupation fixed effects		√	√
Mother's occupation fixed effects		√	√
District fixed effects		√	√
Age fixed effects	√	√	√
$\text{Fields}_{\text{OC}}^{\text{Parent}}$	√	√	√
Census_{2016}	√	√	√
Adjusted R^2	0.024	0.033	0.032
Observations	13505	10132	9976
Sample	All	All	Subsample

Note: Standard errors clustered at the district level are reported in parentheses. The subsample excludes observations with special educational institutions related to nursing and health. Regressions are based on the Eq. (2), where $Heterogeneity$ is $Fields_{\text{OC}}^{\text{Parent}}$. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A.2
Growth effect and reduction effect.

	$Fields_{OC}$			$Fields_{Business}$		
	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) OLS
$Cohort_{18-19} \times Census_{2016}$	0.118***	0.133***	0.132***	0.004	−0.003	−0.005
	(0.027)	(0.027)	(0.026)	(0.021)	(0.024)	(0.025)
$Fields_{OC}^{Parent}$		√	√			
$Fields_{Business}^{Parent}$					√	√
Ethnic fixed effects		√	√		√	√
Nationality fixed effects		√	√		√	√
Father's industry fixed effects		√	√		√	√
Mother's industry fixed effects		√	√		√	√
Father's occupation fixed effects		√	√		√	√
Mother's occupation fixed effects		√	√		√	√
District fixed effects		√	√		√	√
Age fixed effects	√	√	√	√	√	√
$Census_{2016}$	√	√	√	√	√	√
Adjusted R^2	0.004	0.013	0.012	0.010	0.012	0.013
Observations	11,840	8,851	8,690	13,217	9,935	9,800
Sample	All	All	Subsample	All	All	Subsample
	"OC-related" & "others"			"business-related" & "others"		

Note: Standard errors clustered at the district level are reported in parentheses. The subsample excludes the observations with special educational institutions related to nursing and health.
*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Table A.3
Heterogeneity: household income ($Income_{40}$).

	$Fields_{OC}$		
	(1) OLS	(2) OLS	(3) OLS
$Cohort_{18-19} \times Census_{2016} \times Income_{40}$	−0.057	−0.096**	−0.103**
	(0.035)	(0.040)	(0.040)
$Cohort_{18-19} \times Census_{2016}$	0.124***	0.151***	0.154***
	(0.025)	(0.030)	(0.031)
$Census_{2016} \times Income_{40}$	−0.020	−0.008	−0.005
	(0.030)	(0.035)	(0.035)
$Cohort_{18-19} \times Income_{40}$	0.052**	0.079***	0.084***
	(0.021)	(0.017)	(0.018)
$Fields_{OC}^{Parent}$		√	√
Ethnic fixed effects		√	√
Nationality fixed effects		√	√
Father's industry fixed effects		√	√
Mother's industry fixed effects		√	√
Father's occupation fixed effects		√	√
Mother's occupation fixed effects		√	√
District fixed effects		√	√
Age fixed effects	√	√	√
$Income_{40}$	√	√	√
$Census_{2016}$	√	√	√
Adjusted R^2	0.021	0.034	0.033
Observations	13,339	10,122	9,966
Sample	All	All	Subsample

Note: $Income_{40}$ equals to 1 if monthly household income is greater than or equal to 40,000 Hong Kong dollars. Standard errors clustered at the district level are reported in parentheses. The subsample excludes observations with special educational institutions related to nursing and health.
*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Table A.4
Heterogeneity: household income ($Income_{50}$).

	$Fields_{OC}$		
	(1) OLS	(2) OLS	(3) OLS
$Cohort_{18-19} \times Census_{2016} \times Income_{50}$	−0.087*	−0.127**	−0.134**
	(0.049)	(0.051)	(0.052)
$Cohort_{18-19} \times Census_{2016}$	0.127***	0.150***	0.152***
	(0.024)	(0.028)	(0.028)
$Census_{2016} \times Income_{50}$	−0.030	−0.026	−0.024
	(0.031)	(0.031)	(0.030)
$Cohort_{18-19} \times Income_{50}$	0.072*	0.101**	0.104***
	(0.037)	(0.036)	(0.035)
$Fields_{OC}^{Parent}$		√	√
Ethnic fixed effects		√	√
Nationality fixed effects		√	√
Father's industry fixed effects		√	√
Mother's industry fixed effects		√	√
Father's occupation fixed effects		√	√
Mother's occupation fixed effects		√	√
District fixed effects		√	√
Age fixed effects	√	√	√
$Income_{50}$	√	√	√
$Census_{2016}$	√	√	√
Adjusted R^2	0.021	0.035	0.034
Observations	13,339	10,122	9,966
Sample	All	All	Subsample

Note: $Income_{50}$ equals to 1 if monthly household income is greater than or equal to 50,000 Hong Kong dollars. Standard errors clustered at the district level are reported in parentheses. The subsample excludes observations with special educational institutions related to nursing and health.
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

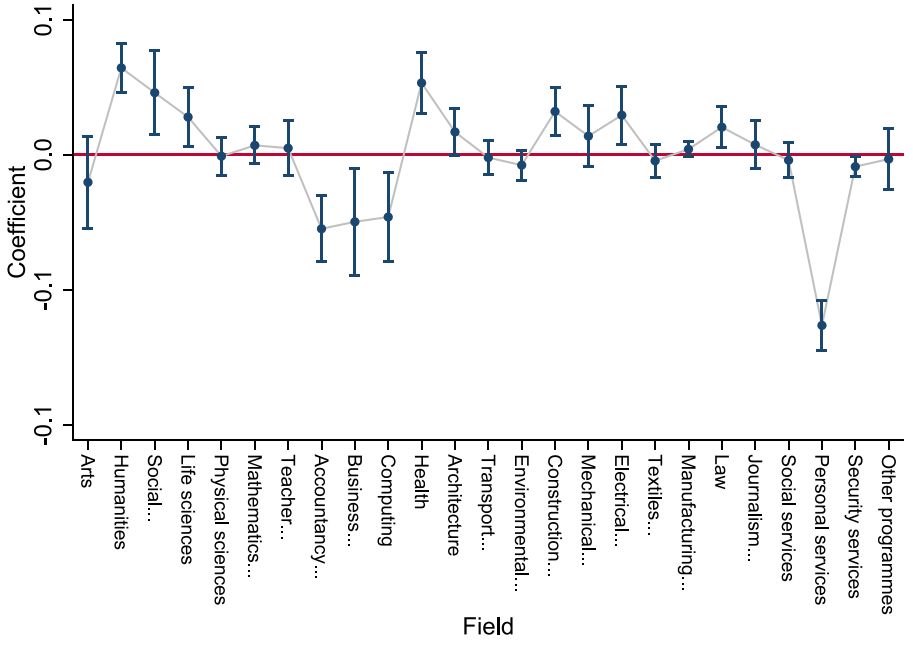
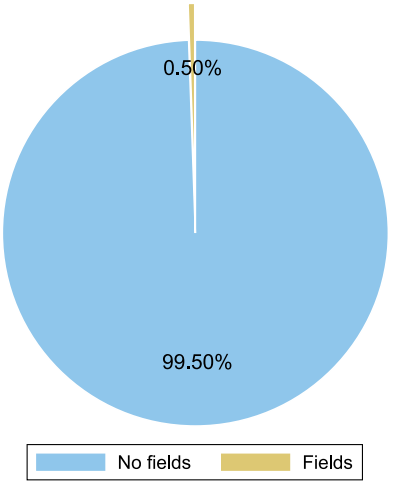
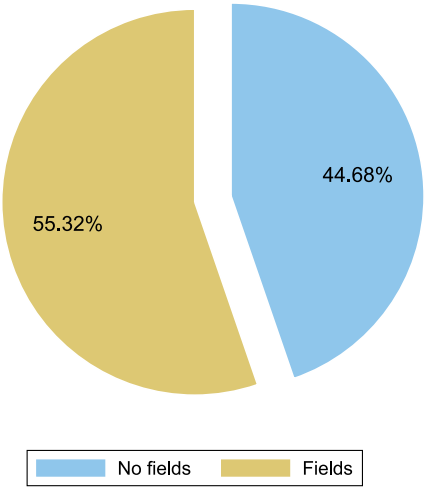


Fig. A.1. Change in highest field of education attended.
Note: $Field_{imt} = \alpha + \beta Census_{2016,t} + \tau_m^{Age} + \epsilon_{imt}$ is run. $Field_{itm}$ denotes the highest field of education attended by individual i aged m in census t. $Field_{itm}$ includes 25 fields listed in the horizontal axis according to the census. $Census_{2016,t}$ equals 1 if t is 2016 and 0 for 2011. τ_m^{Age} refers to the age fixed effects. ϵ_{imnt} is an error term. Robust errors are applied. Standard errors are clustered at the district level. The coefficients of *Census* and the 95% confidence intervals are reported on the horizontal axis. Only observations of cohorts aged 18 to 19 years in the 2016 and 2011 censuses are included in the regression. For the fields on the horizontal axis, please refer to the footnote to Fig. 1.



(a) age < 18



(b) $18 \leq$ age ≤ 19 & $21 \leq$ age ≤ 22

Fig. A.2. Observations with information on the highest field of education completed.
Note: "Fields" refer to observations with information on fields of study; "No fields" refer to observations without information on fields of study or with a field such as "Basic Programs".

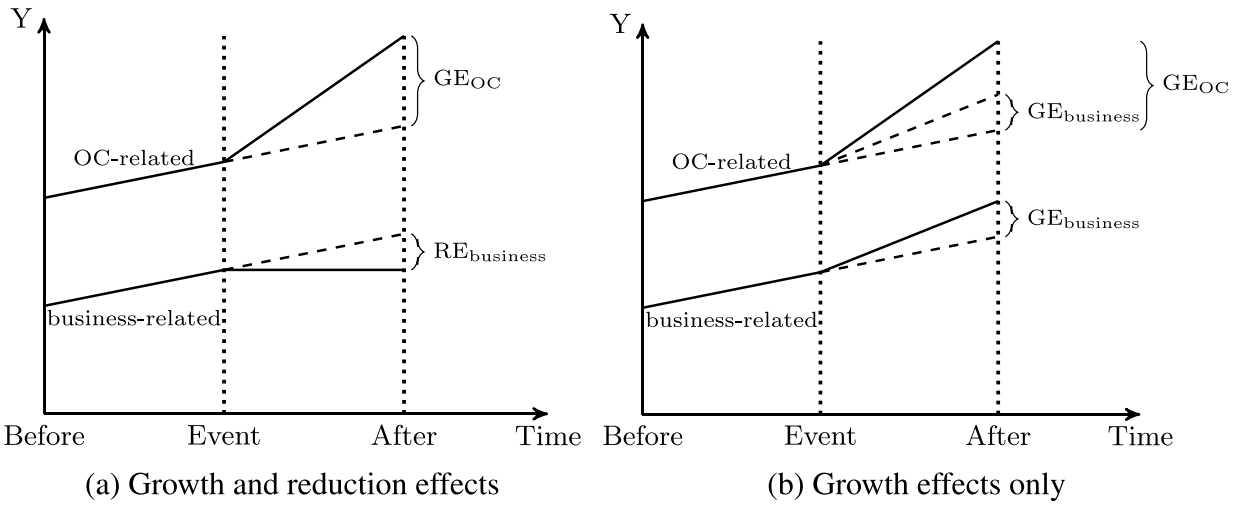


Fig. A.3. Decomposition. Note: "GE" and "RE" denote the growth effect and reduction effect, respectively.

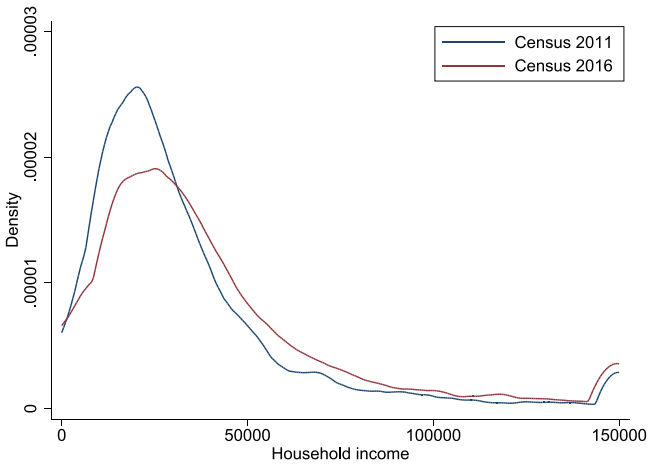


Fig. A.4. Distribution of household income.
Note: Observations with missing information on household income are excluded. A total 13,339 observations are included.

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