Service Jobs and Education: Evidence from Tourism Shocks in Italy*

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Abstract

This study explores how the rise in service jobs impacts educational outcomes in Italy. We identify exogenous variation in the demand for service jobs using shocks to the tourism industry caused by terrorist attacks abroad. We find that an exogenous increase in tourist arrivals decreases college enrollment and completion rates. The decline in enrollment is primarily caused by fewer students entering the humanities and social sciences. Both men and women affected by the shock respond by reducing enrollment and completion. While men tend to respond temporarily to take advantage of the higher labor demand, women, who are more prevalent in the tourism sector, experience a permanent impact. Investigating the mechanism we find a positive effect on employment in the tourism sector and on total employment. This result follows from an increase in labor force participation rather than a decline in unemployment.

Keywords: Service occupations, tourism, human capital, college enrollment, field of study.

JEL Codes: I25, J24, L83, Z32

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1 Introduction

This paper investigates the effect of the increase in demand for service jobs on educational outcomes in Italy between 2010 and 2019. We exploit exogenous variation in the touristic attractiveness of Italy based on the occurrence of terrorist attacks abroad. Our identification strategy captures short-term increases in the demand for service jobs to accommodate the higher number of incoming tourists. We use these positive labor market shocks to analyze the implications for college enrollment and completion of young individuals.

A priori, the effect of an increase in the demand for service jobs on college education is ambiguous. On one hand, the increase in the demand for labor increases the opportunity costs of delaying the labor market entry to pursue a college education. On the other hand, it alleviates financial constraints for low-income households who could use these seasonal, and often part-time, jobs to finance college tuition and living expenses. This therefore constitutes an empirical question that we address in this paper.

Determining the direction of the effect is relevant for understanding the possible implications for inequality, social disparities, and economic growth (Krueger and Lindahl, 2001; Vandenbussche et al., 2006; Gennaioli et al., 2013). Indeed, a college education is a pathway to economic mobility and higher earnings (Cohen and Addison, 1998; Card, 1999, 2001). If changes in the labor market structure adversely affect educational outcomes, and thus limit the supply of high-skill workers, the expansion of service jobs could exacerbate long-term inequality.

Service jobs include roles that are primarily focused on assisting or caring for others (Autor and Dorn, 2013). These positions include such diverse occupations as restaurant and hotel workers, recreation workers, hairdressers, beauticians, gardeners, janitors, security guards, home health aides, and child care workers. Notably, a significant proportion of these occupations are related either directly or indirectly to the rapidly increasing number of tourists. Indeed, tourism-related jobs include for the most part low-skill jobs that do not require tertiary education.[1]

The tourism sector is, therefore, a good proxy to estimate the effect of the expansion of low-skill service jobs on educational outcomes, as it is gaining increasing relevance in developing countries and industrialized economies. International tourism expenses are estimated to have increased from nearly 0.6 to more than 1.8 trillion of real 2019 US dollars between 2000 and 2019 (World Tourism Organization, 2022).

This paper focuses on the impact of tourism on college education in Italy, a country that combines a sizeable tourism industry – which contributes to about five percent of the national GDP, 13 percent considering also the indirect contribution (Petrella, 2018) – with an affordable high-quality education system and therefore constitutes the ideal case study for our analysis.[2]

To identify exogenous variation in tourism, we construct a measure of exposure that exploits security shocks that affect alternative destinations and reduce their attractiveness relative to Italy (Besley et al., 2020; Deem, 2020). We follow González and Surovtseva (2020) in exploiting the variation generated by terrorist attacks abroad and allocate displaced tourists from these countries to Italian provinces according to their previous distribution of tourist flows. The identifying assumption is that our measure of exposure is uncorrelated with Italian provinces' labor markets except through its effect on tourism attractiveness.

To measure tourism flows, we combine data on international tourism inflows to Italian provinces from the Bank of Italy with information on tourism flows across countries from the World Tourism Organization (UNWTO). We integrate detailed data on terrorist attacks from the Global Terrorism Database (GTD). To build measures on education outcomes, we use information on enrollment, completion, and field of study of students from the *Ministero dell'Istruzione e della Ricera* (MIUR). We complement these data with socio-demographic and labor market measures of provinces from the Italian Labor

[1] About 93 percent of tourism employees in Italy have not completed tertiary education (see Figure A1 in the Appendix).

[2] Despite that, Italy has one of the lowest rates of college-educated individuals in Europe, and it has been experiencing a significant brain drain over the last decades (Hellemans, 2001; Cattaneo et al., 2019). Only 26 percent of the population aged between 25 and 64 years has a tertiary education, compared to the OECD average of 44 percent (OECD, 2022).

Force Survey (LFS).

The empirical results show that an exogenous increase in tourism inflows decreases local college enrollment and college completion in the following year. We use an IV approach to quantify this result and find that a province with the average annual growth rate in tourism inflows in our sample period (4.44 percent) experiences a decrease of about seven percent in the yearly growth of college enrollment and completion.

The adverse effect of tourism shocks on enrollment is driven by a decrease in students choosing humanities and social sciences. We find no effect on STEM fields and applied sciences. A plausible explanation for this finding is that STEM fields often require specific skills and early preparation, making them less sensitive to short-term shocks. These individuals are more likely to pursue higher-skilled jobs after college and are less exposed to the increase in the demand for low-skill jobs.

Enrollment and completion rates fall for both men and women in the year following the shock. The size of the effect is similar. For men, however, there is a distinct trend: a notable drop in enrollment and completion followed by a subsequent rebound two years after exposure for college completion and three years after exposure for college enrollment. This suggests that men may be delaying college education to take advantage of better job opportunities. In contrast, for women, the impact appears to have a lasting effect on their educational outcomes, with no comparable rebound in later periods.

We then examine the mechanism through which tourism shocks might affect college enrollment and completion. We confirm that terrorist attacks abroad increase temporarily employment in the tourism sector (González and Surovtseva, 2020). This effect spills over to other sectors, increasing total employment in the province, an effect that persists for some years due to an increase in employment in other sectors such as manufacturing. This result is driven by an increase in labor force participation rather than a decrease in unemployment, suggesting that young people are more likely to enter the labor force right after high school, postpone college enrollment, or not enroll in college at all. In terms of gender, both men and women experience an increase in employment due to increased activity in tourism-related sectors, although women benefit from it for a longer period.

This paper contributes to several streams of the literature. In particular, we contribute to the understanding of the determinants of human capital adjustments. Most of the previous literature analyzed the educational response following economic downturns, including business cycle fluctuations (Betts and McFarland, 1995; Blom et al., 2021), firm-specific shocks (Foote and Grosz, 2020; Weinstein, 2020), international trade (Greenland and Lopresti, 2016), globalization (Hickman and Olney, 2011), and automation (Dauth et al., 2021; Di Giacomo and Lerch, 2023). Only a few papers study the effect of positive labor market shocks. Specifically, Atkin (2016) finds an increase in high school dropouts in Mexico following the expansion of manufacturing industries that require predominantly low-skilled labor. While Cascio and Narayan (2015) examine the impact of fracking on high school dropout rates among male teenagers, finding an increase in comparison to females who are less affected by the shock.

We contribute to this literature in several ways. First, to our knowledge, this paper is the first to identify the consequences of a positive shift in service occupations and the tourism industry on human capital accumulation. Second, we concentrate on college education, exploring both the intensive and extensive adjustment margins in a country where the monetary cost of education is not a primary concern (low opportunity cost). Lastly, we offer insights into the dynamics of adjustment and the timing of individual responses to temporary labor market shocks rather than a long-run change.

More closely aligned with our research, Schanzenbach et al. (2023) examine the impact of minimum wages increases on college enrollment in the US. Since most service occupations pay the minimum wages (Bureau of Labor Statistics, 2022), this leads to a change in the opportunity cost of education due to increased wages in these occupations. Their results on enrollment align with our findings, suggesting that an increase in the minimum wage diminishes college enrollment. Contrary to our results, their study finds only minimal impacts on degree attainment.

We also contribute to the growing number of studies that analyze the impact of tourism on the labor market in developing (Faber and Gaubert, 2019) and developed countries (González and Surovtseva, 2020; Favero and Malisan, 2021; Nocito et al., 2023), and complement this literature by investigating how tourism shocks influence individuals' investments in human capital.

The remainder of the paper is organized as follows. Section 2 describes the data. Section 3 presents the empirical strategy. Section 4 reports the results of the empirical analysis, and Section 5 concludes.

2 Data and descriptives

This section describes the main data sources along with a set of summary statistics.

2.1 Education

We obtain administrative data on the universe of students and graduates of Italian colleges from the *Ministero dell'Istruzione e della Ricera* (MIUR) between 2010 and 2019. This data includes counts of first-year enrollees and graduates, providing information about students' province of residence. As Italian students rarely change their place of residence during their studies, the reported province of residence is a good proxy of their exposure to tourism shocks.

We build a measure of college enrollment using enrollment counts as a share of the resident population aged 18 to 30 years at the province level (N_{pt}^{18-30}):

$$s_{pt} = \frac{\sum_c S_{pct}}{N_{pt}^{18-30}}, \tag{1}$$

where S_{pct} is the number of first-year Bachelor students from province p who are enrolled in college c during academic year t (October to September).[3] We follow an analogous procedure to build college completion rates but use calendar years (January to December) instead of academic years.[4]

Academic year t starts in October of calendar year t and ends in September of calendar year $t + 1$. This implies that enrollment rates of academic year t are not influenced

[3] Note that college c may or may not be located in province p.

[4] Monthly or quarterly data are not available for college completions. These data limitations do not allow us to adjust counts from the calendar years provided to academic years.

by tourism shocks occurring between October and December of calendar year t unless they are anticipated. We address this potential issue by using an exogenous measure of tourism flows, which should be unpredictable. On the other hand, enrollment rates could be affected by tourism shocks that occurred between October and December of calendar year $t-1$. To address this issue, we adjust our measure of tourism inflows to include academic years instead of calendar years. For consistency, we adopt this approach throughout the analysis, except for college completions.

Table A1 in the Appendix reports descriptive statistics on college enrollment and completion between 2010 and 2019. The average share of yearly freshmen in the population aged 18 to 30 years of a province is 3.23 percent. The share of new graduates is 3.77 percent. In our sample period, completions increased by 0.08 percentage points on average and enrollment of freshmen increased by 0.05 percentage points per year.

2.2 Labor markets

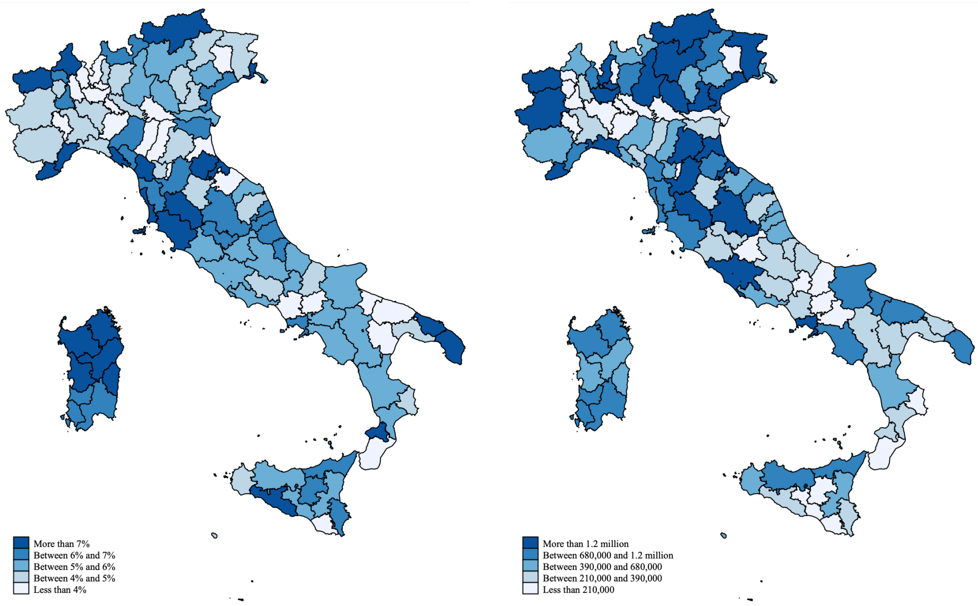
We obtain quarterly microdata about the Italian population between 2009 and 2019 from the Labour Force Survey (LFS) provided by ISTAT. These data are repeated cross-sectional surveys that include 600,000 individuals every year (about 1 percent of the Italian population). They provide a comprehensive set of information at the individual level, including socio-demographic characteristics, labor force status, industry of employment, wages, and province of residence. We restrict our sample to the non-institutionalized civilian population and focus on individuals aged 18 to 30 years since they represent the main group making college enrollment decisions.

Panel A of Figure 1 shows the geographic distribution of tourism employment across Italian provinces in 2010. Tourism employment is fairly widespread throughout the country, with certain areas experiencing higher concentrations than others. Notably, the islands of Sardinia and Sicily feature a great intensity of tourism employment in popular regions like Costa Smeralda, Agrigento, Taormina, and Messina. On the mainland, Tuscany, Valle D'Aosta, and Trentino-Alto Adige are among the areas with a higher share of tourism employment in the local population.

Figure 1: Tourism and employment

Panel A: Tourism employment

Panel B: Tourist inflows



Notes: This figure illustrates the tourist inflows, and tourism employment at the province level in 2010. Panel A shows the share of employment in the tourism sector. Panel B shows the count of foreign tourists in terms of the local population (provinces with more than one million foreign tourists include Rome (5.7), Venezia, (5.0), Firenze (2.9), Verona (2.2), Udine (1.9), Milano (1.7) Bolzano (1.7), Napoli (1.2)).

2.3 Tourism flows

We obtain data on foreign tourism flows from the Survey on International Tourism provided by the Bank of Italy. This data includes monthly information about tourist flows to Italian provinces by country of origin. We consider tourists individuals who travel for holidays or leisure, religious or pilgrimage reasons, cures or spas, and honeymoons. We do not include travel for reasons such as business travellers, cross-border workers, family visits, shopping, transit, or unknown reasons. These inflows would be endogenous to local economic conditions or impacting labor markets through channels different from the tourism sector (e.g. through other businesses). We aggregate tourism inflows at the province-year level.

The average number of tourist arrivals in a provinces is around 500,000 per year, with a range that goes from 40,000 to nine million, with an average growth rate of foreign tourists during our sample period of 4.44 percent (Table A1).

Panel B of Figure 1 shows the distribution of foreign tourists visiting Italy in 2010.

The islands, and the Central-Southern regions, such as Rome, Naples, Salerno, and Bari, are popular touristic destinations, but numbers are even higher in Northern provinces, including Venice, Florence, Verona, Udine, Milan, and Bolzano, each receiving more than one million foreign visitors annually.

2.4 Exogenous tourism flows

As explained in detail in the empirical strategy section below, we capture exogenous tourism exposure using security shocks in foreign countries, which affect tourism towards Italian provinces.

We collect data on security shocks at the country level from the universe of worldwide terrorist attacks provided by the Global Terrorism Database (GTD). A terrorist attack is defined as the use of force or violence by a non-state actor aiming political, economic, religious, or social goals through fear. For each event recorded, the GTD provides information on the date, place, type, and reason for the attack, as well as the number of casualties and wounded individuals. We restrict our measure of the shock to Islamist or jihadist terrorist attacks which involved at least five casualties and ten victims, since these events are likely to receive international media coverage, and therefore affect tourism flows. These restrictions leave us with 1,081 attacks worldwide between 2010 and 2019, out of which 19 happened in Europe (10 in Western Europe). Specifically, Western Europe countries that experienced at least one attack include France (5 attacks), the United Kingdom (2), Belgium (2), and Spain (1).

To measure the relevance of these destinations for international travelers, and therefore to which extent tourists might deviate to Italy after a security shock, we use data on country-to-country flows of international tourists from the World Tourism Organization (UNWTO). These data include information about the tourism flows between more than 150 countries. We use information on arrivals of non-resident tourists at national borders by nationality or country of residence to construct bilateral tourism flows across countries. When this information is not available, we follow González and Surovtseva (2020) and estimate tourism flows based on arrivals of non-resident visitors at national borders or arrivals in hotels and similar establishments.

3 Empirical strategy

Estimating the causal effect of tourism on human capital adjustments poses several identification problems. For example, education outcomes and tourism inflows may be jointly determined by unobserved factors, and the mismeasurement of foreign tourist arrivals may bias the estimates towards zero.[5]

We identify exogenous variation in tourism inflows by building a measure that exploits shocks to the attractiveness of alternative tourist destinations in terms of their (perceived) safety. In particular, we use terrorist attacks abroad that reduce tourism flows to affected countries (Besley et al., 2020; Deem, 2020), and increase the relative attractiveness of competing destinations, such as Italy. We combine these shocks with a composite index that captures the distribution of tourists by country of origin in previous periods. In other words, we suppose that deviating tourists are attracted to destinations that are popular among compatriots (similar to the enclave hypothesis from the immigration literature (Card and DiNardo, 2000)).

Intuitively, the instrument works as follows. Suppose that France is a popular tourist destination among Germans, but only a few Brits spend holidays there. In Italy, German tourists mostly visit the province of Verona, while Brits visit Rome. Therefore, Verona will be more exposed than Rome to tourism inflows that follow from a terrorist attack in France, since it is likely to affect Italy's attractiveness mostly through its impact on German tourism.

Similarly to González and Surovtseva (2020), we build our instrument proceeding in two steps. First, we quantify terrorist attacks in a foreign country d in quarter q of year t using data from the GTD (e.g. number of attacks in France):

$$\text{Shock}_{dq(t)} = \sum\nolimits_i \text{attack}_{idq(t)}. \tag{2}$$

[5] For example, public investment in tourism may reduce the resources available for education, determining both enrollment and tourist inflows.

Second, we build a composite index that captures the tourism-related degree of exposure of Italian provinces to terrorism abroad. In particular, we quantify the intensity of tourist flows across country pairs using data from the UNWTO. For each country of origin o, we compute the share of tourists who travel to country d in year $t-1$ (e.g. the share of German tourists who visit France):

$$\mathrm{OT}_{odt-1} = \frac{\mathrm{outflow}_{odt-1}}{\sum_d \mathrm{outflow}_{odt-1}}, \tag{3}$$

where $\mathrm{outflow}_{odt-1}$ is the number of tourists from country o who visit country d in year $t-1$.[6] This element captures how relevant country of destination d is for tourists from country of origin o.

Then we quantify the intensity of tourist inflows to Italian provinces by assigning them according to the composition of tourist inflows at the province level using data from the Bank of Italy. We compute the share of tourist in province p in quarter q of year $t-1$ arriving from country o (e.g. share of Germans tourists in Verona):

$$\mathrm{IN}_{opq(t-1)} = \frac{\mathrm{inflow}_{opq(t-1)}}{\sum_o \mathrm{inflow}_{opq(t-1)}}, \tag{4}$$

where inflow_{opt-1} is the number of tourists from country o visiting province p in $t-1$.[7] This component captures how relevant tourism from country of origin o is for province p.

Finally, we combine the shock component in Equation 2 with the index obtained from Equations 3 and 4 to obtain a yearly measure of the shock at the Italian province level:

$$\text{Tourism exposure}_{pt} = \sum_{q(t)} \sum_d \sum_o \left(\mathrm{IN}_{opq(t-1)} \cdot \mathrm{OT}_{odt-1}\right) \cdot \mathrm{Shock}_{dq(t)}. \tag{5}$$

As shown in Figure 2, exposure to tourism shocks is not uniformly distributed across space or time. Panel A shows that provinces with higher average exposure levels are

[6] These data are only available at year level.

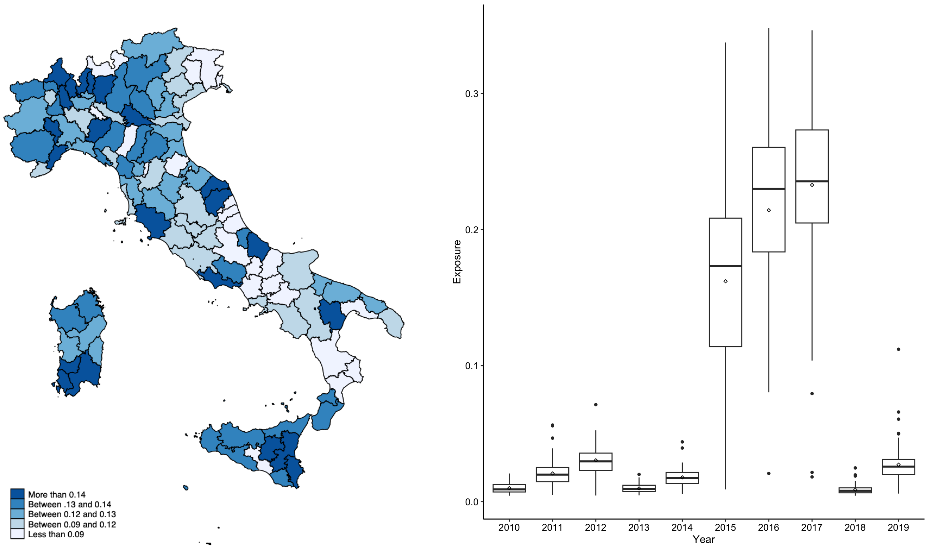
[7] Since the exogeneity of our measure relies on the exogeneity of the shift component (i.e. terrorism abroad), as highlighted in Borusyak et al. (2018), we lag the components of our index by just one period. To ensure completeness in the matrix of origin-destination combinations for smaller provinces and countries with limited data availability, we utilize older shares. This approach helps maintain a comprehensive matrix for each period despite gaps in the data.

scattered across the peninsula, while Panel B shows that tourism shocks were relatively low during 2010, 2011, 2018, and 2019, and large in the period between 2015 and 2017, when major terrorist attacks in Europe happened.

Figure 2: Exogenous measure of tourism exposure

Panel A: Exposure across space

Panel B: Exposure over time



Notes: This figure shows the geographical and temporal distribution of our measure of exposure. Panel A reports the average exposure levels across the Italian provinces during our sampling period. Panel B presents a box plot illustrating the distribution of exposure levels for each year, where dots represent outliers (data points exceeding 1.5 times the interquartile range (IQR)), horizontal lines represent the first, second, and third quartiles, and the dot within the box indicates the average. The whiskers extend from the box to the farthest data point within 1.5 times the IQR of the respective quartile.

3.1 Empirical model

We estimate the dynamic effect of exogenous tourism exposure on educational outcomes between 2010 and 2019 in yearly changes at the province level running the following reduced form regression:[8]

$$\Delta y_{pt} = \gamma_r + \theta_t + \sum_{k-6}^{k=0} \beta_{t+k} \ln(\text{Tourism exposure})_{pt+k} + X_{p,t_0} + \varepsilon_{pt}, \tag{6}$$

where Δy_{pt} measures the change in the outcome variable y in province p between $t-1$ and t. Tourism exposure captures our exogenous tourism inflows to province p and year t

[8] First differences help us to control for any unobserved heterogeneity that is constant by province over time. Moreover, we are analyzing the effect of rather small shocks which makes it economically more meaningful to look at changes rather than levels.

as described in Equation 5, γ_r are region fixed effects, θ_t are time fixed effects, and X_{p,t_0} is a vector of baseline province-level characteristics, which includes province demographics (log population, share of 18-30 years old, share of non-college-educated population, and share of tourism, manufacturing and agricultural employment share, and the share of students), measures of the quality and the availability of higher education institutions (number of institutions, presence of large universities, and the presence of private institutions), and the share of foreign tourists at the province level. Regressions are weighted by the province population in the baseline year. Standard errors are clustered at the province level.

In the reduced form regressions, the identifying assumption is that our measure of exposure is correlated with the labor markets of provinces only through increases in the relative tourism attractiveness generated by terrorist attacks abroad. In a second step, we use our measure of exposure as an instrument for foreign tourist arrivals in Italy. The IV approach will require additional assumptions that will be discussed in Section 4.3.

Despite being plausibly exogenous, our measure of exposure might still be correlated over time under certain circumstances.[9] For example, a terrorist attack in year t can affect the probability of another attack in year $t+1$. This serial correlation could bias our estimates when we use several lags of the shock in the same regression. Therefore, we replace our measure of tourism exposure, $\ln\,(\text{Tourism exposure})_{pt+k}$, with its unpredictable component $\hat{\varepsilon}_{pt}$ obtained running the following regression:

$$\ln(\text{Tourism exposure})_{pt} = \sum_{s-6}^{s=-1} \beta_{t+s} \ln(\text{Tourism exposure})_{pt+s} + \varepsilon_{pt}. \tag{7}$$

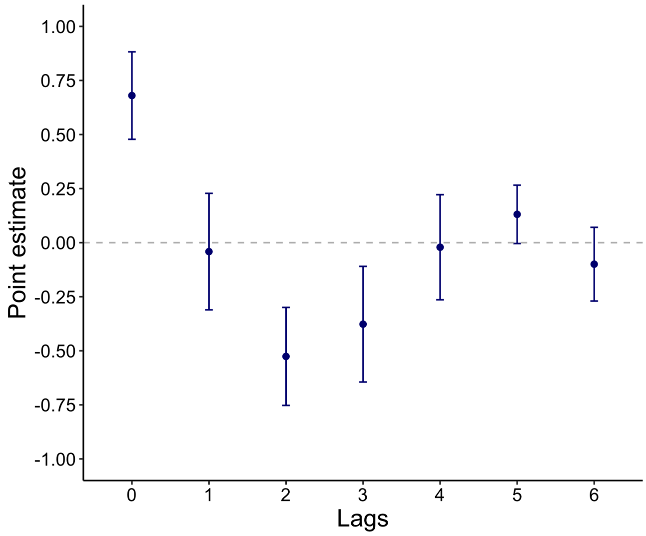
As shown in Appendix A2, our results are robust to the use of the actual variable of tourism exposure or when running separate regressions for each period.

[9] Table A2 in the Appendix reports the correlation matrix of our measure of exposure and its lags.

4 Results

Terrorism and tourism – This section presents the results of the empirical analysis. We start by illustrating the impact of exogenous tourism shocks on tourist arrivals. Figure 3 presents the estimated effect of our measure of exposure on tourism inflows in Italian provinces over time from Equation 6. The figure suggests that higher exposure to security shocks in foreign countries increases a province's tourism inflows in the year of the shock. Specifically, a one standard deviation increase in exposure increases foreign tourist inflow by about 0.7 standard deviations in year t. The effect decreases in the subsequent periods, as the growth rate re-adjusts, stabilizing at its previous level. This finding suggests that, as expected, tourism inflows in Italy caused by security shocks abroad are only temporary.

Figure 3: Foreign tourism in Italy and terrorist attacks abroad



Notes: This figure illustrates estimates of the effect of (standardized) tourism exposure on the (standardized) change in log foreign tourism, obtained using Equation 6 on 918 observations. Coefficients are in percent change. Regressions are weighted by province population in the baseline year, standard errors are robust against heteroskedasticity and allow for clustering at the province level. Confidence intervals are at the 95% level.

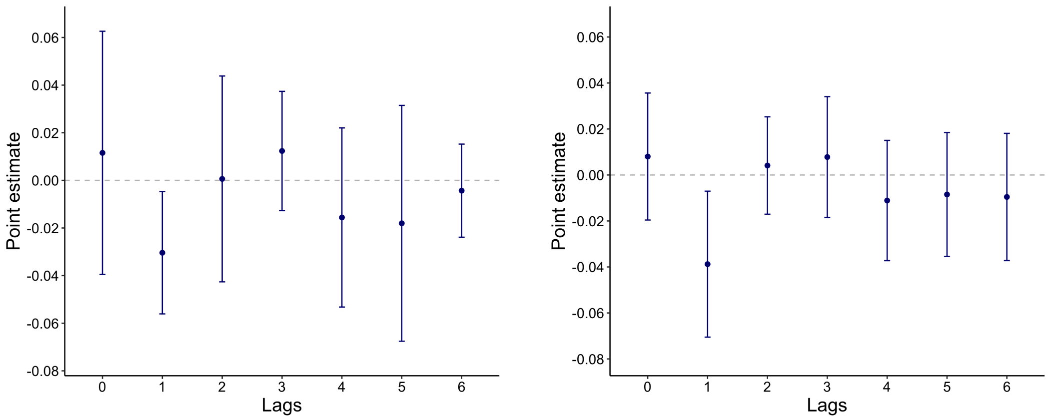
4.1 Tourism and college education

This section describes the main results of our analysis related to college education. In a second step, we quantify the effects on college enrollment and completion using our IV strategy.

Enrollment and completion – We start by examining the impact of tourism exposure on college enrollment and graduation at the province level. The estimates from Equation 6 are illustrated in Figure 4.

Figure 4: The effect of tourism exposure on college enrollment and completion

Panel A: College enrollment   Panel B: College completion



Notes: This figure illustrates the reduced form estimates of the effect of (standardized) tourism exposure on changes in the share of first-year students (Panel A) and on the share of completions (Panel B) at the province level, obtained using Equation 6 on 918 observations. The dependent variable is normalized by the province population between 18-30 years old as described in Equation 1. Coefficients are multiplied by 100. Regressions are weighted by province population in the baseline year, standard errors are robust against heteroskedasticity and allow for clustering at the province level. Confidence intervals are at the 95% level.

Panel A shows results on college enrollment and Panel B on college completion. We find that higher exposure has a negative effect on the share of individuals who enroll or complete college in the subsequent year (lag one in the figure). The decline in completions can result from students either delaying their graduation or dropping out of college. For both outcome variables the results may seem modest. However, when compared to the average of the dependent variables, 0.04 and 0.08 percentage points (see Table A1 in the Appendix), a one standard deviation increase in exposure decreases the average change in enrollment and completion by about 75 and 50 percent respectively. We will quantify in more detail these effects in the IV estimation in Section 4.3.

These results are driven by highly touristic provinces (Figure A2 in the Appendix) and are robust to various changes in specification, including measuring the dependent variable as a share of the working-age population, using unweighted regressions, and using different reference years for the shares (see Section A2).

As shown in Figure 4, we find no statistically significant impact two years after the shock occurred. This result suggests that the initial decline in college enrollment and completion has not been offset in subsequent years. In other words, individuals seem to not enroll in college or drop out permanently, rather than just delaying their enrollment or completion by one year after the shock occurred. However, we will show in the following paragraphs that the aggregate effect masks some heterogeneity by gender.

On the other hand, the lack of response in the year in which the shock occurs can be explained by the timing of enrollment. Students usually enroll in college between September and October, i.e. when the new academic year starts. If a shock occurs in the middle of the academic year, this is not going to affect enrollment in the current academic year, but only in the subsequent year. Similarly, the absence of an immediate response from the number of graduations may be attributed to the fact that students who are very close to the end of their academic programs are less willing to withdraw or delay their graduation. Students who are further away from graduating, on the other hand, are more likely to respond to the shock.

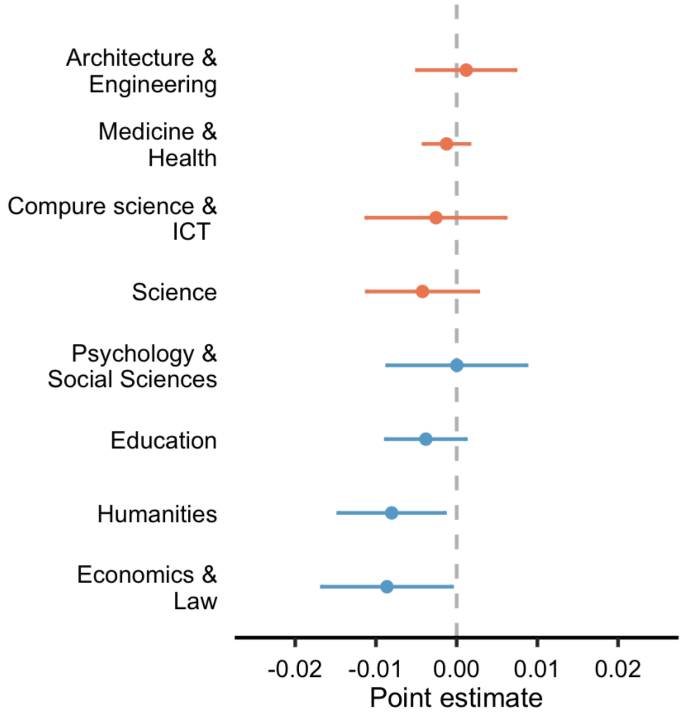
Field of study – To understand which students are more affected by the tourism shock, we decompose the estimate on college enrollment in the year after the shock by 8 fields of study.[10] Figure 5 plots the reduced form estimates from individual regressions on enrollment by each field of study for lag 1. Specifically, the dependent variable is the change in the share of students by field of study group, and the sum of the coefficients across the figure equals the coefficient reported for lag 1 in Panel A of Figure 4.[11]

We find that the impact of tourism on college enrollment is driven by a decrease in the number of students enrolled in fields related to the humanities and social sciences (except political science). On the contrary, STEM or applied sciences like medicine or sport are not affected by the shock.

[10] MIUR data includes the following fields of Study: Economics, Business and Law; Education, Art and Design, Literature and Humanities, Foreign languages; Psychology, Political Science and Communication; Science; Computer Science and ICT; Engineering, Architecture and Civil Engineering; Agriculture, Forestry and Veterinary, Medicine and Health. We cannot disentangle completions by field of study, due to the unavailability of these data by province of residence in the MIUR database.

[11] The dependent variable is computed as the change in $s^i_{pt} = \frac{\sum_c S^i_{pct}}{N^{18-30}_{pt}}$, where S^i_{pct} is the number of first-year Bachelor students from province p that is enrolled in college c in field of study i in academic year t.

Figure 5: Effect on enrollment in $t+1$ by field of study

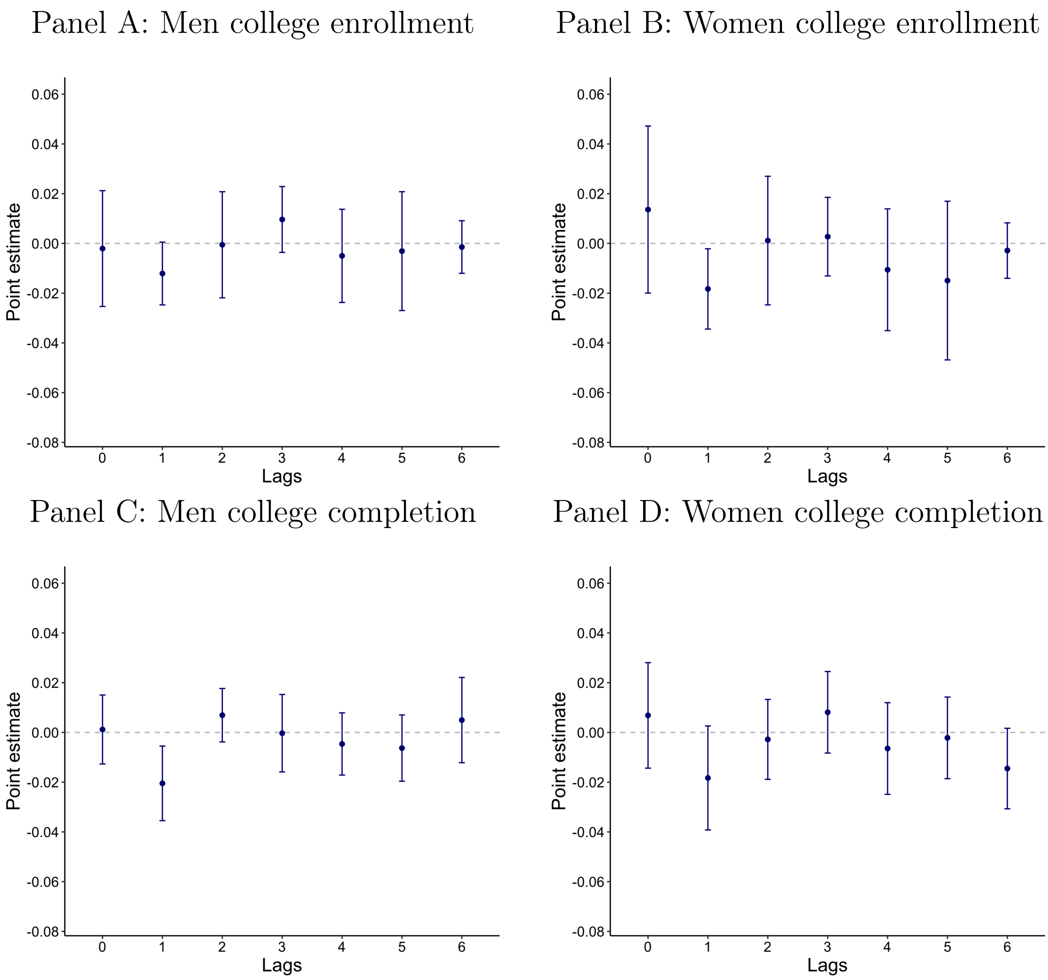


Notes: This figure decomposes the point estimate of the coefficient of lag 1 reported in Panel A of Figure 4 by field of study using MIUR data, obtained using Equation 6 on 918 observations. The dependent variable is computed as the change in $s^i_{pt} = \frac{\sum_c S^i_{pct}}{N^{18-30}_{pt}}$ where S^i_{pct} is the number of first-year Bachelor students from province p that is enrolled in college c, in field of study i in academic year t. Coefficients are multiplied by 100. Regressions are weighted by province population in the baseline year, standard errors are robust against heteroskedasticity and allow for clustering at the province level. Confidence intervals are at the 95% level.

These results can be explained by the different skills required to enroll in these programs and by the fact that tourism wages are not a relevant alternative for STEM or applied science graduated. In addition, it is likely that students interested in engineering or medicine start preparing for their studies well in advance and are therefore not affected by short-term shocks in their enrollment decisions.

Heterogeneity by gender – We now decompose the total effect by gender. Figure 6 reports our results. We find that the shock reduces enrollment and completion in the following year for both men and women. However, we find a different trend by gender. While there is a significant decline for men, there is a subsequent rebound that is almost as large as the initial decline two years after the shock occurred for completion and three years after the shock occurred for enrollment. This result suggests that men are delaying their enrollment when exposed to the shock, a result that we do not find among women, who experience a permanent impact on their educational outcomes.

Figure 6: The effect of tourism exposure on college enrollment by gender



Notes: This figure illustrates the reduced form estimates of the effect of (standardized) tourism exposure on changes in the share of first year students and completions for men (Panel A and C) and women (Panel B and D), obtained using Equation 6 on 918 observations. Changes are expressed in percentage points of the population aged 18 to 30 and are multiplied by 100. The average change in the dependent variable is about 0.02 and 0.04 percentage points for enrollment and completions respectively for both groups. Regressions are weighted by province population in the baseline year, standard errors are robust against heteroskedasticity and allow for clustering at the province level. Confidence intervals are at the 95% level.

Due to the aggregate nature of our data, these results should not necessarily be interpreted to mean that the same individuals who did not enroll in year $t+1$ then enroll in year $t+3$, but rather that for males, a decrease in enrollment after the shock is followed by an increase two years later.

A possible explanation for this heterogeneity could be related to societal expectations and gender roles (Fortin, 2015; Bertrand, 2020). Men could face societal expectations pushing them towards pursuing careers typically regarded as more prestigious or financially rewarding. As a result, temporary spikes in demand for service jobs might prompt these individuals to join the workforce initially, only for them to later return to college for further education once the demand fades.

Conversely, women have typically been urged to prioritize family responsibilities, potentially facing barriers in accessing certain career paths. Therefore, a temporary increase in demand for service jobs might offer women a chance to enter the workforce without the pressure of pursuing additional education later on. Considerations such as starting a family, childcare responsibilities, or cultural norms valuing stability over career advancement could sway women to stay in service jobs.

Furthermore, economic factors may play a crucial role (Blau and Kahn, 2017). Women might perceive service jobs as providing more flexibility to suit their specific circumstances. Indeed, women constitute a substantial portion of the tourism workforce, comprising approximately 53 percent of tourism employment in Italy in 2019. This pattern could arise from several factors, such as lower wages in other sectors, limited availability of flexible job opportunities, or the need to juggle employment with caregiving responsibilities.

4.2 Tourism and labor market

This section analyzes the labor market impact of tourism shocks, which is likely to be a relevant channel through which tourism exposure affects educational outcomes. Figure 7 shows the effect of tourism exposure on tourism employment (Panel A), total employment (Panel B), unemployment (Panel C), and non-participation (Panel D).

We find that exposure to tourism shocks increases employment in the tourism industry and overall employment in the province.[12] In particular, a one standard deviation increase in exposure increases tourism employment by 0.15 percentage points in the period.[13] This increase accounts for about 60 percent of the effect of the shock on total employment reported in Panel B. The effect is driven by low-skill labor and seems to slowly revert to

[12] It is noteworthy that while the impacts on college enrollment and completion happen with a one-year lag, the labor market impact is instead immediate.

[13] Figure A3 of the Appendix decomposes the effect by gender. Results show a comparable increase in employment for both men and women. In line with our previous results, women experience a more persistent effect.

the average in the following periods (Figure A4 in the Appendix).

Panels C and D reveal that this effect stems from an increase in labor force participation rather than a decline in unemployment. This finding aligns with our hypothesis that the tourism shock increases the share of young individuals who enter the labor force after graduating from high school rather than enrolling in college and that students drop out of college to enter the labor force.

Finally, Table A3 analyzes the employment effects further by breaking them down by broad sectors provided by the Italian LFS. We find that the increase in tourism employment is paired with an increase in employment in construction and manufacturing (although more noisily estimated). Notably, the overall employment increase persists for longer than the increase in tourism employment due to a lasting increase in manufacturing employment. This outcome is in line with the results of Faber and Gaubert (2019) for Mexico but differs from the findings of González and Surovtseva (2020) for Spain (who focuses on a shorter time horizon after the shock).

4.3 IV estimates

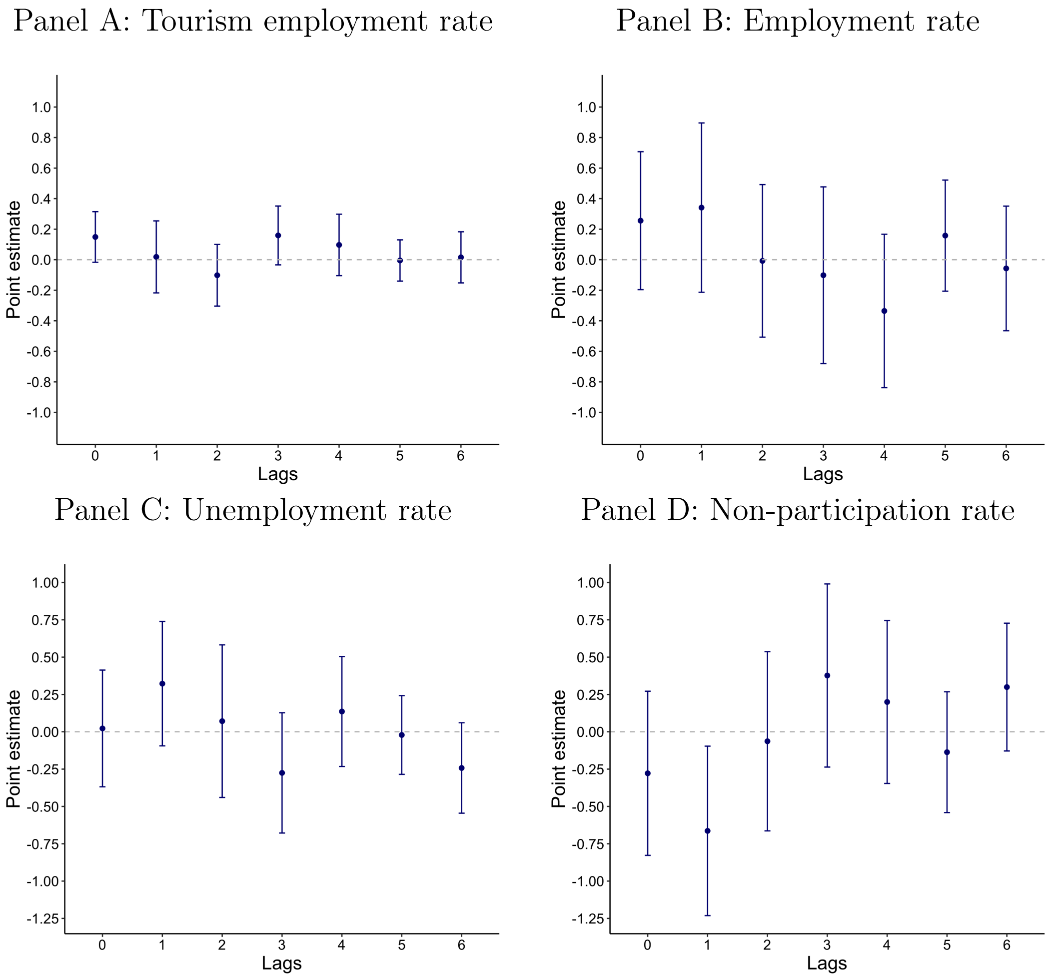
To quantify the effect of tourism shocks on educational outcomes, we instrument the tourism flows to Italian provinces with our measure of exposure to tourism shocks. As discussed in the previous section, the impact of tourism exposure on educational outcomes is concentrated one year after the shock occurs. Consequently, we focus on assessing the effect of the shock in year t on educational outcomes in year $t+1$ by running the following IV regression:

$$\Delta y_{pt} = \gamma_r + \theta_t + \beta \, \Delta \ln \text{ Foreign tourists}_{pt-1} + X_{p,t_0} + \varepsilon_{pt}, \tag{8}$$

where Δy_{pt} is the change in educational outcomes for province p between year $t-1$ and t, and $\Delta \ln$ Foreign tourists$_{pt-1}$ is the change in the log number of foreign tourists visiting province p between $t-2$ and $t-1$.

In the IV estimation, we introduce additional assumptions compared to those applied

Figure 7: The effect of tourism exposure on labor market outcomes



Notes: The figure presents reduced form estimates of the impact of (standardized) tourism exposure on various employment indicators. Panel A shows the effect of tourism employment rate, Panel B on total employment rate, Panel C on the unemployment rate, and Panel D on non-participation rate, derived from Equation 6 on 918 observations. The average of the dependent variable is 0.13 for tourism employment, -0.69 for total employment, 0.24 for unemployment, and 0.44 for non-participation. Regressions are weighted by province population in the baseline year, standard errors are robust against heteroskedasticity and allow for clustering at the province level. Confidence intervals are at the 95% level.

in the reduced form analysis. The identifying assumption now is that terrorist attacks in foreign countries are correlated with foreign tourist arrivals in Italy (relevance assumption) but are unrelated to domestic labor market conditions (exclusion restriction).

Regarding the first assumption, Panel A in Table 1 shows the relation between the change in log tourism inflows and our measure of exposure. The first-stage relationship suggests that higher exposure to security shocks in foreign countries increases a province's tourism inflows. Specifically, a one standard deviation increase in tourism exposure increases foreign tourist arrivals by 0.344 to 0.507 percentage points, depending on whether tourism exposure is computed based on the academic year (Column 1) or on the calen-

Table 1: IV estimates

	Enrollment	Completion
	(1)	(2)
	Panel A: First-stage	
$\ln(\text{Tourism exposure})_{t-1}$	0.728 ***	0.622 ***
	(0.103)	(0.109)
	Panel B: OLS	
Δ $\ln(\text{Foreign tourists})_{t-1}$	-0.002	-0.013 *
	(0.007)	(0.007)
	Panel C: IV	
Δ $\ln(\text{Foreign tourists})_{t-1}$	-0.042 **	-0.059 **
	(0.021)	(0.027)
Observations	918	918
KP F-stat	48.630	26.000
Covariates	✓	✓

Notes: This table depicts the first stage, the OLS, and the IV estimates of the impact of the (standardized) change in foreign tourist inflows on the changes in college enrollment and completion. Specifically, Columns 1 and 2 report the estimates of the effect on college enrollment (measured in academic year) and completion (measured in calendar year). Panel A reports the first-stage, Panel B the OLS estimates, while Panel C displays the IV. The dependent variable is normalized by the province population aged 18 to 30 years as described in Equation 1. Coefficients are multiplied by 100. Standard errors are robust against heteroskedasticity and allow for clustering at the province level. Coefficients with $***$, $**$, and $*$ are significant at the 1%, 5% and 10% confidence level.

dar year (Column 2). The table also shows that the F-statistic is high, validating the relevance assumption for our instrument.

To fulfill the exclusion restriction, terrorist attacks in other countries should not affect Italian labor markets except through alterations in tourism inflows. Since terrorist attacks abroad have a limited impact on the overall economic activity of the affected countries, the exclusion restriction likely holds (González and Surovtseva, 2020).

Panel B reports OLS estimates of the impact of tourism inflows on educational outcomes. We find a small negative and noisy association between tourism inflows and college enrollment and completion. However, we consider these estimates to be biased towards zero due to potential measurement errors in the tourist inflow and the possibility of reverse causality.

Finally, Panel C reports IV estimates. We find that a one standard deviation increase in tourism inflows decreases college enrollment and college completion by 0.046 and 0.079 percentage points respectively. In provinces with an average growth rate in tourism inflows of 4.44 percent, these results are equivalent to about seven percent of the average yearly growth in enrollment and graduations in our sample period.[14] Therefore, tourism shocks represent an economically relevant source of fluctuations in college enrollment and completion. Though not overwhelmingly large, these effects contribute significantly to understanding the dynamics of educational attainment.

5 Conclusions

This paper analyzes the impact of an increase in the demand for service occupations on educational outcomes in Italy. We proxy the demand for labor in the service sector using exogenous shocks to the tourism industry. In particular, we identify increases in tourism inflows to Italian provinces caused by security shocks abroad which affects the local demand for services.

We find that a temporary exogenous increase in tourism inflows decreases college enrollment rates and completions. The impact is similar for both genders, but the effect is only temporary for men. We also show that the drop in enrollment is mostly driven by fewer individuals enrolling in fields of study related to the humanities and social sciences. We find no impact on enrollment in STEM fields.

Our findings suggest that this effect is, at least partially, driven by better labor market opportunities and therefore higher opportunity cost of college education.

In conclusion, our study sheds light on the intricate relationship between short-term increases in service job demand, as evidenced by tourism employment, and the pursuit of a college education. The negative correlation we observe underscores the importance of delving deeper into the long-term effects of service job development on human capital accumulation. Understanding these dynamics is crucial for comprehending the potential ramifications for economic growth.

Additionally, our findings suggest that individuals may be making suboptimal decisions, potentially influenced by informational biases when choosing between college

[14] The first result has been computed using the value of one standard deviation of the log change in foreign tourists from Table A1 (0.4616) multiplied by the average tourist growth (0.044) and divided by the average growth rate of college enrollment (0.5 percentage points): $0.046 \times \frac{0.044}{e^{(0.4616)}-1} \times \frac{1}{0.05} = 6.9\%$. Similarly, for completion we have: $0.079 \times \frac{0.044}{e^{(0.4616)}-1} \times \frac{1}{0.08} = 7.4\%$.

education and immediate employment opportunities. Despite the positive college wage premium and greater job stability associated with higher education, some individuals may be overlooking these benefits. This underscores the need for targeted policy interventions aimed at addressing information gaps and encouraging informed decision-making regarding education and employment. Moving forward, further research in this area is essential for crafting effective policies that promote both individual prosperity and economic development.

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Online Appendix:
Service Jobs and Education:
Evidence from Tourism Shocks in Italy

Giuseppe Di Giacomo   Benjamin Lerch

A1 Additional figures and tables

Table A1: Descriptive statistics

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 50	Pctl. 75	Max
Share of students (18-30)	918	3.23	0.46	1.20	2.96	3.24	3.49	4.73
Share of completion (18-30)	918	3.77	0.58	1.34	3.38	3.76	4.13	5.56
Δ share of students (18-30)	918	0.05	0.20	-0.72	-0.08	0.05	0.18	0.98
Δ share of completion (18-30)	918	0.08	0.21	-0.68	-0.04	0.08	0.21	1.06
Population 18-30 (thousand)	918	79.88	90.40	11.09	33.40	51.05	91.02	562.51
Foreign tourists (thousand)	918	482.14	1 077.87	0.41	35.31	109.73	439.76	8 986.39
Δ ln Foreign tourists	918	4.44	46.16	-230.59	-15.87	4.69	24.37	366.22
Exposure	918	0.13	0.22	0.00	0.01	0.03	0.19	1.82

Notes: This table illustrates descriptive statistics of the main variables used in the empirical analysis at the province level. Population shares are multiplied by 100.

Table A2: Tourism exposure correlation matrix

	Exp._t	Exp._{t-1}	Exp._{t-2}	Exp._{t-3}	Exp._{t-4}	Exp._{t-5}
Exp._{t-0}	1.000					
Exp._{t-1}	0.301***	1.000				
	(0.000)					
Exp._{t-2}	-0.183***	0.303***	1.000			
	(0.000)	(0.000)				
Exp._{t-3}	-0.199***	-0.128***	0.369***	1.000		
	(0.000)	(0.000)	(0.000)			
Exp._{t-4}	-0.076**	-0.171***	0.147***	0.782***	1.000	
	(0.024)	(0.000)	(0.000)	(0.000)		
Exp._{t-5}	0.247**	0.411***	-0.058*	-0.026	0.049	1.000
	(0.000)	(0.000)	(0.079)	(0.432)	(0.140)	

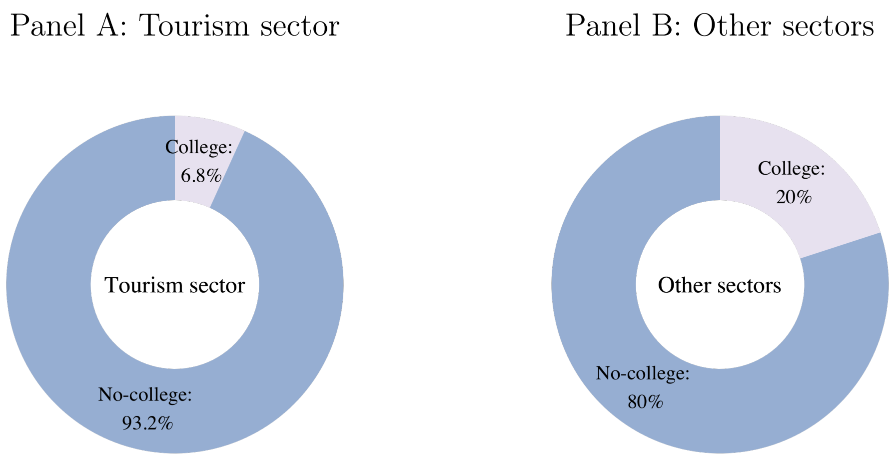
Notes: This table reports the correlation coefficients for our measure of exposure and its lags. P-values are reported in brackets. Coefficients with $***$, $**$, and $*$ are significant at the 1%, 5% and 10% confidence level.

Table A3: Employment by industry

	Total	Tourism	Retail	Construction	Agriculture	Manufacturing	Other
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ln(Tourism exposure)$_t$	0.256	0.149 *	-0.170	0.124	0.027	0.121	0.006
	(0.228)	(0.083)	(0.157)	(0.091)	(0.079)	(0.175)	(0.160)
ln(Tourism exposure)$_{t-1}$	0.341	0.018	0.058	-0.015	-0.019	0.534 ***	-0.235
	(0.280)	(0.119)	(0.138)	(0.101)	(0.071)	(0.152)	(0.201)
ln(Tourism exposure)$_{t-2}$	-0.008	-0.102	-0.064	-0.034	-0.016	0.022	0.185
	(0.252)	(0.102)	(0.145)	(0.154)	(0.081)	(0.208)	(0.186)
ln(Tourism exposure)$_{t-3}$	-0.102	0.159	0.180	-0.182	0.030	-0.130	-0.159
	(0.292)	(0.097)	(0.175)	(0.149)	(0.082)	(0.162)	(0.217)
ln(Tourism exposure)$_{t-4}$	-0.336	0.097	0.130	-0.111	-0.055	-0.118	-0.278
	(0.253)	(0.102)	(0.144)	(0.093)	(0.077)	(0.181)	(0.214)
ln(Tourism exposure)$_{t-5}$	0.158	-0.005	0.091	0.200	-0.017	-0.087	-0.026
	(0.183)	(0.068)	(0.095)	(0.130)	(0.051)	(0.161)	(0.129)
ln(Tourism exposure)$_{t-6}$	-0.057	0.016	-0.120	-0.122	0.025	0.118	0.026
	(0.206)	(0.084)	(0.109)	(0.122)	(0.059)	(0.167)	(0.159)
Observations	918	918	918	918	918	918	918
Covariates	✓	✓	✓	✓	✓	✓	✓

Notes: This table illustrates the reduced form estimates of the effect of (standardized) tourism exposure on changes in employment by industry. Changes are expressed in percentage points of the 18-30 years old population and are multiplied by 100. Data on outcomes are from LFS. Standard errors are robust against heteroskedasticity and allow for clustering at the province level. Coefficients with $***$, $**$, and $*$ are significant at the 1%, 5% and 10% confidence level.

Figure A1: Employment education by industry

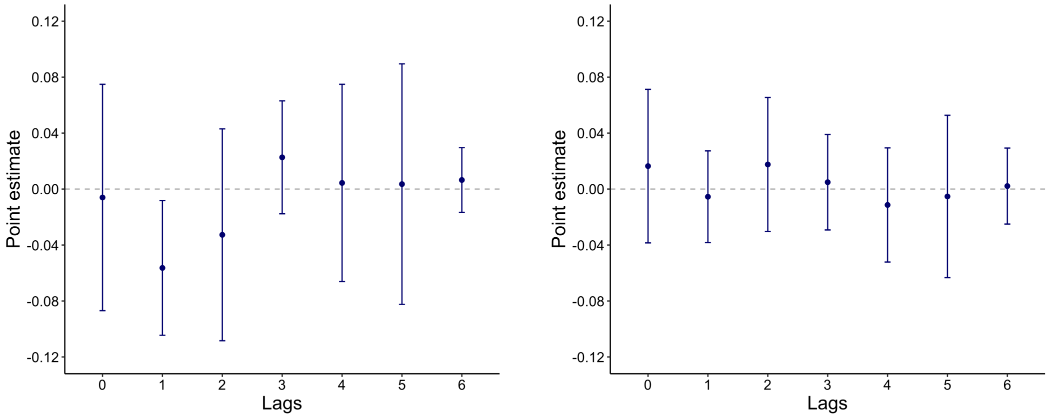


Notes: This figure illustrates the share of employment with tertiary education by industry in 2019 using data from LFS. Panel A reports the averages for the tourism sector, while Panel B aggregates all the non-tourism sectors.

Figure A2: The effect of tourism exposure on college enrollment for touristic and non-touristic provinces

Panel A: Touristic provinces

Panel B: Non-touristic provinces

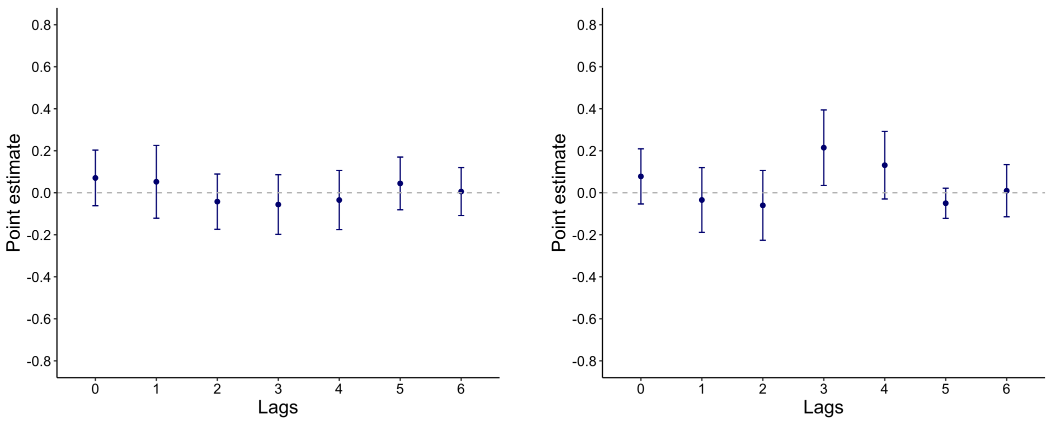


Notes: This figure illustrates the reduced form estimates of the effect of (standardized) tourism exposure on changes in the share of first-year students from touristic (Panel A) and non-touristic (Panel B), obtained using Equation 6. Provinces are defined as touristic when the share of tourism employment is above the median of Italian provinces in the baseline year. The dependent variable is normalized by the province population between 18-30 years old as described in Equation 1, and the average change is 0.045 and 0.051 percentage points for touristic and non-touristic provinces respectively. Coefficients are in percent change and multiplied by 100. Regressions are weighted by province population in the baseline year, standard errors are robust against heteroskedasticity and allow for clustering at the province level. Confidence intervals are at the 95% level.

Figure A3: The effect of tourism exposure on employment by gender

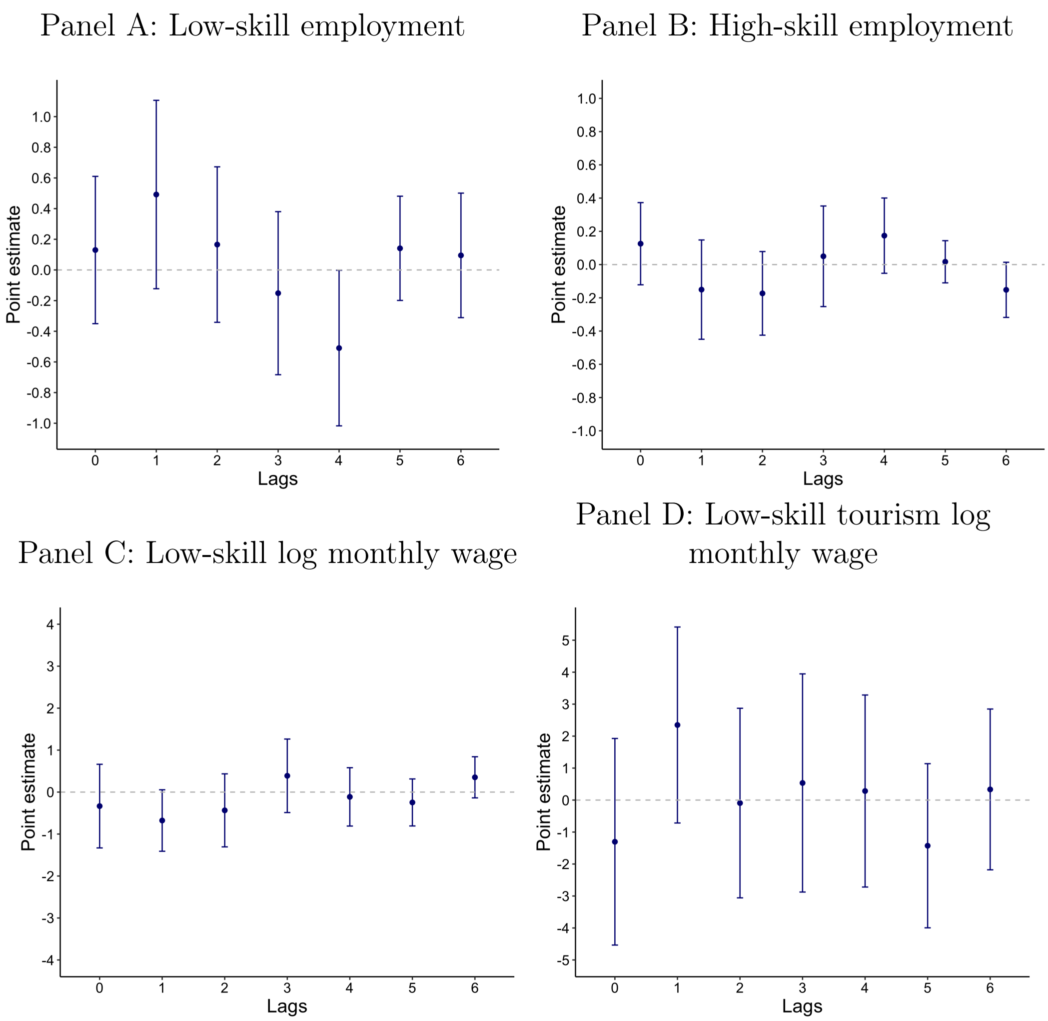
Panel A: Men tourism employment

Panel B: Women tourism employment



Notes: This figure illustrates the reduced form estimates of the effect of (standardized) tourism exposure on changes in tourism employment of men (Panel A) and women (Panel B), obtained using Equation 6 on 918 observations. The dependent variable is normalized by the province population between 18-30 years old as described in Equation 1. Coefficients are in percentage points and multiplied by 100. Regressions are weighted by province population in the baseline year, standard errors are robust against heteroskedasticity and allow for clustering at the province level. Confidence intervals are at the 95% level.

Figure A4: Tourism exposure and low-skill workers



Notes: This figure illustrates the reduced form estimates of the effect of (standardized) tourism exposure on changes in the employment rate of low-and high-skill workers in Panel A and B, on changes in low-skill log monthly wages in Panel B, and on changes in low-skill log monthly wages in tourism in Panel C. Estimation is performed using Equation 6 on 918 observations for Panel A and B. The number of observations drop to 765 for Panel C due to data availability. In Panel A, the dependent variable is normalized by the province population between 18-30 years old as described in Equation 1, and coefficients are expressed in percentage points and multiplied by 100. Panel B and C are measured in log changes, and coefficients are expressed in percent. Regressions are weighted by province population in the baseline year, standard errors are robust against heteroskedasticity and allow for clustering at the province level. Confidence intervals are at the 95% level.

A2 Robustness checks

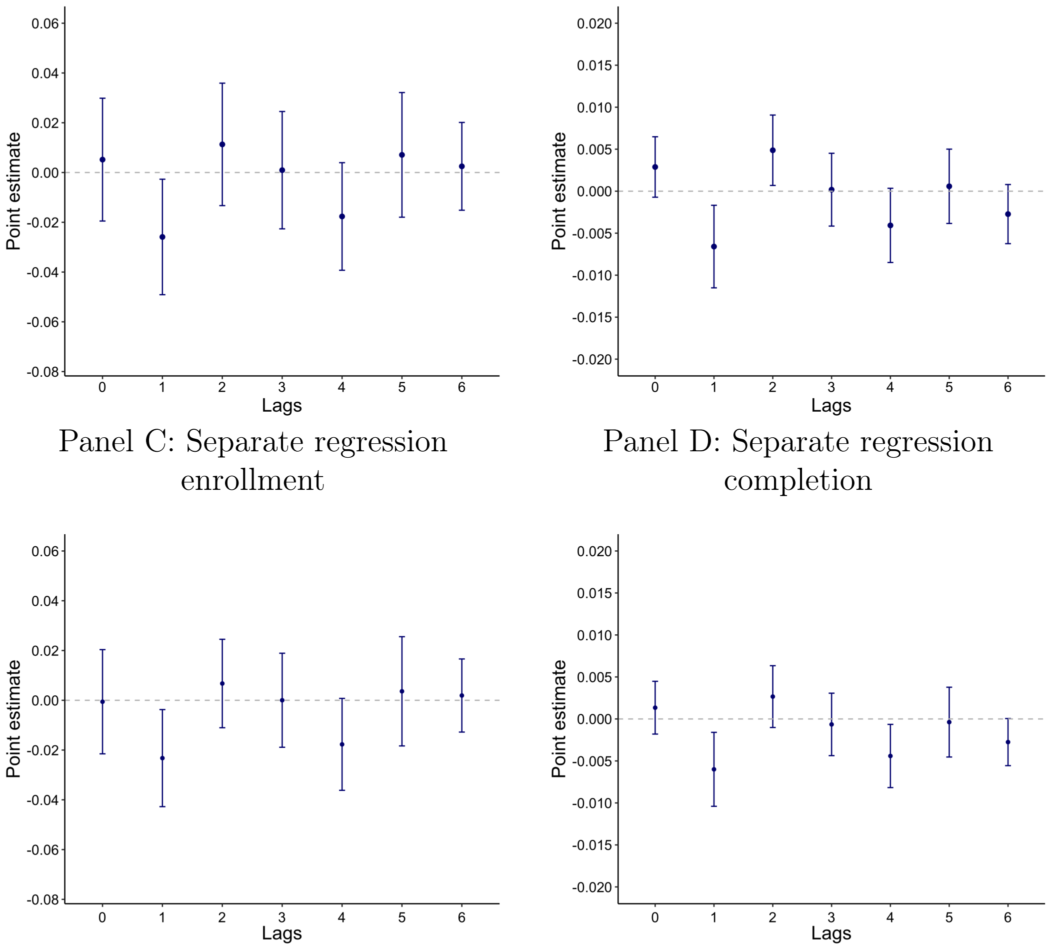
This section presents a set of robustness checks in support of our preferred specification.

Different dynamic model – In Section 3.1, we emphasize that while terrorist attacks are considered exogenous, our measure of exposure may still exhibit autocorrelation (see Table A2). Consequently, we employ Equation 7 to isolate the unpredictable component of our shock and substitute it into our estimation Equation 6.

Figure A5: Educational outcomes: Different dynamic specification

Panel A: College enrollment

Panel B: College completion



Notes: This figure illustrates the reduced form estimates of the effect of (standardized) tourism exposure on changes in the share of first-year students and completions without isolating the unpredictable component of the shock (Panel A and B) and using separate regression for each lag (Panel C and D). Changes are expressed in percentage points of the population aged 18 to 30 and are multiplied by 100. Regressions are weighted by province population in the baseline year, standard errors are robust against heteroskedasticity and allow for clustering at the province level. Confidence intervals are at the 95% level.

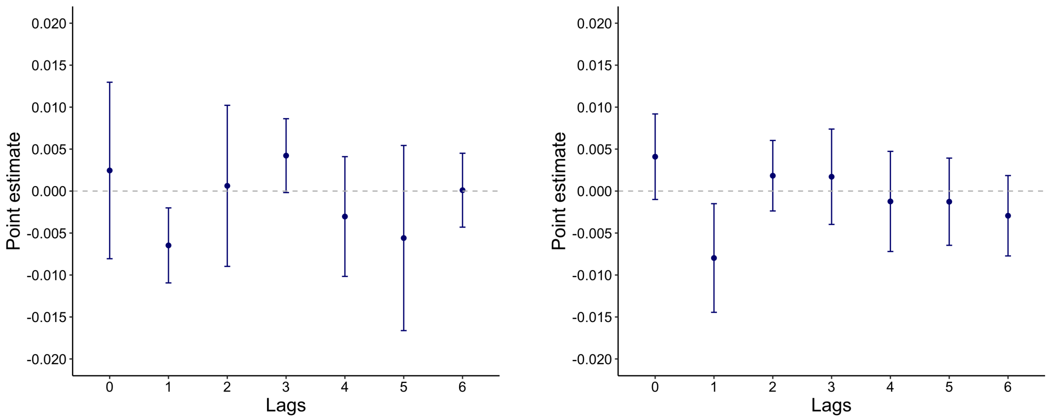
Interestingly, our findings remain largely unaffected when using our original equation with *ln Tourism exposure* rather than $\hat{\epsilon}_{pt}$, or when we address potential autocorrelation by conducting individual regressions for each lag of our exposure measure. As anticipated, the first approach might be subject to multicollinearity, while the latter could be subject to omitted variable bias. The outcomes are illustrated in Figure A5.

We find that our estimates remain concentrated primarily in the year after the tourism shock occurred. However, within OLS estimation, multicollinearity and omitted variable bias would undermine the reliability of the coefficients.

Educational outcomes on total population – In Figure 4 we reported the effect of tourism exposure on enrollment and completion measuring these two variables relative to the population aged 18 to 30 years. Figure A6 shows that our estimates are similar when using the overall working-age population.

Figure A6: College enrollment and completion share of total population

Panel A: College enrollment Panel B: College completion

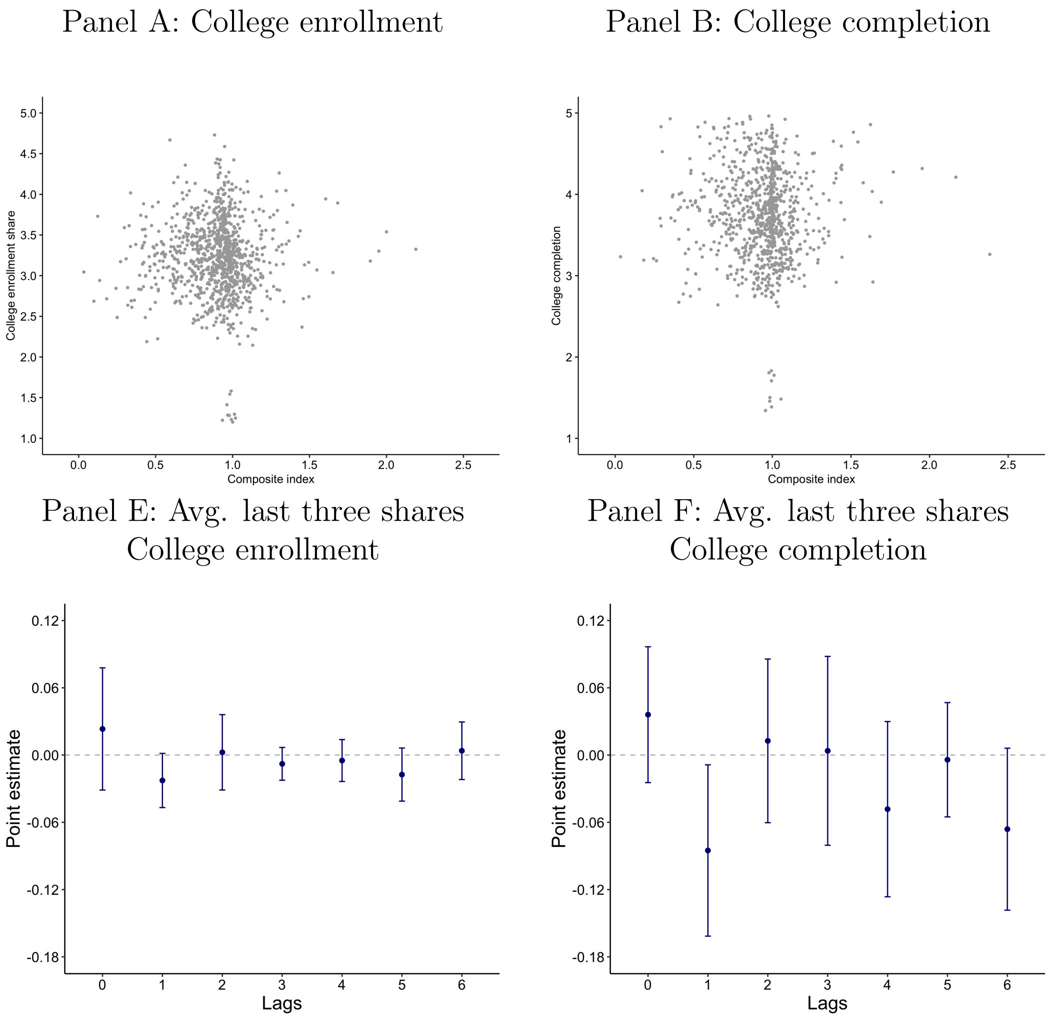


Notes: This figure illustrates the reduced form estimates of the effect of (standardized) tourism exposure on changes in the share of first-year students (Panel A) and on the share of completions (Panel B) at the province level, obtained using Equation 6 on 918 observations. The dependent variable is normalized by the province population between 18-64 year old. Coefficients are multiplied by 100. Regressions are weighted by province population in the baseline year, standard errors are robust against heteroskedasticity and allow for clustering at the province level. Confidence intervals are at the 95% level.

Shock measures – As discussed in Section 3, our exogenous measure of tourism exposure captures the variation in Italy's tourism attractiveness due to terrorist attacks abroad. Consequently, the exogeneity of our measure depends on the exogeneity at the shock level, as emphasized by Borusyak et al. (2018).

However, in this section, we also show that the value of our composite index used for the allocation of the exposure across Italian provinces (outlined in Equation 5) is uncorrelated with the initial shares of college enrollment and completion. To address this potential concern, we test whether the composite index is correlated with the initial shares of educational outcomes.

Figure A7: Composite index and dependent variables: Robustness and alternative construction



Notes: The figure depicts the relationship between the composite index, derived from Equation 3 and 4, used to distribute terrorist attacks across Italian provinces (described in Equation 5), and its association with the yearly baseline of college enrollment and completion. Panel A shows the relation between the index and college enrollment share, yielding a coefficient of 0.11 (se = 0.09). Panel B shows the correlation between the index and college completion share, resulting in a coefficient of 0.0005 (se = 0.04). Additionally, Panels C and Panel D display the effect of (standardized) tourism exposure on enrollment and completion, when the composite index for the shock in time t is computed using the average of shares from the previous three periods instead of the latest available one. Changes are expressed in percentage points of the population aged 18 to 30 and are multiplied by 100. Regressions are weighted by province population in the baseline year, standard errors are robust against heteroskedasticity and allow for clustering at the province level. Confidence intervals are at the 95% level.

Figure A7 depicts the relationship between the composite index (derived from Equation 3 and 4) and the initial shares of college enrollment and completion in each period. Panel A shows the correlation between the index and college enrollment shares and Panel

B shows the correlation between the index and college completion shares.

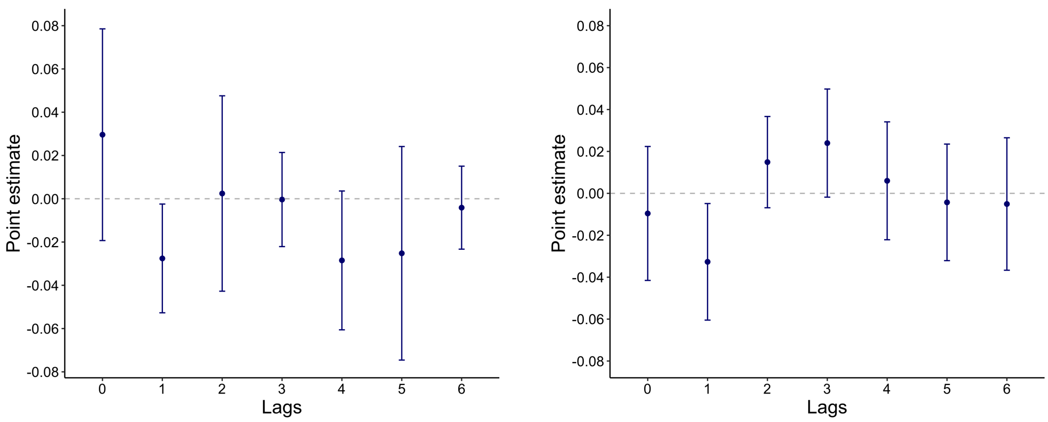
The results show that there is no discernible pattern to the correlation. Specifically, the regression analysis reveals a coefficient that approximates zero and lacks statistical significance.

In addition, Panels C and D of the figure report the results for college enrollment and completion, respectively, when the composite index for the shock is computed using the average number of tourists over the previous three periods instead of the most recent share available. While this approach has the advantage of fixing the composite index to one, it exhibits lower performance in the first stage compared to our primary approach. This observation underlines the volatility of tourism inflows, highlighting that the distribution of tourism by country of origin in the year immediately preceding the shock captures these fluctuations better. Despite this finding, the reduced form regressions on educational outcomes are in line with the results reported in the main analysis.

Unweighted regressions – Results reported in Figure 4 show that tourism exposure decreases enrollment and completion in Italian provinces. Figure A8 replicates the main result without weighting the estimates by the province population in the baseline year, showing that the effects in period $t + 1$ remain negative and statistically significant.

Figure A8: Tourism exposure and educational outcomes: Unweighted regressions

Panel A: College enrollment　　Panel B: College completion



Notes: This figure illustrates the reduced form estimates of the effect of (standardized) tourism exposure on changes in enrollment (Panel A) and completions (Panel B) at the province level, obtained using Equation 6 on 918 observations. The dependent variable is normalized by the province population aged 18 to 30 years as described in Equation 1. Coefficients are multiplied by 100. Standard errors are robust against heteroskedasticity and allow for clustering at the province level. Confidence intervals are at the 95% level.