The Tradeoff between Work and Education: Evidence from Public Transportation Penetration to Arab Towns in Israel

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Abstract

Disadvantaged communities are often geographically segregated from employment and higher education opportunities. Increasing access can entail substantial welfare gains, but this can also affect the tradeoff faced by young adults between investing in higher education and working for pay. We evaluate the introduction of bus services to Arab towns in Israel, which substantially and differentially increased access either to work only or to work and higher education opportunities among a disadvantaged population. Exploiting the variation that different bus line connections created in the cost of accessing higher education institutions, we find that young adult male responses are consistent with a tradeoff between investing in higher education and working for pay. For females, our results are less clear-cut and while there is evidence of responses in terms of the probability of currently studying, we do not observe sufficiently concise labor market responses. Our results demonstrate the importance of accounting for potential reductions in educational attainment when expanding work opportunities to disadvantaged communities.

JEL Classifications: I24; I25; J22; J61; O18.

Keywords: Public Transportation; Spatial Mismatch; Higher Education; Opportunity Cost

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1 Introduction

Economic and social disparities can persist or even widen if disadvantaged communities have limited access to work and/or education opportunities. However, increased access to economic opportunities can affect the tradeoff individuals face between long-term investment in educational attainment or working for pay. On the one hand, increased access to education institutions should encourage greater schooling through decreases in the cost of attending school, and this in turn could contemporaneously decrease labor market outcomes (Becker (1965)). On the other hand, greater access to unskilled work opportunities can increase the opportunity cost of schooling and can negatively or positively affect the returns to schooling, depending on how this increase compares with increased access to skilled work opportunities. Policies intended to improve the economic welfare of disadvantaged communities through increased access to work and/or education opportunities should take into account these potential equilibrium implications.

This study assesses a reform that introduced public transportation to Arab towns in Israel and substantially increased the access of disadvantaged communities to work and higher education opportunities. Most Arabs in Israel reside in segregated and peripheral towns with very limited employment opportunities. Higher education institutions in Israel are located almost entirely in Jewish towns and cities. Despite this, their significant economic disadvantage and their low vehicle ownership rates, Arab communities in Israel have been historically deprived of public transportation infrastructure. This began to change in 2007, when the Ministry of Transportation (MOT) announced a reform to invest heavily in public transportation services to and within Arab towns. The new bus lines connected Arab towns to Jewish cities with large labor markets as well as higher education institutions. We evaluate how this increased access affected the labor market and educational attainment decisions of young adults residing in these newly connected Arab towns.

Our empirical strategy enables us to differentiate between two potentially opposing effects that the introduction of public transportation may have on the cost of schooling and the impact this may have on young adults' educational attainment and labor market decisions. We distinguish between bus lines that connect Arab towns to higher education institutions and bus lines that do not and evaluate their effects on educational attainment and labor market outcomes. Our underlying assumption is that both bus types connect to new employment opportunities, thereby increasing the opportunity cost of schooling. However, buses that connect to higher education institutions also decrease the cost of schooling due to greater physical access to higher education institutions. Our analysis thus enables us to empirically address the tradeoff faced by young adults between time allocated to work and to education and examine the choices of individuals who experienced increased accessibility to both opportunities in a developed economy.

A common challenge in estimating the effects of greater accessibility to labor markets or higher education institutions is the endogeneity of the mode that increases access. In our case, it seems highly plausible that additional bus lines and their frequencies are correlated with town characteristics that may also be determinants of residents' labor market outcomes and educational attainment. We overcome this potential bias by relying on randomness in the exact timing of bus line introductions and frequency changes. This randomness is generated due to an often prolonged bureaucratic process required by the MOT, which bears the regulatory responsibility for all public transportation networks and any changes to their routes or frequencies. The exact length for MOT approval is random, and we assume that it is exogenous to our outcomes of interest, conditional on fixed effects. Our regressions include town and subdistrict-year fixed effects. Town fixed effects control for unobserved town-specific factors that may be correlated with the timing or intensity of bus services. Subdistrict-year fixed effects control for time-variant shocks or policies among clusters of towns that are in geographic proximity to each other. We present evidence of the exogeneity of our bus intensity measures by establishing a lack of a correlation between these measures and time-varying town-level demographic characteristics (Section 5.2). We also alleviate concerns for pre-trends in our outcomes of interest through a leads and lags analysis and a placebo test in Sections 6.3 and 7.1, respectively.

Our data links respondents in four cross-sectional surveys covering several thousand Arab households from 2004-2014 to detailed bus line data - including their frequencies and routes - provided by Israel's MOT three times annually for the years 2008-2014. Most of our analysis is separate for males and females due to considerable gender differences in terms of labor force participation within this highly traditional population. Our main dependent variables are whether the individual reported working last week and whether they report currently studying. We focus our analysis on young adults ages 18-27, the primary population segment that faces a choice between higher education and work, and who rely heavily on public transportation as their major mode of transport.

We find that the response of young adult males to buses that do not connect to higher education institutions exhibits a tradeoff between work and higher education, namely labor market outcomes increase and the probability of studying decreases. However, in response to buses connecting to higher education institutions we observe an increase in the probability of studying, without a decrease in labor market outcomes, thereby suggesting that these bus lines increase the pool of young adult males that are either studying or working. The lack of change in labor market outcomes in response to college buses also indicates that male labor force attachment is strong within this population.

For young adult females, labor market outcomes mostly do not respond to the penetration of bus lines, although we do present some evidence of changes in the intensive margin for females residing in the lowest socioeconomically ranked towns in our sample. The probability of currently studying exhibits response patterns that are similar to those of males - increased probability in response to college buses and decreased probability in response to non-college buses.

The adverse effects of spatial mismatch on labor market outcomes have been widely documented in the U.S. (Kain (1968); Holzer (1991); Stoll (1999); Weinberg (2000); Andersson et al. (2018); Miller (2018)) and to a much lesser extent internationally or in developing countries (**?**). Numerous place-based policy measures have been proposed and evaluated for the purpose of addressing spatial mismatch - enterprise zones, transport infrastructure, telecommunication and internet infrastructure, mobilizing communities, and much more (see Neumark and Simpson (2015) for a review). Our work contributes to the literature on alleviating spatial mismatch through increased access to modes of transit that connect disadvantaged communities to labor markets and employment opportunities.[1] However, our work is distinct from this literature in that we also examine educational attainment responses, rather than just focusing on employment outcomes. We further expand upon the spatial mismatch literature by specifically evaluating access to higher education institutions, in addition to access to labor markets. Our work thus integrates the interplay between investing in schooling and working for pay with the spatial mismatch literature, which to our knowledge has not considered educational attainment implications of greater labor market access, despite this being a fundamental component of human capital accumulation theories.

Our work is closely-related to research on the development and economic effects of transport infrastructure. While most transport infrastructure literature focuses on either roads or railroads,[2] our work evaluates bus lines. Bus lines differ from roads or railroads, as they primarily serve the residential population and to a much lesser extent local businesses or economic establishments in the newly connected locality that now face new import and export opportunities (Duranton and Turner (2012); Duranton et al. (2014); Ghani et al. (2016)). This allows us to more precisely isolate the effect of greater access to work and education opportunities from other economic factors that may simultaneously change when roads or railways connect disadvantaged communities to outside markets.[3]

We are familiar with two recent studies on transport infrastructure that specifically evaluate the effect of greater access to labor markets on educational attainment. Adukia et al. (2020) and Aggarwal (2018) study India's national rural road construction program and its effect on middle school enrollment and child and adolescent educational attainment, respectively. Both studies find increases in middle school enrollment in response to greater connectivity to outside labor markets, although Aggarwal (2018) also finds decreases in high school enrollment accompanied by greater adolescent labor force participation. Our work complements Adukia et al. (2020) and Aggarwal (2018) by highlighting the importance of accounting for changes in the opportunity cost of schooling when evaluating disadvantaged communities' increased access to labor markets. Our analysis exploits variation in the overall cost of schooling - including both the opportunity

[1] Kawabata (2003), Baum (2009) and Gautier and Zenou (2010) show how vehicle ownership positively affects labor market outcomes for low-skilled workers, single mothers with low education levels, and minority workers, respectively. Holzer et al. (2003), Sanchez (1999), and Tyndall (2017) show that public transportation can decrease spatial mismatch of employment prospects among minorities in U.S. metropolitan areas, and Ong and Houston (2002) show this for women on welfare in Los Angeles. In Phillips (2014) and **?**, when public transit travel subsidies are provided to job seekers from segregated areas in Washington D.C. or the outskirts of Addis Ababa in Ethiopia, respectively, job searches intensify and their time spans shorten. Martinez et al. (2020) find that improvements in the bus transit network in Lima, Peru increased employment rates and earnings among women.

[2] See Jacoby (2000); Jacoby and Minten (2008); Donaldson and Hornbeck (2016); Donaldson (2018).

[3] We acknowledge that greater access via public transportation networks can affect other margins, besides higher education and labor market outcomes. Specifically, access to health services may also increase, which can have direct implications on human capital formation. However, in our setting, primary care health services are readily available at the local level even within small and remote communities in Israel, and this is through Israel's national health insurance plan that covers all citizens. Secondary health care services require travel to larger (Jewish) cities, but this is less relevant for the young adult population. Indeed, in another study, we assess the effect of greater access to secondary health care services following public transportation penetration to Arab communities on the health of adults ages 50-75, a population for whom secondary health care services are relevant (Abu-Qarn and Lichtman-Sadot (2020)).

cost and the cost of physically reaching the education institution - due to varying degrees of increased access to higher education institutions, and this is in contrast to the variation in Adukia et al. (2020)'s heterogeneous analysis that is based on labor market characteristics or the discrete measure of having a road or not in Aggarwal (2018). Both Adukia et al. (2020) and Aggarwal (2018) do not exploit the new connectivity in the context of greater access to higher education institutions, as we do. Furthermore, while Adukia et al. (2020) focus in their work solely on schooling outcomes resulting from increased access to regional markets,[4] Aggarwal (2018) evaluates both school enrollment and labor force participation simultaneously, as in our study, although our population of interest is young adults, slightly older than the population evaluated in Aggarwal (2018).

Our study is also related to past studies that have shown a positive relationship between educational attainment and the wage premium gap between higher skilled work and lower skilled work using cyclical variation in the demand for unskilled labor.[5,6] In these studies, the opportunity cost of investing in education changes due to labor demand conditions. We analyze the tradeoff between work and education when demand conditions in the labor market remain constant in terms of macroeconomic shocks and all that changes is the accessibility of work and/or education opportunities.

Two recent studies besides our study have evaluated the effect of public transportation penetration to Arab towns in Israel on labor market outcomes (Barak (2019); Greenwald et al. (2018)). However, they do not focus on the young adult population, as we do, and they do not distinguish between buses that connect to higher education institutions and buses that do not. We believe that for these reasons, and several additional differences between our study and these studies that we detail in Section 3.2, their results show null effects while our results show statistically significant effects of public transportation on male labor market outcomes.

The paper proceeds as follows. Section 2 outlines our conceptual framework concerning greater accessibility to work and higher education opportunities, the tradeoff between work and higher education, and changes in the cost of obtaining an education. Section 3 provides background on public transportation in Israel and in particular within Arab communities, while highlighting the long bureaucratic process often involved with introducing bus lines or changing them. Section 4 discusses our data on public transporta-

[4]In Asher and Novosad (2020), the authors from Adukia et al. (2020) separately evaluate the effect of the Indian road project on economic outcomes and employment, although for the entire adult population, while their school enrollment analysis is at the middle school level.

[5]In Charles et al. (2018), housing market booms improved labor market opportunities for young adults without a college education, thus reducing educational attainment for those with the smallest expected gains from a college degree. Natural resource industries typically employ larger shares of unskilled workers, and Cascio and Narayan (2015), Morissette et al. (2015), and Black et al. (2005) show lower high school completion rates or college degree attainment in response to tighter labor markets in the natural gas, oil, and coal industries, respectively. However, these responses may reflect only a delay of educational attainment rather than an overall decrease, as Emery et al. (2012) demonstrate following the oil boom affecting Alberta, Canada in the 1970's. Gradstein and Ishak (2020) also show reduced schooling among those experiencing positive oil price shocks during adolescence in African oil-producing countries. Also in developing economies, Shah and Steinberg (2017) show that variation in agricultural output due to drought shocks in India affected educational attainment, and Atkin (2016) shows that greater labor demand in Mexico due to export expansions following international trade reforms decreased educational attainment.

[6]There is also literature demonstrating a negative relationship between child labor and educational attainment (Edmonds (2006); Edmonds and Pavcnik (2006); De Hoop and Rosati (2014); Baker et al. (2020)).

tion in Arab towns and labor market and education outcomes among the Arab population in Israel. Section 5 discusses the empirical strategy and identification, followed by results presented and discussed in Section 6, and then in Section 7 robustness checks are presented. Concluding remarks are provided in Section 8.

2 Conceptual Framework

In standard models of human capital accumulation, individuals initially choose whether or not to make a long-term investment in education and forego current earnings in exchange for greater future earnings (Becker (2009)). Factors affecting whether or not investment in education is beneficial include: the opportunity cost of obtaining an education, determined by the earnings from unskilled work that are foregone when investing in education; other costs of obtaining education, such as the time it takes to reach education institutions or the effort required to succeed in obtaining the desired education level; and the returns to schooling, determined by the wage premium for high skilled versus low skilled jobs.

When public transportation networks are introduced to disadvantaged communities, work and higher education opportunities may become more accessible. The opportunity cost of obtaining an education increases as more work opportunities are available. However, the cost of obtaining an education decreases as it is easier and potentially less costly in terms of time and money to physically get to a higher education institution. The returns to schooling may be affected through the different types of work opportunities that are more accessible. Put together, young adult work and human capital investment decisions in these newly connected towns can be affected in various directions.

Changes in the opportunity cost of obtaining an education are in the opposite direction of the changes in the cost of reaching a higher education institution. Our empirical strategy addresses these opposing effects by distinguishing between those bus lines that connect to higher education institutions and those that do not. We assume that both bus line types positively affect town residents' opportunity cost of schooling as they expand labor market opportunities outside the town.[7] However, bus lines that connect to higher education institutions also have a negative effect on the cost of obtaining an education through the reduced transportation costs to higher education institutions.[8] While it is not clear whether the latter effect is more dominant than the former effect for buses connecting to higher education institutions, it should be the case that if the decrease in the cost of schooling due to connectivity to higher education institutions is sufficiently large, then different responses in terms of educational attainment and labor market outcomes will be observed in response to the two different bus types.

The effect on the returns to schooling depends on the types of jobs that become available through greater bus connectivity. Increased access to high skilled jobs should entail higher returns to schooling, whereas greater access to lower skilled jobs should entail a decrease in the returns to schooling. In practice, it is

[7]Note that buses connecting to higher education institutions also connect to work opportunities.

[8]Distance to higher education institutions has been shown to affect educational attainment (Frenette (2006)), and this has been further validated by studies using proximity to colleges or their availability as instrumental variables for college education (Card (1993); Currie and Moretti (2003)).

difficult to assess for each bus line whether it connects to more high skilled or low skilled job opportunities, due to diverse labor markets in many bus destinations and numerous labor markets served by single bus lines. Furthermore, data on the labor market in each locality in Israel is quite limited. In addition, disadvantaged young adults may *perceive* their high/low skilled job opportunities differently from what is accessible to them, as they are often surrounded primarily by individuals with low skilled jobs and may not be entirely aware of the full set of higher skilled job opportunities, especially if they have recently become available. Due to these limitations, we do not integrate changes in the returns to schooling into our empirical framework.

While it is true that access to opportunities outside of town is more precisely measured using time traveled to get to various destinations, rather than whether buses serve the town or whether they connect directly or indirectly to higher education institutions, we argue that our bus intensity measures provide a rough proxy for travel time for a couple of reasons.[9] First, bus frequency captures a time component because waiting for the bus can be considered part of the travel time. Second, as buses in Israel generally do not run frequently and their timing often lacks coordination with the arrival of other bus lines, having to change buses in order to get to a higher education institution should entail longer travel time than a direct bus. We thus acknowledge that buses that do not directly connect to higher education institutions may also increase access to higher education through connections to other buses that eventually reach higher education institutions. However, it is still reasonable to assume that direct connection to a higher education institution eases access in terms of time, effort and monetary cost of two buses versus one, more than an indirect connection.

3 Background

3.1 The Arab Population in Israel

Arabs comprise roughly 20% of the population of Israel (8 million in 2014). They are citizens of Israel, although the majority of them identify themselves as Arab or Palestinian by nationality and Israeli by citizenship. In terms of religious affiliation, most are Muslim (~85%), but there is a significant Arab Christian minority and a Druze minority. Their language is Arabic, although most are bilingual with their second language being modern Hebrew.

The vast majority of the Arab population in Israel resides in separate towns and cities, which for the most part are ranked low socioeconomically - their population is characterized by low income, low employment rates, low educational attainment and high fertility rates. Many of these communities are traditional in that they set barriers for women to obtain a higher education and developing careers, although this is slowly changing.[10]

[9] Unfortunately, data is also not available on bus travel time (especially historical data).

[10] Car ownership and driving licenses among females within the Arab population have become much more common in recent years.

Arab communities in Israel lack employment opportunities. Industrial and commercial zones hardly exist in or near Arab localities. According to data from the Israel Ministry of Economy in 2010, although Arabs comprised 51% of the population in Northern Israel, only 18% of the industrial areas in that region were under the jurisdiction of Arab localities (Jabareen (2010)). Thus, Arabs who wish to expand their work opportunities often need to find modes of transportation to outside their home town.

3.2 Public Transportation in Israel and within Arab Communities

Public transportation in Israel is primarily via buses, taxis or inter-city trains. Public transportation services are not provided within a free market - rather, they are under the regulatory supervision of the Israeli Ministry of Transportation (MOT), which determines the extent of competition between operators for each region and locality, provides permits and licenses for each route, and sets the routes, stations, frequencies and prices.

Despite private car ownership rates being relatively low among Arabs, due to economic constraints, and many women not being able to drive due to traditional barriers, Arab communities within Israel have been significantly deprived of public transportation infrastructure until the last decade. According to an Israeli Government report from 2016, in 2009 41% of Arab localities in Israel had no public transportation services and an additional 43% had only a low level of public transportation services (Greenwald et al. (2018)). For many communities (including cities with populations of several tens of thousands), the only option for mobility prior to the introduction of public transportation was either walking to a bus/train station outside the community (usually more than a few kilometers) or taking vans with no official public transportation provision license. These vans cost significantly more than public transportation bus services in Israel, were sporadic in their time schedules, and posed a constraint on women from these traditional communities, who could not travel in crowded vans among men.

After several decades of historical neglect of public transportation infrastructure in Israel's non-Jewish communities, in 2007 the minister of transportation announced a 5-year plan to invest over 200 million NIS annually[11] in public transportation infrastructure within Arab communities. At the same time, a few Arab communities were already seeing greater investment in public transportation with new tenders being issued for bus line operators, and this was following local campaigning for the introduction of public transportation in these communities.[12] The actual investment in public transportation infrastructure ended up being substantially less than what was announced by the MOT in 2007. In 2011, the new minister of

Furthermore, fertility levels for the Arab population have declined substantially over the last 15 years and in 2016 have actually reached nearly identical levels to that of the Jewish population. During 2000-2004 the average number of children for Muslim women was 4.6, in comparison to 2.9 for Jewish women. Arab women employment rates have increased substantially in recent years. In 2009, employment among Arab women was 25%, in comparison to 73% for Jewish women (*The Arab Population in Israel: Facts & Figures 2018* (2018)).

[11] roughly equivalent to 57 million USD in 2007.

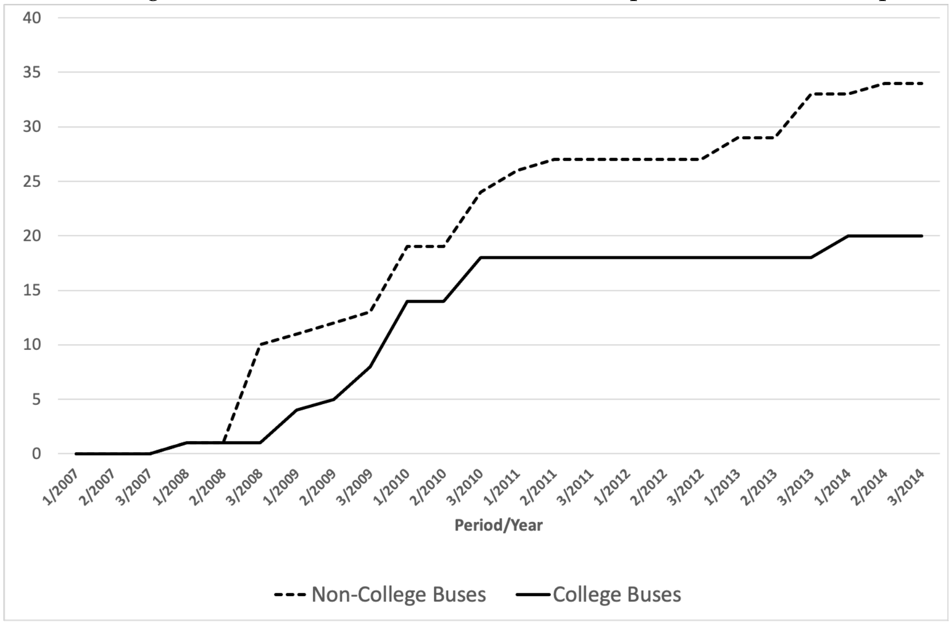
[12] In July 2007, the MOT announced that it will operate the first public transportation network serving Bedouin communities in Southern Israel in 3 towns - Rahat, Lakiya and Hura. This was shortly after the MOT's announcement of its 5-year public transportation plan in Arab communities, but it was after roughly two years of local campaigns run by the Bedouin community for the introduction of public transportation into their communities.

transportation announced that over 400 million NIS were spent on infrastructure and public transportation over the last few years and that 3.5 million passengers from Arab towns and communities utilize the improved public transportation network annually. The new bus networks gradually developed over the next years and increased significantly residents' mobility within and between their communities and access to large Jewish cities located close to them, thus expanding work and education opportunities to these residents. Despite substantial investment and improvements, the gaps in public transportation between Jewish and non-Jewish communities remain considerable, as demonstrated in a 2012 report by a non-profit organization (Naali-Yosef and Cohen (2012)).

Two recent studies evaluate public transportation expansions to Arab communities in Israel and the effect of this on labor market participation among Arabs. Barak (2019) and Greenwald et al. (2018) assign town-level bus line frequencies for the period 2010-2015 to individual-level or town-level data, respectively. These studies find either no effect or very small effects in response to greater bus line intensities. Neither Greenwald et al. (2018) nor Barak (2019) focus in their analysis on young adults, the population segment having the lowest vehicle ownership and which public transportation is likely to affect most. Moreover, Barak (2019) and Greenwald et al. (2018) do not separately evaluate the effects of buses connecting to higher education institutions as opposed to buses not connecting to higher education institutions, but rather examine the effects of bus networks in general. Our study demonstrates that this is vital for fully understanding the underlying effects of public transportation penetration on Arab communities, as the two different types of bus lines have opposite effects and evaluating them jointly can produce a null effect. In addition, our bus line data begins two years earlier than the bus line data utilized in Barak (2019) and Greenwald et al. (2018). This is important methodologically, as it is during 2008-2009 that many Arab communities transitioned from having no public transportation to having some public transportation, and as such, we are able to limit our sample to towns that had no public transportation until the start of 2008 and compare changes in response to public transportation penetration using a larger time span, beginning already in 2004. We believe that it is due to these methodological and data precision differences that our results for the young adult Arab population are stronger and more robust than those presented for the broader Arab population in Barak (2019) and Greenwald et al. (2018).

Figure 1 presents the gradual penetration of public transportation to the towns in our sample over time. The vertical axis provides number of towns served by each of the two types of bus lines we examine in our analysis, and the horizontal axis is a timeline, with periods 1, 2, and 3 referring to representative Tuesdays in March, June, and end of December, respectively. By construction, all 38 towns in our sample had no public transportation services at the end of 2007, whereas by the end of 2014, all sample towns were served by at least one bus type - 34 towns were served by at least one bus line that did not connect to higher education institutions, and 20 towns were served by at least one bus line that connected to a higher education institution.

Figure 1: The Number of Towns in the Sample with Public Transportation Penetration



Notes: This figure presents the gradual penetration of the two types of bus lines to the towns in our sample over time. Our sample covers 38 towns. Periods 1, 2, and 3 on the horizontal axis refer to representative Tuesdays in March, June, and end of December, respectively. The vertical axis is the number of towns served by the bus types - Non-College Buses refers to buses that serve the town and connect to labor markets but not to a higher education institution; College Buses refers to buses that serve the town and connect both to labor markets and to higher education institutions. See Data Section for further details on our bus line data.

3.3 Higher Education Enrollment in Israel

The academic school year in Israeli universities and colleges begins during the second half of October. Enrollment is by field of study, with acceptance based on high school matriculation exam scores combined with test scores from a standardized test. For a large fraction of fields of study, with the exception of those in highest demand (medicine, computer science, etc.), enrollment is generally still open even a few weeks prior to the start of the school year, as long as the minimal score threshold set in advance for acceptance to the institution and field is met. This is even more so for college enrollment, despite having lower acceptance thresholds for comparable fields of study. In addition, for most fields of study, it is possible to begin studying in the Spring semester, which generally starts at the beginning of March. Thus, individuals experiencing changes in the availability of bus lines to various opportunities outside their home town can have the flexibility to adjust their higher education investment decision within a short time frame.

4 Data

Our data are obtained primarily from two sources. Data on all bus lines in Israel, their frequencies, origin and final destination were provided to us by the Israeli MOT for the period 2008-2014. Data on outcomes concerning educational attainment, school attendance and labor force participation of individuals in Arab communities in Israel were extracted from a survey of the Arab minority in Israel conducted by the Galilee Society in 2004, 2007, 2010, and 2014 (Arab Survey, hereafter).[13]

Each cycle of the Arab Survey covers roughly 15,000 individuals from about 3,000 households, with the exception of the 2010 cycle which was limited to 8,500 individuals from 1,900 households. All four cycles are repeat cross-sections, and it is not possible to follow households through the years of the survey. Household members were asked about household and demographic characteristics, as well as their employment and education. We complement our data with general statistics concerning the population of each Arab community for each year available from the Israeli Central Bureau of Statistics (CBS).

The MOT data on bus lines details every bus line in Israel, its frequency, and other details on three representative Tuesdays - at the end of March, June and December each year between 2008 and 2014.[14] Bus line data could not be obtained from prior to 2008. As such, if a town was served by bus lines as of early 2008, we could not know when these bus lines were introduced.[15] We thus could not determine what the treatment variable values should be for these towns prior to 2008. As a result, we excluded 17 towns from our sample that were served by bus lines as of early 2008.[16]

To avoid potentially biasing our results by comparing towns that experienced public transportation penetration to towns that did not experience pubic transportation penetration, we limit our sample to towns that had bus services by the end of 2014, the last year in our sample period. Thus, out of 58 towns covered in the Arab Survey and without bus services as of late 2007, we exclude 20 towns that received no public transportation penetration, resulting in a final sample of 38 towns. A list of the towns in our analysis, when public transportation was introduced to them, and the years each of these towns is covered in the Arab Survey is in Table 7 in the Appendix. Results are also provided in Appendix Table 8 for regressions including all 58 Arab Survey towns, rather than the 38 treated towns, and these are very similar to the results presented in the paper.

We defined two important route characteristics on which we based the construction of our variables of interest concerning public transportation penetration. First, we defined a town as being served by public transportation only if that town had a bus line entering and stopping inside the town. If the town was only

[13]The Galilee Society is a Palestinian Arab non-government organization located in Israel. The Arab Survey is conducted by the Rikaz Center for Social Research within the Galilee Society and its funding is provided by organizations such as the European Union, among others. The Arab Survey is advantageous over several other databases covering the Arab population in Israel - including official Israel Central Bureau of Statistics surveys - for several reasons: first, it inquires about individuals' current educational status; second, it may draw more precise responses from the Arab population in Israel as it is not linked to the Israeli government that may arouse suspicion among some of the Arab population - this is particularly concerning labor force participation measures as a large share of the Arab population work in unreported positions; and lastly, when compared to the Israeli Labor Force Survey, the Arab Survey does not suffer from a major break in the sampling methods in 2012, which the Israeli Labor Force Survey underwent and significantly affects comparisons across years during this period (Etkes (2014)).

[14]Note that the end of December is a normal work week in Israel. The dates selected - at the end of March, June and December - were determined by the MOT based on its capabilities in terms of extracting data from its system.

[15]MOT data for bus lines begin only in 2008 because prior to that all documentation of bus lines in Israel were not digitized by the MOT and no data was found available (we further contacted bus companies for this purpose and they could not provide us with data prior to 2008).

[16]A total of 26 Arab towns were served by bus lines as of early 2008, according to our data. Out of these, 19 towns are covered in the Arab Survey, but for two of those towns we were able to verify that public transportation was indeed only introduced to them in January 2008, so we kept them in the sample.

served by bus lines that stopped outside the town, then this town was not considered as being served by public transportation, as this frequently entails walking up to several kilometers to the nearest bus stop for a large fraction of the town population. Second, we distinguished between buses serving at least one destination with a higher education institution and buses not serving a higher education institution. In order to define relevant higher education destinations, we listed from the 2007 and 2010 Arab Surveys the institutions that the adult population (ages 30-45) reported receiving a higher education certificate from. Any bus line that connected to a destination with a higher education institution that more than 3% of Arab higher education certificate holders reported attending was considered a bus line serving a higher education institution.[17]

For each of the three periods observed, we then calculated two bus intensity measures for the two bus types. For each bus type, we took the daily frequency of all bus lines of that type and divided it by that year's town population in thousands. We stress that both bus types - those connecting to higher education institutions and those that do not - connect the town to outside labor markets, thereby increasing residents' employment opportunities.

The bus line data was then merged with individual-level data from the Arab Survey for the years 2004, 2007, 2010 and 2014. For each year, we know individuals' interview date,[18] and as such, individuals are assigned the bus intensities that are documented for the date that is closest to their interview date. While the bus measures are intended to represent the prevailing intensity of bus services while the individual in the Arab Survey is interviewed, the effect measured in our regression analysis does not necessarily represent an immediate effect, as it may also be that these bus intensities prevailed for some time (e.g., several months) prior to the individual's interview date.[19]

Because our analysis focuses on the choice between work and educational attainment, our sample covers the young adult population ages 18-27.[20] Young adults should also be more responsive to public transportation, as car ownership is more common among the older population in Arab communities. Given the significant traditional differences between men and women within the Arab population, which are most pronounced in terms of labor force participation patterns (Yashiv and Kasir (2011, 2013)), all labor market results are reported separately by gender. Our two main dependent variables are whether the individual reported working last week and whether the individual is currently studying in a higher education institution. We also present some results for individuals' reporting of their usual weekly hours worked, monthly salary, and whether they neither worked nor studied, although this is complementary to the main results

[17]Our higher education institutions were the following: Achva Academic College, Ariel University, Beit Berl College, Ben-Gurion University of the Negev, Haifa University, Hebrew University of Jerusalem, Sakhnin College, Sapir College, Tel Aviv University. We further investigated whether the addition of bus lines changed the higher education institutions most frequently attended by the Arab population using 2014 data for college graduates aged 22-35 and the list of higher education institutions remained the same.

[18]In some cases, the interview date was not provided. When this occurred, we derived the interview date from the median date for that town and year. Our results are robust to excluding these observations (not presented in the paper).

[19]Our regression results are also robust to changing the bus intensity measures such that they correspond to the prevailing bus intensity around the time of the start of the academic year prior to the interview date (not presented in the paper).

[20]Different age ranges that can still be representative of the young adult population for each gender resulted in similar estimates, although less precise at times.

that arise from examining work and higher education decisions directly. All monthly salary figures are in 2014 New Israeli Shekel (NIS). Our sample of treated towns that did not have public transportation services at the end of 2007 consists of over 1,900 male observations and roughly 1,800 female observations - the number of observations for each regression varies due to missing values for some of the dependent variables.

One of our regression specifications examines differential effects based on Arab towns' socioeconomic (SE) ranking, as constructed by Israel's Central Bureau of Statistics. Towns' SE rankings are based on demographic variables, such as the mean age, ratio of adults to children, the share of families with 4 or more children, educational attainment, employment and retirement, and living standards. The ranking is in integers ranging from 1 - the lowest - to 10 - the highest. The index is updated every 2-3 years, with the exception of a break in updates between 2008 and 2013. Arab towns in Israel are ranked low in this index - in our sample of 38 towns, more than half are ranked 1 or 2. A SE ranking of 1 (2) in 2013 implied a mean of 9 (11) years of schooling for those aged 25-54, in comparison to the national Israeli mean of 13.5 years of schooling. Mean per capita monthly income in towns with a SE ranking of 1 (2) was 1,181 (1,994) NIS, equivalent at the time to $325 ($549), in comparison to the national Israeli mean of 4,057 NIS ($1,118). The Arab towns that are not ranked 1 or 2 according to the SE index are also not very highly ranked SE, with the vast majority ranked at 3 or 4. For a SE ranking of 4, the mean years of schooling for the population aged 25-54 in 2013 was 12.7 and the mean per capita monthly income was 3,183 NIS ($877).

Our regression specifications control for time-variant region-specific shocks and policies using subdistrict-year fixed effects. Israel is divided into 6 administrative districts - North, Haifa, Tel Aviv, Central, Jerusalem, and South. Within these districts, there is further division into subdistricts. Overall, there are 16 subdistricts in Israel, 3 of which cover an entire district (the districts that are smaller geographically). A subdistrict reflects a small geographic division with towns and localities that are in close proximity to each other and exhibit closer economic and social ties. Towns are defined part of a subdistrict based on the large (Jewish) city that serves these towns for local economic activity. Public transportation bus lines are also more likely to be intertwined between localities within a subdistrict.

4.1 Summary Statistics

In Table 1, we present summary statistics for our sample of males and females aged 18-27 in the 38 Arab towns covered in the Arab Survey. According to Table 1, there are significant differences between men and women in our sample. Women participate much less in the labor market and are much more likely to be married, though they are hardly household heads. Women, however, are more likely to be studying in higher education institutions than men. This is consistent with evidence on gender gaps in favor of females in educational attainment among disadvantaged populations (Autor et al. (2019)) and specifically among the Israeli Arab population, although primarily in STEM fields (Friedman-Sokuler and Justman (2020)).

Differences in the intensity of treatment between towns ranked differently socioeconomically are also documented in Table 1. Towns with lower socioeconomic rank have substantially lower frequencies of buses (normalized by their population) that do not connect to higher education institutions (Non-College Bus Intensity), conditional on non-zero values. Town fixed effects in our regression specifications control for systematic differences between towns with earlier or later introduction of bus lines, as well as lower or higher frequencies of bus service.

5 Empirical Strategy

5.1 Regression Specification

Our detailed bus line data enable us to assign for each individual a measure for the intensity of bus lines serving their town at the time of the interview. We are further able to distinguish between the intensity of bus lines that serve destinations with higher education institutions and bus lines that do not. Thus, when estimating the effect of public transportation within a locality on various outcomes, our baseline specification takes the following form:

$$\begin{aligned} Outcome_{itmy} &= \alpha_0 + \alpha_1 NonCollegeBusIntensity_{tmy} + \alpha_2 CollegeBusIntensity_{tmy} \\ &\quad + \eta X_{itmy} + \mu_{s,y} + \gamma_t + \rho_m + \varepsilon_{itmy} \end{aligned} \tag{1}$$

We evaluate outcomes related to labor force participation or educational attainment for individual i in town t surveyed in month m in year y. Town t is part of subdistrict s. $NonCollegeBusIntensity_{tmy}$ and $CollegeBusIntensity_{tmy}$ measure the intensity of buses that do not connect or do connect to higher education institutions, respectively, and serve town t in month m in year y. We control for individual-level and town-level demographic characteristics in equation (1) (X_{ity}) - quadratic function of age, a series of indicators for the individual's relation to household head, the number of household members, and the town's socioeconomic ranking. $\mu_{s,y}$ is subdistrict-year fixed effects, γ_t is town-level fixed effects, and ρ_m is fixed effects for the month of interview. All standard errors are clustered at the town level, to account for the possibility of within-town correlation of the error term, ε_{itmy} (Bertrand et al. (2004)).

Two coefficient estimates are of greatest interest in equation (1): α_1 and α_2. α_1 measures the impact of buses that connect the town to potential employment opportunities but not to higher education institutions. α_2 measures the impact of buses that connect the town both to employment opportunities *and* higher education institutions. α_1 and α_2 tell us how our dependent variable changes when an additional bus per day per 1000 residents serves the town without or with connecting to higher education institutions, respectively. The underlying assumption is that all buses connect to potential employment opportunities, but buses that connect to higher education institutions differentially reduce the cost of schooling in com-

Table 1: Summary Statistics

	All Towns		Low Socioeconomically Ranked Towns		Higher Socioeconomically Ranked Towns	
Variable	Males	Females	Males	Females	Males	Females
Observations	1966	1804	1039	1013	927	791
Worked Last Week	0.579	0.212	0.597	0.191	0.560	0.239
	(0.494)	(0.409)	(0.491)	(0.393)	(0.497)	(0.427)
Currently Studying	0.186	0.268	0.187	0.251	0.184	0.291
	(0.389)	(0.443)	(0.390)	(0.434)	(0.388)	(0.454)
Usual Work Hours	22.49	6.55	23.08	5.62	21.83	7.74
	(23.89)	(14.71)	(24.22)	(13.61)	(23.51)	(15.94)
Usual Work Hours	45.32	34.57	45.68	33.33	44.91	35.82
Conditional on Non-Zero	(10.73)	(13.16)	(11.33)	(13.23)	(10.00)	(13.00)
Monthly Salary (2014 NIS)	2081.5	678.1	2051.5	610.3	2115.2	765.4
	(3194.7)	(1636.8)	(2526.5)	(1546.7)	(3810.8)	(1743.0)
Monthly Salary (2014 NIS)	4764.5	3596.9	4598.4	3500.9	4960.3	3701.1
Conditional on Non-Zero	(3252.4)	(1927.3)	(1608.7)	(1900.0)	(4467.3)	(1957.0)
Non-College Bus Intensity	1.020	1.010	1.275	1.149	0.733	0.830
	(2.262)	(2.311)	(2.394)	(2.302)	(2.068)	(2.312)
Non-College Bus Intensity	3.725	3.939	3.932	4.018	3.377	3.805
Conditional on Non-Zero	(2.937)	(3.051)	(2.689)	(2.647)	(3.290)	(3.636)
College Bus Intensity	0.535	0.471	0.489	0.374	0.586	0.595
	(1.766)	(1.511)	(1.144)	(1.029)	(2.272)	(1.959)
College Bus Intensity	2.474	2.334	1.959	1.745	3.286	3.211
Conditional on Non-Zero	(3.107)	(2.643)	(1.537)	(1.597)	(4.490)	(3.516)
Age	22.07	21.98	21.95	21.84	22.20	22.15
	(2.87)	(2.87)	(2.87)	(2.89)	(2.87)	(2.83)
Married	0.130	0.350	0.147	0.341	0.112	0.361
	(0.337)	(0.477)	(0.354)	(0.474)	(0.315)	(0.480)
Household Head	0.126	0.004	0.139	0.004	0.112	0.005
	(0.332)	(0.066)	(0.346)	(0.062)	(0.315)	(0.071)
Son/Daughter of HH Head	0.864	0.636	0.855	0.647	0.874	0.622
	(0.343)	(0.481)	(0.352)	(0.478)	(0.332)	(0.485)
Num of HH Members	6.022	5.684	6.652	6.148	5.311	5.086
	(2.503)	(2.624)	(2.837)	(2.923)	(1.817)	(2.030)
Interview Month	6.724	6.961	6.765	7.030	6.678	6.871
	(2.789)	(2.808)	(2.740)	(2.832)	(2.844)	(2.777)

Notes: The sample is males and females aged 18-27. Standard deviations are in parenthesis. Non-College Bus Intensity and College Bus Intensity refer to the daily (weekday) frequency of buses serving the town for each 1000 town residents. Low socioeconomically ranked towns are ranked 1 and 2 in the CBS ranking (scale of 1-10). Higher socioeconomically ranked towns are for the most part ranked 3 and 4 and the highest value in the sample is 5.

parison to buses that do not connect to higher education institutions. A tradeoff between investment in education and work is evident through α_1 in equation (1) if the results show increases in work outcomes and decreases in the probability of studying in response to greater public transportation solely to work opportunities (*Non-College Buses*). α_2's sign in equation (1) can show what is actually chosen when both education and work opportunities become more available; furthermore, opposite signs for α_2 in regressions with work versus education outcomes as dependent variables is evidence of the tradeoff between the two.

Equation (1) is similar to a standard difference-in-differences (DID) specification, only the main variable of interest is an intensity of treatment measure, rather than an indicator variable, and it is split into two - the intensity of treatment of non-college buses and of buses reaching higher education institutions. All towns are treated at some point during the sample period but there are varying points in time when public transportation is introduced so individuals in some of the treated towns serve as a control before the introduction of buses in their town, and the post-treatment period varies between towns, based on the timing that bus lines began to serve them.

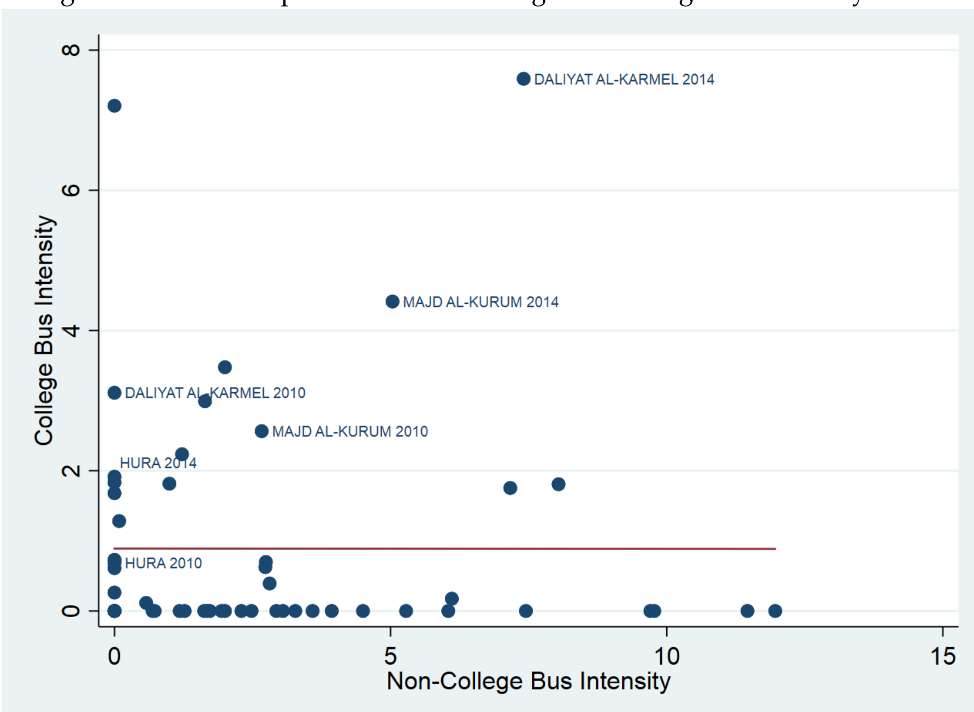
Figure 2 illustrates the relationship between the intensity of non-college and college buses by plotting for each town-year combination during 2010 and 2014 the mean values of non-college versus college bus intensities. The means are obtained across individuals, for whom bus intensities at the town-year level may vary due to differences across individuals in interview timings. As can be seen, the variables are not correlated - the correlation coefficient for all town-year combinations in our sample is -0.0008, with a p-value of 0.995.[21] Figure 2 also labels three towns from the sample, and this is to demonstrate the variation some towns exhibited in their bus intensity measures between 2010 and 2014.

Recent econometric literature has raised concern regarding staggered adoption in difference-in-differences designs, such as in equation (1) . Goodman-Bacon (2018) and De Chaisemartin and d'Haultfoeuille (2020) have shown that models of this form yield estimates that are a weighted average of all possible combinations of pairwise difference-in-differences estimators, where a pair is either the never-treated control group paired with a cohort of newly-treated observations at period t, or a cohort of newly-treated observations at period t paired with a cohort of already-treated observations during $t' < t$. The estimates derived from the latter pairings can have weights attached to them that have a negative sign. If there are negative weights and treatment effect heterogeneity over time, the two-way fixed effects estimate may have a negative (positive) sign when the true average treatment effect is positive (negative).

We address these concerns with two sets of analysis that are consistent with what has been proposed in this literature. First, our leads and lags analysis (Section 6.3) presents estimates that are derived only from comparing between the never-treated control group and treated observations (for each bus type). Second, following Callaway and SantÕAnna (2020), we estimate separate regressions for each treated cohort

[21]From this calculation, one town in the sample, Ein Raffa, was omitted due to being a significant outlier with a mean college bus intensity greater than 20 in 2014 (this did not change substantially the results in terms of coefficient correlation coefficient p-value). We also checked for a correlation using our individual-level data by running regressions with college bus intensity as the dependent variable and non-college bus intensity as the independent variable, in addition to town and subdistrict-year fixed effects, as in our regression specifications. This resulted in a coefficient estimate of 0.308 and a p-value of 0.199.

Figure 2: Relationship between Non-College and College Bus Intensity for Town-Year Combinations



Notes: The sample includes 38 towns, with the exception of Ein Rafa, which was an outlier in terms of its college bus intensity measure for 2014. The sample is limited to 2010 and 2014, the years when bus intensity measures were non-zero. For each town-year combination, the figure plots the mean value of Non-College Bus Intensity (horizontal axis - buses that serve the town and connect to labor markets but not to a higher education institution) versus College Bus Intensity (vertical axis - buses that serve the town and connect both to labor markets and to higher education institutions). Mean values are across individuals at the town-year level who may have varying bus intensity measures due to differences in interview timing. See Data Section for further details on our bus line data and towns in the sample. The line represents the linear fit of the scatter plot.

and post-treatment calendar year and then take a weighted average of these cohort-calendar year point estimates, with weights equal to each cohort-calendar year share of all treated observations (Table 9 in the Appendix). As in our leads and lags analysis, these decomposed and reweighted estimates do not compare between newly-treated towns and towns that have already been treated. The results for both sets of analysis are in line with our main results.

5.2 Identification

An ideal setting for causally identifying the effect of public transportation on labor market and educational attainment outcomes would randomly assign bus line penetrations and their frequency changes across towns. Obviously, it is plausible that these factors are not randomly assigned but rather are correlated with town characteristics that are also determinants of residents' labor market and educational attainment outcomes. To overcome this potential bias, our identification strategy exploits randomness in the exact timing of bus line penetration and frequency changes within clusters of towns that are in geographic proximity to each other, and in accordance with this, our regression specifications include town and subdistrict-year fixed effects.[22]

Our identification assumption is that absent the introduction of public transportation or changes in bus line frequencies in the towns in our sample, outcomes for individuals residing in towns that received bus line services would have followed the same path over time as outcomes for individuals residing in towns that received bus line services later in our sample period, after controlling for town and subdistrict-year fixed effects. Subdistrict-year fixed effects flexibly control for differential changes over time within clusters of towns with geographic proximity to each other and alleviate concerns that clusters of towns with populations tending more towards higher labor force participation rates or higher educational attainment received greater public transportation services. Town fixed effects control for systematic differences between towns that received public transportation services earlier versus later and between towns with lower or higher intensity levels of public transportation services. Month of interview fixed effects control for seasonality in our outcomes of interest, which may be correlated with changes in bus intensity, particularly given the subdistrict-year fixed effects which entail that some of the variation in our regression analysis is derived from variation within year.

The exact timing of implementing changes in public transportation in Israel indeed has a random component to it, and this is due to the highly centralized approval process that characterizes Israel's public transportation infrastructure. In essence, all decisions - even at the most local level - must pass through the MOT.[23] This relatively prolonged bureaucratic process generates randomness in the exact timing of bus

[22] Town-Year fixed effects could not be implemented in our regression analysis, as the variation at the town-year level - while exists for quite a few town-year combinations due to various interview timings - is still relatively minimal, especially concerning the *College Bus* intensity measure.

[23] As reference to this out-of-the-ordinary centralized planning held by the MOT, see the newspaper article in Ha'aretz from March 2019 (in Hebrew): https://www.themarker.com/dynamo/cars/.premium-1.7041329 - "Katz's Single Mistake - that we're all paying for" by Meirav Arlozorov. In this article, Israel's centralized transportation planning is described as unprecedented anywhere else in

line introductions and their frequency changes.[24]

We test for the randomness in the exact timing of bus intensity measures of non-college and college buses in the top panel of Table 2. We run regressions with annual town-level characteristics as dependent variables and mean annual bus intensity measures for the town as the explanatory variable, while controlling for town and year fixed effects. The period examined is 2003-2015. If the exact timing of changes in bus lines is indeed random, then the correlation between these changes and changes in town-level characteristics should not be statistically distinguishable from zero. Only one of ten coefficient estimates in the top panel of Table 2 is statistically significant at the 10% level.

Our claims of causality would be compromised if the Arab population responds to changes in public transportation penetration by migrating across towns. We stress that the Arab population in Israel is highly immobile with the vast majority residing in the same town they were born. The main exception is females who get married to someone outside of their birth town, in which case they move to the husband's hometown. Nevertheless, the bottom panel of Table 2 tests whether changes in the population of towns respond to bus intensity measures. Similar regressions to those in the top panel of Table 2 are run, only the explanatory variables are bus intensity measures from last year rather than the current year to allow for a lagged response in terms of town-level population compositional changes. None of the coefficient estimates are statistically significant, thus providing further reassurance that results presented in our main analysis cannot be driven by migration responses. Table 2 also shows that the mean outward and inward migration flows for our sample towns range from 2.6 to 5.2 persons per 1000 residents, which is very small.[25]

6 Results

6.1 Baseline Regression Results

Table 3 presents results for our baseline specification - equation (1). The top panel of Table 3 presents results for the young adult male population and the bottom panel for the young adult female population. For each dependent variable, we present results for specifications without individual-level controls, followed by results with individual-level controls. For the most part, the coefficient estimates do not vary substantially between the two specifications for each dependent variable, especially when they are statistically significant, thus validating to some extent that our variables of interest are not correlated with individual-level characteristics.

The top panel of Table 3 suggests that for the young adult male population, the probability of working,

the world and extreme examples are provided such as the need for MOT approval even for local road signs or traffic lights.

[24]One example of the randomness in the time until MOT approval is the introduction of bus lines to Beduin communities in southern Israel. The MOT announced its plan to introduce public transportation networks to three Beduin communities in Southern Israel in July 2007 - Rahat, Laqiye and Hura (all in our sample). In practice, Hura was introduced its first bus line in the beginning of 2008, Rahat in the middle of 2009, and Laqiye at the end of 2010.

[25]As a comparison, these figures are in the 40's for similarly-sized Jewish towns. Adukia et al. (2020) rule out meaningful migration patterns in their analysis of the effect of roads in India on middle school enrollment based on showing that no more than 4 individuals exit or enter villages with average populations that are around 1000.

Table 2: Public Transportation and Town Characteristics

	Demographic Town Characteristics Dependent Variables					
Dependent Variable	Perc. Employed Earning Less than Minimum Wage	Mean Male Salary (2010 NIS)	Mean Female Salary (2010 NIS)	Percent Graduating with Matriculation Certificate	Class Size in Elementary School	Private Cars per 1000 Adults
End of This Year Non-College	0.197	-11.16	-13.65	-0.373	0.0344	6.071*
Buses Intensity (per 1K Residents)	(0.140)	(9.256)	(11.95)	(0.512)	(0.0916)	(3.188)
End of This Year College Buses	-0.188	-4.654	-10.11	-0.340	-0.195	-2.266
Intensity (per 1K Residents)	(0.220)	(13.08)	(25.44)	(0.670)	(0.172)	(3.898)
Number of Observations	416	379	379	401	417	398
R^2	0.770	0.916	0.833	0.615	0.764	0.959
Mean Dependent Variable	52.48	5531	3172	51.13	27.76	377.6
	Migration / Population Composition Dependent Variables					
Dependent Variable	Dependent Ratio	Population Change per 1K Residents	Male Internal Migration (per 1K Residents)	Female Internal Migration (per 1K Residents)	Male Out Migration (per 1K Residents)	Female Out Migration (per 1K Residents)
End of Last Year Non-College	-8.276	0.115	0.103	0.157	-0.0690	-0.0247
Buses Intensity (per 1K Residents)	(7.44)	(0.162)	(0.125)	(0.158)	(0.0422)	(0.0799)
End of Last Year College Buses	2.457	0.243	-0.0856	-0.0465	0.0484	0.0278
Intensity (per 1K Residents)	(7.76)	(0.172)	(0.152)	(0.199)	(0.0688)	(0.124)
Number of Observations	340	455	449	455	450	453
R^2	0.937	0.911	0.457	0.431	0.577	0.603
Mean Dependent Variable	877.2	23.24	3.011	5.172	2.601	4.811

Notes: The sample period is 2003-2015. The towns are from our sample of 38 towns. Total number of towns varies based on dependent variable availability from 30 to 35. All Bus Intensity refers to the sum of Non-College and College Buses per 1000 residents. The top panel (demographic town characteristics) coefficient estimate presented is for this year's bus intensity measure and the bottom panel (migration dependent variables) coefficient estimate presented is for last year's bus intensity measure. All regressions include town and year fixed effects. Standard errors clustered at the town level are in parenthesis. Data source for town-level characteristics is Israel CBS. *** p<0.01, ** p<0.05, * p<0.1

weekly hours usually worked (p-value 0.166), and monthly salary increase in response to buses that do not connect to higher education institutions. Furthermore, the probability of currently studying decreases in response to these bus lines. When assessing the effect of buses that do connect to higher education institutions, we observe an increase in the probability of studying but the coefficient estimates on *College Bus Intensity* for labor market outcomes are not statistically significant (despite being consistently negative). We interpret this as evidence that non-college buses result in young adult males trading off greater work opportunities at the expense of higher education. However, college buses increase higher education enrollment, though this may largely be in addition to individuals who were working or studying as is - i.e., new individuals are joining the pool of young adult males who were working or studying without the additional college buses. The last two columns of Table 3 attempt to assess this by evaluating changes in the probability of neither working nor studying. The coefficient estimates exhibit a decline in the probability of neither working nor studying but they are not statistically significant, although the p-value for the response to non-college buses is less than 0.12. The p-value for college buses is nearly 0.4, so it is not possible to conclude that the population of males that neither studies nor works declined in response to college buses.

Quantitatively, each non-college bus per 1000 residents increases the probability of male young adults to be currently working by 4.06 percentage points, usual weekly hours worked by 0.96 hours, and monthly salary by 175 NIS. With a mean non-college bus value in our sample of 3.7 per 1000 residents among treated individuals (see Table 1), this implies a mean increase equivalent to 25.4, 13.4, and 33.2 percent of the pre-treatment mean probability of working, weekly hours worked, and monthly salary, respectively, in response to non-college buses. For the probability of studying, the mean intensity value of non-college buses decreases the probability of young adult males studying by 50.1 percent of the pre-treatment mean in this population. The probability of studying in response to college buses increases by 2.31 percentage points. With a mean college bus value in our sample of 2.47 among treated individuals, this implies a mean increase in the probability of studying that is equivalent to 33.2 percent of the pre-treatment mean.

For the female young adult population, we do not observe any changes in labor force participation outcomes, but we do observe opposite studying responses to non-college and college buses, as for the males. Quantitatively, these changes represent 24-32 percent of the pre-treatment mean among female young adults. While increases in the probability of studying without changes in labor market outcomes may imply an influx of new students from the population of young adult females who without the policy change would not study or work, it is more difficult to explain a decrease in the probability of studying without changes in labor force participation. Indeed, this decrease is also observed in the last two columns of Table 3, exhibiting a statistically significant increase in the probability of females neither working nor studying in response to non-college buses.

A potential explanation for the increase in females neither studying nor working in response to non-college buses may be changes in marriage patterns - females may marry more or earlier due to greater male labor market prospects and this is on account of educational attainment. While the data for this study cannot provide conclusive evidence of this hypothesis, we have found suggestive evidence of an increase in the probability of marriage among females aged 18-23 in response to non-college buses, thus supporting this channel.[26]

In order to focus on the tradeoff between working and studying, most of the subsequent analysis will be limited to the dependent variables "Worked Last Week" and "Currently Studying".

6.2 Differential Effects based on Socioeconomic Status

The effect of public transportation can vary based on an individual's socioeconomic (SE) background. Individuals from towns with a lower SE background have less access to private vehicles[27] and may perceive their economic opportunities in terms of employment differently, given potentially reduced exposure to individuals in high skilled occupations.

We examine differential effects based on socioeconomic ranking by altering equation (1) such that separate estimates are obtained for the effects on individuals from low versus higher SE ranked towns. Specifically, we split the variables $NonCollegeBusIntens$ and $CollegeBusIntens$ into two separate variables that each measure the respective bus intensity measure for individuals that are either observed in the lowest socioeconomically ranked towns (ranked 1-2) or the higher socioeconomically ranked towns (3 or over) by interacting our bus intensity measures with indicators for residing in a town ranked lowest or highest. Table 4 presents the results for this. For males, the results suggest that the effects observed in Table 3 are stronger among individuals residing in towns ranked lower socioeconomically. We note that only the college low and high socio coefficient estimates for "Currently Studying" are statistically distinguishable from each other. However, in Table 10 in the Appendix, we examine with the same specification the Hours Worked and Monthly Salary dependent variables and for the former it is also very apparent that the effects are stronger for individuals ranked lower socioeconomically (and the differences between the different SE ranked coefficient estimates are statistically significant). Table 10 in the Appendix also presents suggestive evidence of a decrease in the probability of neither working nor studying among males residing in the lowest SE ranked towns, and this is consistent with the pool of males working or studying increasing among males presenting the strongest studying response to college buses.

For females, Table 4 suggests that the probability of working is not affected by public transportation penetration for individuals from both low and high SE ranked towns. The probability of studying is statistically significantly affected by non-college buses only among low SE ranked females and college buses only among higher SE ranked females. However, other coefficient estimates in the female studying results

[26]Specifically, we ran our standard regression specification (equation (1)) with an indicator variable for being married for the sample of young adult females ages 18-23. The coefficient estimate for non-college buses is positive with a p-value slightly under 0.12. The college buses coefficient estimate is far from statistically significant. The mean dependent variable for the male sample at this age range is less than 3 percent so results for males (which are statistically insignificant) are difficult to interpret.

[27]This is verified in town-level CBS data on private vehicle ownership. In 2013, Arab towns ranked socioeconomically 2 or less had 0.4 private vehicles for each adult resident in the town aged 20-64; Arab towns ranked 3-5 socioeconomically had 0.49 private vehicles for each adult resident in the town aged 20-64.

Table 3: Public Transportation Penetration - Differential Effect based on Bus Destination

Dependent Variable	Worked Last Week		Hours Worked Usual		Monthly Salary		Currently Studying		Neither Worked nor Studying	
					Males					
Non-College Bus Intensity	0.0485***	0.0406***	1.169*	0.956	208.1***	174.9**	-0.0253***	-0.0235***	-0.0193**	-0.0139
	(0.0107)	(0.0106)	(0.641)	(0.676)	(62.54)	(67.11)	(0.00799)	(0.00754)	(0.00891)	(0.00868)
College Bus Intensity	-0.0298**	-0.0117	-1.106	-0.194	-94.74	-45.79	0.0365***	0.0231**	-0.00601	-0.0123
	(0.0119)	(0.0146)	(0.894)	(1.175)	(64.67)	(65.44)	(0.00884)	(0.0107)	(0.0130)	(0.0144)
Number of Observations	1,951	1,951	1,961	1,961	1,980	1,980	1,966	1,966	1,941	1,941
R^2	0.096	0.207	0.157	0.261	0.071	0.143	0.072	0.116	0.104	0.146
Mean Dependent Variable (Pre-Treatment)	0.591	0.591	26.48	26.48	1953	1953	0.172	0.172	0.272	0.272
					Females					
Non-College Bus Intensity	0.00328	-0.00113	0.0645	-0.137	32.24	12.13	-0.0226***	-0.0214***	0.0153*	0.0187**
	(0.0108)	(0.0106)	(0.290)	(0.329)	(43.55)	(40.03)	(0.00706)	(0.00690)	(0.00768)	(0.00749)
College Bus Intensity	0.0143	0.00886	0.600	0.441	36.63	-11.10	0.0247**	0.0239**	-0.0154	-0.00754
	(0.0108)	(0.0114)	(0.580)	(0.593)	(34.95)	(44.91)	(0.00956)	(0.0102)	(0.00983)	(0.0108)
Number of Observations	1,791	1,791	1,811	1,811	1,814	1,814	1,804	1,804	1,784	1,784
R^2	0.092	0.173	0.083	0.141	0.086	0.183	0.083	0.189	0.120	0.170
Mean Dependent Variable (Pre-Treatment)	0.186	0.186	6.353	6.353	529.4	529.4	0.250	0.250	0.587	0.587
Town Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Subdistrict-Year Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Individual Controls		✓		✓		✓		✓		✓

Notes: The sample is males/females in the sample towns ages 18-27. Each column in each panel (males vs. females) presents the coefficient estimates for α_1 and α_2 from equation (1). Control variables are the following: quadratic function of age, indicators for relation to household head, indicators for month of interview, number of household members, town's socioeconomic ranking (indicators). Standard errors clustered at the town level are in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

are still in the right direction and at the same order of magnitude, just not statistically significant. We note that in Table 10 in the Appendix hours worked increase in response to non-college buses and decrease in response to college buses among females from low SE ranked towns, perhaps suggesting that changes in labor force participation among females from low SE ranked towns are at the intensive rather than extensive margin.

6.3 Leads and Lags Analysis

Estimating separate effects for periods leading up to treatment and post-treatment primarily serves two purposes. First, the pre-treatment estimates allow us to examine whether differential pre-treatment trends existed in our outcomes of interest. Second, the time span that has elapsed since the initial introduction of public transportation to one's town may matter in terms of awareness, adaptation, and social and traditional perceptions.

We perform a leads and lags analysis that is similar to an event study analysis as it allows us to test for pre-trends and differential effects over time in our outcomes of interest. However, our leads and lags analysis varies from standard event studies, as our post-treatment variables (the lags) are not indicator variables but rather intensity of treatment variables. This is due to the importance of bus intensity measures in our setting for evaluating the effect of public transportation penetration, and this is demonstrated in Table 11 in the Appendix.[28] As such, , our leads and lags regression specification takes the following form:

$$
\begin{aligned}
Outcome_{itmy} \quad = \quad & \pi_0 + \sum_{p=-4}^{-1} \pi_p^{NC} NonCollegePrePeriod_{tmy}^p + \sum_{p=-4}^{-1} \pi_p^{C} CollegePrePeriod_{tmy}^p \\
& + \sum_{p=1}^{3} \pi_p^{NC} NonCollegePostPeriodIntens_{tmy}^p + \sum_{p=1}^{3} \pi_p^{C} CollegePostPeriodIntens_{tmy}^p \\
& + \eta X_{itmy} + \mu_{s,y} + \gamma_t + \rho_m + \varepsilon_{itmy} \qquad (2)
\end{aligned}
$$

Equation (2) evaluates the effect of non-college and college buses for seven periods - four pre-treatment and three post-treatment. Treatment begins with initial public transportation penetration for the respective bus type (non-college versus college). The pre-treatment periods are: 7 or more, 5-6, 3-4, and 1-2 years pre-treatment, for values of p that are -4, -3, -2, and -1, respectively. The post-treatment periods are 0-1, 2-4, and 5 or more years post-treatment for values of p that are 1, 2, and 3, respectively. The pre-treatment variables are indicator variables, while the post-treatment variables are bus intensity measures. Thus, for example, individuals observed two years after the initial introduction of non-college buses to their town will receive a non-zero value for the variable $NonCollegePostPeriodIntens^2$ that is equal to the bus intensity

[28]In Table 11 in the Appendix, we conducted a regression analysis with indicator variables for non-zero bus intensity measures and our results demonstrate the importance of the actual intensity measures rather than just indicator variables to attain a complete understanding of the effect of public transportation penetration.

Table 4: Public Transportation Penetration - Differential Effects based on Bus Destination and Town's Socioeconomic Ranking

Dependent Variable	Worked Last Week	Currently Studying	Worked Last Week	Currently Studying
	Males		Females	
Non-College Bus Intensity - Low Socio	0.0467***	-0.0354***	0.00593	-0.0274***
	(0.0110)	(0.0121)	(0.00991)	(0.00712)
College Bus Intensity - Low Socio	-0.00856	0.0625***	-0.0114	0.0284
	(0.0316)	(0.0179)	(0.0207)	(0.0214)
Non-College Bus Intensity - High Socio	0.0305*	-0.0186**	-0.00524	-0.0127
	(0.0151)	(0.00792)	(0.0198)	(0.0109)
College Bus Intensity - High Socio	-0.0175	0.0263***	0.00901	0.0297***
	(0.0164)	(0.00826)	(0.0119)	(0.0102)
Number of Observations	1,951	1,966	1,791	1,804
R-Squared	0.208	0.117	0.173	0.189
Mean Dependent Variable (Pre-Treatment) - Low Socio	0.621	0.176	0.153	0.237
Mean Dependent Variable (Pre-Treatment) - High Socio	0.561	0.167	0.227	0.266
P-Value T-Test Non-College	0.415	0.247	0.613	0.244
P-Value T-Test College	0.622	0.00247	0.0760	0.922
Town Fixed Effects	✓	✓	✓	✓
Subdistrict-Year Fixed Effects	✓	✓	✓	✓
Individual Controls	✓	✓	✓	✓

Notes: Each column presents coefficient estimates from a variation of equation (1) that interacts the non-college and college bus intensity measures with indicator for low and high SE ranked towns. Control variables are the following: quadratic function of age, indicators for relation to household head, indicators for month of interview, number of household members, town's socioeconomic ranking (indicators). Low (High) Socio refers to individuals from towns ranked 1-2 (3-5) in the CBS socioeconomic ranking - see Section 4 for details on the CBS socioeconomic town ranking. P-Value T-Test refers to the p-value for t-tests of equality between college/non-college low and high socio coefficient estimates. Standard errors clustered at the town level are in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

measure assigned to that individual when observed.[29]

We note that equation (2) varies from standard event study specifications in that it does not have an excluded period. This is possible due to using bus intensity measures, rather than indicator variables, for the post-treatment periods. Thus, the interpretation of the non-college and college coefficient estimates in equation (2) is in comparison to individuals in towns that did not receive non-college or college buses, respectively, during the sample period - i.e. a control group for each of the bus types.[30] This is in contrast to the standard event study coefficient estimate interpretation that is the difference relative to the excluded period. As the pre-treatment variables are indicator variables, their non-college and college coefficient estimates measure the mean change in the outcome of interest for each pre-treatment period in comparison to individuals in towns that did not receive any non-college or college buses, respectively. As the post-treatment variables are bus intensity measures, their non-college and college coefficient estimates measure the mean change in the outcome of interest for each additional bus per 1000 residents in comparison to individuals in towns that did not receive any non-college or college buses, respectively.

For presenting the results from equation (2), we plot the mean effect of each bus type for each period in Figure 3. This is done for the dependent variables and samples that have already exhibited meaningful results in Sections 6.1 and 6.2: males reporting whether they worked last week and both sexes reporting whether they are currently studying. We combine both sexes for the Currently Studying results as they exhibited similar patterns in their response to buses (even quantitatively) in Table 3 and the precision of the estimates increases with this larger sample. Overall, for each dependent variable, equation (2) has 14 coefficients of interest: four pre-treatment periods and three post-treatment periods for non-college and college buses. Because the pre-treatment variables in equation (2) are indicator variables, while the post-treatment variables are intensity of treatment variables, the scales of the coefficient estimates differ. The former estimate the mean effect of being observed several periods prior to initial public transportation penetration, while the latter estimate the mean effect for each additional bus per 1000 residents of being observed several periods after the initial introduction of public transportation. Therefore, in our plotting we rescale the post-treatment coefficient estimates such that they are equal to the overall mean effect of being observed several periods after initial public transportation introduction. We do this by multiplying the coefficient estimate by the mean corresponding bus intensity measure for that period and adjusting the standard errors accordingly.

The male results for whether individuals worked last week are consistent with the results observed in Table 3. We see a positive response to non-college buses that appears to be fairly stable up to four years after the initial introduction of public transportation and possibly even beyond that although the mean effect of non-college buses more than five years later is larger in magnitude and noisier. The male work

[29]Note that as in a standard event study analysis, this individual will receive zero values for all other pre- and post-treatment period variables defined in equation (2).

[30]According to Table 7, there are four and eighteen towns that received no non-college and no college buses, respectively. Although the non-college control group consists of only four towns, we note that they are geographically diverse and cover three of the five regions in Israel.

response to college buses is for the most part not statistically significant, although 2-4 years after the initial introduction of public transportation there appears to be a positive effect that is statistically significant at the 10 percent level. Taken together, all the mean estimated effects on male work in response to college buses are consistent with the null effect observed in Table 3, although there may be an increase in the probability of working in response to college buses after 2-4 years. Importantly, the pre-treatment estimated effects for males working are not statistically distinguishable from zero, which is reassuring for establishing the validity of our research design concerning pre-treatment parallel trends between the treatment and control groups.[31]

When Currently Studying is the dependent variable, the post-treatment estimates show a decrease in the probability of studying in response to non-college buses that seems to grow in magnitude over time since the initial introduction of non-college buses.[32]The college bus effect appears to be positive in terms of the point estimates and their statistical significance, but this is not conclusive given the large value of the coefficient estimate 3-4 years pre-treatment. The statistically significant coefficient estimate 3-4 years before the initial introduction of college buses produces less concise evidence on pre-existing trends when Currently Studying is the dependent variable. We note that this is one of 16 pre-treatment coefficient estimates presented in Figure 3.[33]

7 Robustness Checks

7.1 Placebo Analysis

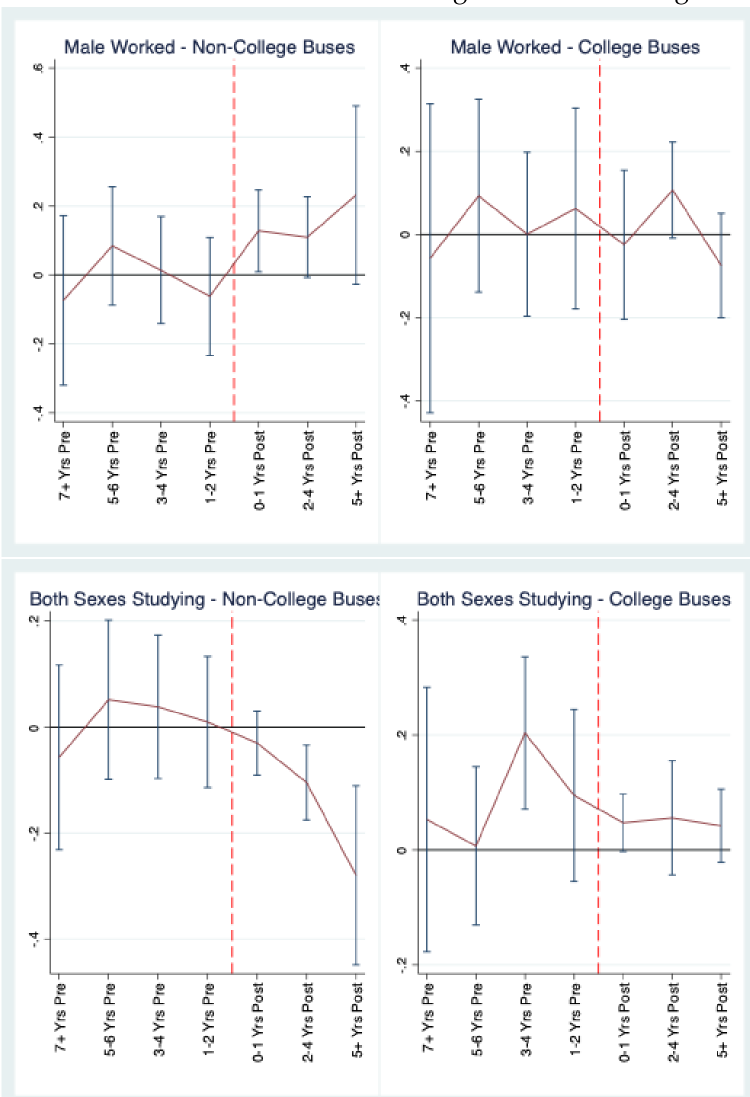
In Table 5, we test for pre-existing trends in our outcomes of interest by using the same sample of individuals from our analysis, only excluding 2014, and for 2004, 2007, and 2010 observations, we assign bus intensities from 2009, 2012, and 2015, respectively. We note that in 2010, many towns already had positive bus service measures in our data, but we still maintain that year in our analysis so that null effects will not be driven by a substantially smaller sample size. In the top panel of Table 5, the placebo analysis is presented. In the bottom panel of Table 5, an analysis with the true bus intensity measures is presented with just 3 years of data - 2007, 2010 and 2014 - for the purpose of showing that the null effects observed in the top panel of Table 5 are not driven by lack of statistical power. Indeed, the results from Table 3 still hold in the bottom panel of Table 5.

[31]The results for females reporting whether they worked last week exhibited no evidence of pre-existing trends, although the post-treatment effects estimated were noisy.

[32]The non-college response increase over time is not just a result of our adjustment for obtaining the mean effect by multiplying the coefficient estimate in equation (2) by the mean intensity of non-college buses for the different periods, which is possible if the bus intensity increases over time. Rather, the coefficient estimates π_1^{NC}, π_2^{NC}, and π_3^{NC} increase over time as well in the regression result for equation (2) with Currently Studying as a dependent variable.

[33]Separate results by gender with Currently Studying as a dependent variable exhibited similar patterns for the most part, although the male college response was more clearly positive than the female, which only exhibited a statistically significant response 5+ year after the initial introduction of college buses. For both genders, the non-college response increased in magnitude over time, although this was more apparent among males. Both genders also exhibited a statistically significant college coefficient estimate 3-4 years before the initial introduction of college buses.

Figure 3: Leads & Lags Estimates



Notes: Each figure plots the estimated mean effect of non-college and college buses in the left and right sides, respectively, for each period based on equation (2) for Worked Last Week as the dependent variable for the male sample and Currently Studying as the dependent variable for the male and female samples combined in the top and bottom figures, respectively. 95 percent confidence intervals that account for within-town clustering are reported with vertical lines. The pre-treatment estimates presented are π^{NC}_{-4}, π^{NC}_{-3}, π^{NC}_{-2}, and π^{NC}_{-1}, and π^{C}_{-4}, π^{C}_{-3}, π^{C}_{-2}, and π^{C}_{-1} from equation (2) for non-college and college buses, respectively. The post-treatment estimates presented are π^{NC}_{1}, π^{NC}_{2}, and π^{NC}_{3}, and π^{C}_{1}, π^{C}_{2}, and π^{C}_{3} from equation (2) multiplied by the mean corresponding bus intensity measure for that period, for non-college and college buses, respectively. Standard errors for the post-treatment estimates presented are adjusted accordingly.

Table 5: Placebo Analysis - Assigning Bus Intensities Five Years Later for 2004-2010 Data

Dependent Variable	Worked Last Week		Currently Studying	
	Males	Females	Males	Females
	Placebo Results			
Non-College Bus Intensity	-0.0204	-0.0157	0.000691	-0.00676
	(0.0128)	(0.0102)	(0.00528)	(0.0121)
College Bus Intensity	-0.0329	0.0122	0.00332	0.0317
	(0.0251)	(0.0123)	(0.0145)	(0.0259)
Number of Observations	1,648	1,502	1,654	1,510
R-Squared	0.206	0.174	0.108	0.194
Mean Dependent Variable (2004-2007)	0.591	0.186	0.172	0.250
	3-Year Analysis			
No College Bus Intensity	0.0408***	-0.00670	-0.0189**	-0.0175**
	(0.0137)	(0.0110)	(0.00930)	(0.00776)
College Bus Intensity	-0.0214	0.0162	0.0293**	0.0207**
	(0.0156)	(0.0122)	(0.0112)	(0.00962)
Number of Observations	1,459	1,299	1,474	1,312
R-Squared	0.214	0.190	0.129	0.207
Mean Dependent Variable (Pre-Treatment)	0.590	0.158	0.171	0.231
Town Fixed Effects	✓	✓	✓	✓
Subdistrict-Year Fixed Effects	✓	✓	✓	✓
Individual Controls	✓	✓	✓	✓

Notes: Each column presents the coefficient estimate for α_1 and α_2 from equation (1) for regressions with either males or females for each dependent variable. Control variables are the following: quadratic function of age, indicators for relation to household head, indicators for month of interview, number of household members, town's socioeconomic ranking (indicators). The placebo results (top panel) use 2004, 2007 and 2010 data and assign to individuals in these years 2009, 2012 and 2015 bus measures, respectively. The bottom panel uses the true bus intensity measures with 2007, 2010 and 2014 data. Standard errors clustered at the town level are in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

7.2 Older Adult Population

We ran the same regressions in equation (1) on all individuals aged 35-50 from our sample of 38 towns. Our dependent variables are whether the individual worked last week and the years of schooling completed. The former dependent variable allows us to verify that quantitatively different effects based on bus destination do not hold for the older adult population. For them, the tradeoff between working and investing in higher education that the young adult population faces is irrelevant. Furthermore, older adult males' labor force outcomes should be less affected by public transportation penetration as their access to private vehicles is greater. The latter dependent variable allows us to test for a correlation between a central demographic characteristic - completed years of schooling - and bus intensity measures.

The results of these regressions are presented in Table 6. We observe a null effect for both types of buses on males' probability of working last week. For females, the non-college bus coefficient is not statistically significant but a positive effect cannot be ruled out with certainty and the college bus coefficient shows increased probabilities of working. Given that public transportation likely increased female mobility even among older adults, this result makes sense. The effects of buses on years of schooling are not statistically significant, thus lending further support to a lack of correlation between pre-determined demographic characteristics and bus intensity measures beyond Table 2.

7.3 Additional Robustness Checks

In the Appendix, we present results for four additional robustness checks: Results with a single explanatory variable rather than both types of bus intensity measures are presented in Table 12. The results are very similar to those presented in Table 3. This table also includes results for regression specifications with just the intensity of all buses as the single explanatory variable, which highlights the importance of accounting for differential effects based on bus destination in assessing public transportation penetration; Expanding the sample for the regression analysis to include all towns in the Arab Survey that did not have public transportation as of the end of 2007 (58 towns), rather than our limitation to treated towns that had at least one bus line during our sample period (Table 8). The results are quite similar; Excluding districts from our regression analysis (Table 13) - this alleviates concern that our results are driven by a single district or a group of towns in close proximity to each other.

8 Concluding Remarks

Improving access to employment and higher education institutions for disadvantaged communities has received much attention in the past few decades, as this is expected to generate benefits economically, socially, and morally in terms of equal opportunities. This study evaluates one policy measure - public transportation investment - and shows that it yields improvements in employment and educational attainment. Nonetheless, consideration of the tradeoff between investing in education and working for pay

Table 6: Public Transportation Penetration and the Older Adult Population (Ages 35-50)

Dependent Variable	Worked Last Week	Years of Schooling	Worked Last Week	Years of Schooling
	Males		Females	
Non-College Bus Intensity	0.00876	0.118	0.0101	0.00776
	(0.00946)	(0.0963)	(0.00913)	(0.0749)
College Bus Intensity	0.00181	0.0666	0.0193*	-0.120
	(0.0179)	(0.0840)	(0.0109)	(0.105)
Number of Observations	1,665	1,580	1,731	1,615
R-Squared	0.142	0.223	0.140	0.334
Mean Dependent Variable (Pre-Treatment)	0.753	10.93	0.174	9.139
Town Fixed Effects	✓	✓	✓	✓
Subdistrict-Year Fixed Effects	✓	✓	✓	✓
Individual Controls	✓	✓	✓	✓

Notes: Each column presents the coefficient estimate for α_1 and α_2 from equation (1) for regressions with either males or females for each dependent variable for the sample of adults ages 35-50. Control variables are the following: quadratic function of age, indicators for relation to household head, indicators for month of interview, number of household members, town's socioeconomic ranking (indicators). Standard errors clustered at the town level are in parenthesis. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

among young adults is essential in order to fully assess the impact of any policy measure expected to increase access to employment and/or education opportunities. In line with this, our results demonstrate that greater connectivity to work opportunities should be accompanied by greater connectivity to higher education as well - otherwise, the greater connectivity can backfire in terms of the long-run human capital investment decisions among the young adult population.

Our results additionally suggest that physical accessibility may not be the only factor inhibiting proper integration of females from traditional communities into the economy - traditional barriers and marriage opportunities may also play a role, as potentially demonstrated by less conclusive results concerning the effect of public transportation on young adult females' labor market outcomes.

We believe our results concerning the tradeoff between work and higher education can be relevant to numerous geographically segregated disadvantaged communities in many developed economies. Furthermore, if public transportation penetration changes higher educational attainment or labor market patterns, then this can have long-term effects that our results do not entirely account for due to the relatively short time horizon in our data in terms of years post initial public transportation penetration. In particular, changes in human capital accumulation can shape the long-term aspirations of adolescents and young adults through role model effects or exposure to various opportunities that some of the population was unaware of prior to greater access to opportunities outside of town. Future research, if additional data is made available, may wish to examine these aspects. An additional aspect that our data is not capable of addressing concerns the distinction between being employed and labor force participation. Our data only reports whether individuals worked last week, thus only capturing employment outcomes, but we are unable to determine whether changes in employment are driven by changes in labor force participation or by changes in unemployment rates.

When compared to the costs of schooling and road infrastructure, or establishing mass employment centers within disadvantaged communities, the cost of public transportation seems rather minimal, especially if it is in terms of bus lines. Thus, public transportation may not only be effective in enhancing the welfare of disadvantaged communities but also cost-beneficial, especially when compared to numerous alternative policy measures.

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Appendix

A List of Towns in the Sample

Table 7 provides a list of all 38 towns in our sample with information on when the different types of buses were initially introduced, and the number of observations (young adults ages 18-27) during each year.

B Public Transportation Penetration - Including Towns without Bus Service at the End of the Sample Period

Table 8 presents our regression results with the sample of towns that includes towns without bus lines at the end of 2014. As can be seen, the results are highly similar to the results in Table 4.

C Reweighted Difference-in-Differences Estimates

The staggered introduction of public transportation within our difference-in-differences framework raises concern that the estimates produced by a standard OLS regression of equation (1) may be biased due to already-treated towns serving as a control group to newly-treated towns along with the potential for heterogeneous treatment effects over time (De Chaisemartin and d'Haultfoeuille (2020); Goodman-Bacon (2018)). In addition to our leads and lags analysis presented in Section 6.3, where the estimates are derived from comparisons between the never-treated control observations and treated observations, we also deal with this concern by presenting alternative difference-in-differences estimates, as suggested in Callaway and SantÕAnna (2020).

Our new estimates are volume-weighted means of difference-in-differences estimates across each cohort of towns based on the year of initial bus penetration for each bus type (i.e., non-college and college buses). These are compared to observations from never-treated towns for the specific bus type. Each regression is further limited to a single post-treatment calendar year among the potential post-treatment years in our sample. Specifically, to construct this estimate, we ran separate regressions for each treated cohort using only observations from towns whose treatment begins in year y along with observations from never-treated towns and using only the pre-treatment observations and one post-treatment year from within this sample. Note that we did this separately for each bus type, as treatment timing and the control group vary between the two bus types. Next, we took a weighted average of each of the derived point estimates with each weight equal to the number of observations in the treated cohort in the cohort-calendar year-specific regression divided by the sum of these observations for all cohort-calendar year-specific regressions - in other words, weights are equal to each cohort-calendar year share of all treated observations.

Table 7: Town List

Town Name	District	Non-College Bus Introduction	College Bus Introduction	2004 Obs	2007 Obs	2010 Obs	2014 Obs
Jaljulye	Central	Q3-4 2008	-	28		7	16
Kafar Bara	Central	Q3-4 2008	-	17	29	18	
Kafar Qasem	Central	Q2 2011	-	16	52	24	8
Qalansawe	Central	Q3-4 2013	Q1 2010	17	40	37	20
Tayibe	Central	Q3-4 2013	Q1 2010	68	42	40	35
Tire	Central	Q3-4 2013	Q1 2010	71	111	28	36
Zemer	Central	Q3-4 2008	-		20	25	
Ar'Ara	Haifa	Q3-4 2010	Q1 2014	42	23	40	
Daliyat Al-Karme	Haifa	Q1 2011	Q1 2010	61	53	58	29
Jisr Az-Zarqa	Haifa	Q3-4 2013	-	36	26	10	23
Kafar Qara	Haifa	Q3-4 2010	Q1 2014	34	16	37	
Ma'Ale Iron	Haifa	Q1 2013	-	75	26	15	19
Meiser	Haifa	Q3-4 2008	-			8	10
Umm Al-Fahm	Haifa	Q3-4 2010	Q3-4 2010	96	127	12	8
Abu Ghosh	Jerusalem	-	Q1 2009		23		16
Ein Rafa	Jerusalem	-	Q1 2009		32		13
Beit Jann	North	Q3-4 2008	-	38	31		26
Fassuta	North	Q1 2011	-			26	
I'Billin	North	Q1 2010	Q1 2010		29	33	17
Iksal	North	Q3-4 2008	-	25	41	16	25
Judeide-Maker	North	Q1 2010	-	32	36	26	23
Julis	North	Q1 2010	-			25	
Kabul	North	Q1 2010	Q3-4 2009		25	36	
Kisra-Sumei	North	Q3-4 2008	-		22	34	
Majd Al-Kurum	North	Q1 2009	Q1 2010		10	53	15
Muqeible	North	Q3-4 2008	-	28			12
Nahef	North	Q1 2010	Q1 2009	46		51	13
Peqi'In (Buqei'A)	North	Q3-4 2008	-		30		21
Sajur	North	Q3-4 2009	-	43			20
Sha'Ab	North	-	Q3-4 2009	31	33	32	
Tuba-Zangariyye	North	Q1 2013	-		20		23
Yirka	North	Q1 2010	-	29	27	27	32
Ar'Ara-Banegev	South	Q3-4 2010	Q3-4 2010	43	49	25	30
Hura	South	Q2 2014	Q1 2008		39	22	35
Kuseife	South	Q1 2008	Q3-4 2009		44	30	18
Laqye	South	Q3-4 2010	Q3-4 2010		53		25
Rahat	South	Q2 2009	Q2 2009	75	127	103	51
Tel Sheva	South	-	Q3-4 2010	33	29	28	

Notes: Total number of towns: 38. Non-College/College Bus Introduction is quarter during which the relevant type of bus was initially introduced. Interview Difference is the number of days between the first and last interview for that year in the sample. Obs is the number of males and females ages 18-27 interviewed from that town in that year.

Table 8: Including Towns without Bus Lines at the end of 2014

Dependent Variable	Worked Last Week	Currently Studying	Worked Last Week	Currently Studying
	Males		Females	
Non-College Bus Intensity	0.0312**	-0.0192**	0.00252	-0.0185***
	(0.0124)	(0.00741)	(0.00984)	(0.00628)
College Bus Intensity	-0.0185	0.0257**	0.0104	0.0249**
	(0.0143)	(0.00982)	(0.0114)	(0.0102)
Number of Observations	2,285	2,304	2,091	2,107
R-Squared	0.200	0.118	0.176	0.195
Mean Dependent Variable (Pre-Treatment)	0.591	0.172	0.186	0.250
Town Fixed Effects	✓	✓	✓	✓
Subdistrict-Year Fixed Effects	✓	✓	✓	✓
Individual Controls	✓	✓	✓	✓

Notes: Each column presents the coefficient estimates for α_1 and α_2 from equation (1) with the entire sample of towns in the Arab Survey that did not have bus lines serving them before 2008. Control variables are the following: quadratic function of age, indicators for relation to household head, indicators for month of interview, number of household members, town's socioeconomic ranking (indicators). Standard errors clustered at the town level are in parenthesis. Number of towns in these regressions is 58. *** p<0.01, ** p<0.05, * p<0.1

Table 9: Cohort-Calendar Year Estimation

Dependent Variable	Worked Last Week Males		Currently Studying Both Sexes	
	Standard Regression	Wgt. Avg. of Cohort-Calendar Yr	Standard Regression	Wgt. Avg. of Cohort-Calendar Yr
Non-College Bus Intensity	0.0406***	0.0895	-0.0227***	-0.2483
	(0.0106)		(0.00552)	
College Bus Intensity	-0.0117	-0.0067	0.0230***	0.0133
	(0.0146)		(0.00698)	

Notes: For each dependent variable, the first column presents results from equation (1) (as in Table 3 only the Currently Studying results are combined for both genders). The second column reports the results obtained by estimating equation (1) separately based on treatment timing and a single post-treatment calendar year and then creating a weighted average of these estimates based on the each treatment timing cohort-calendar year share of all treated observations (following Callaway and SantÕAnna (2020)).

Results are presented in Table 9 for the two dependent variables with the main results of the paper: Worked Last Week for the young adult male population and Currently Studying for the young adult male and female population. For each dependent variable, the first column presents the OLS estimates, while the second column presents the new weighted estimates. The new estimates show positive and negative effects where the OLS estimates yield statistically significant positive and negative effects, respectively. Although the magnitude of the effect of the new estimates is not entirely aligned with that of the OLS estimates, and for Currently Studying the non-college is substantially larger, the direction of the new estimates is in line with the OLS results.

D Differential Effects based on Socioeconomic Ranking - Additional Dependent Variables

Table 10 complements Table 4 by presenting the same results only for our three other outcomes: usual hours worked last week, monthly salary, and neither working nor studying. As in Table 4, the statistically significant effects appear to be primarily driven by individuals in the towns ranked lowest socioeconomically. Furthermore, the probability of males in low SE ranked towns neither working nor studying decreases in response to college buses (p-value 0.15). This is consistent with our hypothesis that the pool of males working or studying increases in response to these buses. An additional interesting result arises with regards to females in the towns ranked lowest socioeconomically, who are exhibiting similar patterns to those of males in terms of the effect of non-college and college bus intensity on usual weekly hours worked. This raises the possibility that public transportation affects labor market outcomes even among females ranked lowest socioeconomically, although this is at the intensive margin rather than the extensive margin, as exhibited

Table 10: Differential Effects based on Socioeconomic Ranking - Other Dependent Variables

Dependent Variable	Hours Worked Usual	Monthly Salary	Neither Worked nor Studying	Hours Worked Usual	Monthly Salary	Neither Worked nor Studying
		Males			Females	
Non-College Bus Intensity - Low Socio	2.277***	236.7***	-0.00655	0.671**	1.968	0.0208**
	(0.620)	(77.44)	(0.0117)	(0.263)	(51.60)	(0.00880)
College Bus Intensity - Low Socio	-3.505**	-127.5	-0.0517	-1.463***	4.183	-0.00672
	(1.595)	(178.0)	(0.0355)	(0.419)	(99.01)	(0.0217)
Non-College Bus Intensity - High Socio	0.0920	109.3	-0.0120	-0.768**	23.63	0.0145
	(0.793)	(70.16)	(0.0134)	(0.348)	(69.55)	(0.0156)
College Bus Intensity - High Socio	-0.752	-85.32	-0.0120	0.269	-4.867	-0.0108
	(0.786)	(62.32)	(0.0155)	(0.255)	(52.83)	(0.0105)
Number of Observations	1,961	1,980	1,941	1,811	1,814	1784
R-Squared	0.265	0.143	0.148	0.146	0.183	0.17
Mean Dependent Variable (Pre-Treatment) - Low Socio	27.949	1925.491	0.237	4.952	418.551	0.631
Mean Dependent Variable (Pre-Treatment) - High Socio	25.004	1981.021	0.309	8.124	668.949	0.534
P-Value T-Test Non-College	0.0324	0.196	0.760	0.00111	0.805	0.736
P-Value T-Test College	0.00661	0.756	0.0727	3.27e-08	0.865	0.738
Town Fixed Effects	✓	✓	✓	✓	✓	✓
Subdistrict-Year Fixed Effects	✓	✓	✓	✓	✓	✓
Individual Controls	✓	✓	✓	✓	✓	✓

Notes: Each column presents coefficient estimates from a variation of equation (1) that interacts the bus intensity measures with indicators for low or higher SE ranked towns. Control variables are the following: quadratic function of age, indicators for relation to household head, indicators for month of interview, number of household members, town's socioeconomic ranking (indicators). P-Value T-Test refers to p-value for t-tests of equality between college/non-college low and high socio coefficient estimates. Standard errors clustered at the town level are in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

by the null effects for whether females worked last week in Table 4.

E Public Transportation Penetration - Indicator Variables Instead of Intensity of Treatment

Table 11 presents our regression results from equation (1) but with indicator variables for non-zero bus intensity measures rather than the bus intensity measures themselves. The results present coefficient estimates that are qualitatively in the same direction as those presented in Table 3, and in several cases the t-statistics are greater than 1. However, all but one coefficient estimate is statistically significant, and this is in contrast to the results in Table 3. Clearly one cannot rely on such variation to present meaningful

Table 11: Public Transportation Penetration with Indicator Variables the Main Explanatory Variables

Dependent Variable	Worked Last Week	Currently Studying	Worked Last Week	Currently Studying
	Males		Females	
Non-Zero Non-College Buses	0.111	-0.00997	0.0843**	-0.0866
	(0.0817)	(0.0729)	(0.0415)	(0.0561)
Non-Zero College Buses	-0.00454	0.0659	0.0399	-0.0181
	(0.0721)	(0.0696)	(0.0471)	(0.0499)
Number of Observations	1,951	1,966	1,791	1,804
Mean Dependent Variable (Pre-Treatment)	0.591	0.172	0.186	0.250
Town Fixed Effects	✓	✓	✓	✓
Subdistrict-Year Fixed Effects	✓	✓	✓	✓
Individual Controls	✓	✓	✓	✓

Notes: Each column presents the coefficient estimates for α_1 and α_2 from equation (1) but the variables of interest are indicator variables for non-zero bus intensity measures rather than the bus intensity measures themselves. Control variables are the following: quadratic function of age, indicators for relation to household head, indicators for month of interview, number of household members, town's socioeconomic ranking (indicators). Standard errors clustered at the town level are in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

results on the effect of public transportation penetration on labor market and schooling outcomes, thus highlighting the importance of accounting for the intensity of treatment in the analysis.

F Separate Regressions for Each Explanatory Variable

Our regression specification - as outlined in equation (1) - measures the effect of non-college and college buses on labor market and schooling outcomes in a single regression that includes both explanatory variables. In Table 12, we present results when the regression is run on each explanatory variable separately. In addition, we also present results when the single explanatory variable in the regression is the intensity of all buses, the sum of the non-college and college bus intensity measures. The regression specification and sample is exactly the same as in equation (1). Each cell under each dependent variable in Table 12 presents the coefficient estimate from a separate regression when the single bus explanatory variable in that regression is the variable stated in the left-most column.

For the top two rows, with coefficient estimates for Non-College and College Bus Intensity, the magnitude and statistical significance of the coefficient estimates is very similar to those presented for the same variables in the regression specification with both explanatory variables in Table 3. This is also consistent with the lack of correlation between these two variables presented in Figure 2. For the All Bus Intensity measure, presented in the third row, there are some statistically significant results suggesting that male labor market outcomes are positively affected by greater bus penetration and females' and to some extent males' probability of studying is negatively affected. However, comparing the All Bus Intensity measure results in Table 12 with the results of Table 3 clearly demonstrates that a regression specification taking both types of bus measures into account provides a much more informative picture and in some cases - particularly for the dependent variable whether the individual is currently studying - highlights the qualitatively different effects of each bus type.

G Excluding Districts

Table 13 presents our regression results from equation (1) with a different set of towns (based on their district) excluded in each panel. The results for the most part remain quite similar to the results observed in Table 3.

Table 12: Public Transportation and Labor Market and Schooling Outcomes - Separate Regressions for Each Explanatory Variable

Dependent Variable	Worked Last Week	Currently Studying	Worked Last Week	Currently Studying
	Males		Females	
Non-College Bus Intensity	0.0398***	-0.0218***	-0.000422	-0.0195***
	(0.0103)	(0.00778)	(0.0104)	(0.00605)
College Bus Intensity	-0.00244	0.0177*	0.00852	0.0176
	(0.0201)	(0.00983)	(0.0105)	(0.0122)
All Bus Intensity	0.0271**	-0.0114	0.00130	-0.0104*
	(0.0107)	(0.00766)	(0.00760)	(0.00534)
Number of Observations	1,951	1,966	1,791	1,804
Mean Dependent Variable	0.591	0.172	0.186	0.250
Town Fixed Effects	✓	✓	✓	✓
Subdistrict-Year Fixed Effects	✓	✓	✓	✓
Individual Controls	✓	✓	✓	✓

Notes: Each column presents results from a variation of equation (1), only with a single explanatory variable measuring bus intensity, rather than the two College and Non-College bus intensity explanatory variables. Thus, each row presents the estimates for the main coefficient of interest from a single regression. The first and last two columns are results for the young adult male and female population, respectively. Control variables are the following: quadratic function of age, indicators for relation to household head, indicators for month of interview, number of household members, town's socioeconomic ranking (indicators). Standard errors clustered at the town level are in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

Table 13: Public Transportation Penetration - Excluding Districts

Excluded District/s	North	Haifa	Jerusalem & Center	South	North	Haifa	Jerusalem & Center	South
	Worked Last Week - Males				**Worked Last Week - Females**			
Non-College Bus Intensity	0.0601***	0.0401***	0.0343***	0.0229	0.0150	-0.00708	-0.00262	0.00308
	(0.00703)	(0.0107)	(0.00997)	(0.0147)	(0.00995)	(0.00948)	(0.0113)	(0.0207)
College Bus Intensity	-0.0252*	-0.0122	0.0276	-0.0260**	-0.0305**	0.0164	-0.00729	0.0139
	(0.0138)	(0.0153)	(0.0395)	(0.0121)	(0.0135)	(0.0111)	(0.0182)	(0.0106)
Number of Observations	1,341	1,515	1,457	1,540	1,260	1,349	1,404	1,360
R^2	0.200	0.203	0.215	0.224	0.198	0.176	0.162	0.182
Mean Dependent Variable (Pre-Treatment)	0.589	0.609	0.565	0.601	0.185	0.178	0.171	0.209
	Currently Studying - Males				**Currently Studying - Females**			
Non-College Bus Intensity	-0.0273**	-0.0237***	-0.0269***	-0.0156	-0.0321***	-0.0199***	-0.0176**	-0.0184
	(0.0120)	(0.00741)	(0.00793)	(0.00927)	(0.00686)	(0.00657)	(0.00691)	(0.0117)
College Bus Intensity	0.0273	0.0232**	0.0425***	0.0162	0.0336*	0.0178*	0.0207	0.0238**
	(0.0172)	(0.0112)	(0.0126)	(0.00964)	(0.0170)	(0.0103)	(0.0210)	(0.00934)
Number of Observations	1,352	1,528	1,470	1,548	1,265	1,365	1,413	1,369
R^2	0.113	0.119	0.126	0.112	0.182	0.191	0.190	0.203
Mean Dependent Variable (Pre-Treatment)	0.181	0.154	0.175	0.175	0.253	0.242	0.244	0.260

Notes: Each column presents the coefficient estimates for α_1 and α_2 from equation (1). Each panel excludes towns from the district listed at the top of the panel. Control variables are the following: quadratic function of age, indicators for relation to household head, indicators for month of interview, number of household members, town's socioeconomic ranking (indicators). Standard errors clustered at the town level are in parenthesis. *** p<0.01, ** p<0.05, * p<0.1