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Once NEET, Always NEET?

A Synthetic Panel Approach to Analyze the Moroccan Labor Market

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Abstract

In many regions of the world, the persistent, and growing, proportion of young people who are currently not in employment, education, or training is of global concern. This is no less true of Morocco: about 30 percent of the Moroccan population between ages 15 and 24 are currently not in employment, education, or training. Drawing from various rounds of Moroccan labor force surveys, this paper contributes to understanding the complex dynamics of labor markets in developing countries. First, it identifies the socioeconomic determinants of Morocco's young population not in employment, education, or training. Second, employing a synthetic panel methodology in the context of labor market analysis, the paper describes how the conditions of individuals in this group has changed over time. One striking, and worrisome, pattern that emerges from the 2010 synthetic panel data is that, even after 10 years, a majority of the young population not in employment, education, or training remained outside the labor market or education, with very little chance of moving out of their situation. Their chronic stagnancy confirms the powerful effect that initial conditions have on determining young people's future outcomes.

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1. Introduction

Using a synthetic panel methodology, this paper analyzes the evolution of Moroccan NEETs, an acronym for young people (between 15 and 29, or 15 and 24, depending on the definition) who are Not in Employment, Education or Training.

Appearing for the first time in the mid-1990s, the acronym was formulated to capture the social situation of a growing category of the population: youth who do not build human capital in the traditional way through work, education or training. Part of the reason the term was formulated is that development experts began to recognize that the conventional metrics and predictors of success—such as employment, academic education, and/or vocational training—no longer sufficiently captured the multidimensional nature of the challenges faced by many young people during their schooling years or during their transition from school to the labor market, nor the resulting long-term fragility that marks their lives.

According to the most recent national census (RGPH, 2014), there are about 6 million Moroccans between the ages of 15 and 24. Morocco is currently in a development window that demographers call a “demographic bonus”. This means that the proportion of working-age people in the total population is high, compared to the share of the population who are either younger or older than the productive age bracket (15–64 years old).

HCP-WB (2017) estimates that Morocco’s demographic bonus will end in 2040 when the progressive aging of the population, combined with increased life expectancy, begins to raise the share of the population aged 65 and above. With such a high proportion of people in the productive age range, and a low proportion of dependents, a demographic bonus therefore presents a country—for a limited number of decades—with a one-time opportunity for accelerated economic growth.

The current age distribution of Morocco’s population represents such an opportunity, but it also presents the major challenge of harnessing that human capital and putting it to the best use (HCP-WB, 2017). Until now, the Moroccan labor market has not been able to absorb all of its new entrants in an optimal way. Calculations based on subsequent rounds of the Moroccan Labor Force Survey (see data section) indicate that of some 390,000 new entrants in the national workforce every year, barely a third manage to find employment in the formal or informal sector.

Because of the importance of this age group, the NEET phenomenon has increasingly gained attention in both developed and developing countries. In Morocco, by contrast, labor market analysis (see, for example, Verme et al., 2016a, 2016b) has tended to focus on understanding what determines unemployment or inactivity within the entire population, with no specific focus on those between 15 and 24 years old. The present paper aims at filling this informational gap by providing a first-of-its-type comprehensive analysis of the characteristics and dynamics of NEETs in the last decade.

Examining NEET profiles is a relatively straightforward exercise using repeated cross-sections on the labor force, but without access to longitudinal data, it is rather more complicated to construct transition matrices that trace their movement in and out of the NEET condition. The Moroccan Labor Force Surveys do have a panel component (50 percent of the sample) but it rotates every two years, making it all but impossible to construct a transition matrix over a longer period than that.

Yet because of the extreme importance of gaining an understanding of the duration and persistence of the NEET condition, our team worked diligently to overcome the data limitations of existing methods by constructing a Synthetic Panel (SP) of individuals between 15 and 24 over a nine-year period (2010-2018). To our knowledge, this represents a primer in the synthetic panel literature, which has so far focused on welfare dynamics and only occasionally on labor market outcomes.[1] The adaptation of synthetic panel methodology to the labor market also opens up the possibility of conducting panel-type analyses in this field without relying on panel data sets, which are often scarce in developing countries. An important advantage we intend to exploit in constructing the SP is the possibility of comparing year-on-year estimates (for example, from 2010 to 2011) to the corresponding panel component within the data.

The paper is organized in six sections. The first is the current Introduction. The second section profiles NEETs, drawing comparisons in different countries around the world. Section 3 summarizes research and findings related to the NEET phenomenon. Section 4 presents data and the methodology we applied, while section 5 displays results. Section 6 draws conclusions.

[1] Using a synthetic panel approach to study the German labor market during the 1993-2014 period, Burda and Seele (2013) document the vital role played by part-time employment in reallocating a modest increase in total hours worked over a large number of new workers, leading to net employment growth. Beblavy et al. (2013) undertake a synthetic panel analysis of adult learning for cohorts aged 25 to 64 in 27 European countries, using the European Labour Force Survey and studying the factors affecting educational attainment, participation in education and training.

2. Profiling the NEETs: Who Are They, and What Are Their Life Conditions?

The transition from education to the world of work is one of the most important life decisions young people face. Of particular concern are those who are neither employed, in school, nor in a training program of any sort. Fully one-fifth of the global population between the ages of 15 and 24 fall in this NEET category.

In 2019, the Organisation for Economic Co-operation and Development (OECD) released the latest update of its own perspective on NEETs. The OECD defines NEETs as people aged between 15 and 29 who are neither enrolled in a formal educational or training program, nor in paid employment (defined as at least one hour per week) during the relevant survey reference period. As Table 1 shows, in 2018 the average NEET rate for the 15-29 years-old population across OECD countries is around 13 percent, ranging from 6.1 percent in Iceland to 26.5 percent in Turkey. Southern European countries, Mexico and Turkey exhibit the highest NEET rates, whereas Northern and Central European countries show the lowest rates. The 2018 OECD report highlights that in almost all OECD countries, NEET rates are higher for women than for men; the OECD average rate for young women is almost 4 percentage points higher than the rate for young men. In Mexico and Turkey, female rates are around 25 percentage points higher than male rates. By contrast, Austria, Belgium, Canada, Luxembourg, Portugal, and Switzerland show a NEET rate higher for males than for females yet the difference is negligible.

Table 1: NEET Rates for 15- to 29-Year-Olds in OECD Countries

Country	2006	2011	2018	Country	2006	2011	2018
Iceland	5.1	9.8	6.1	**Estonia**	11.4	15.2	12.7
Netherlands	6.2	6.9	7.0	**Poland**	17.4	15.5	12.7
Malta	13.6	12.1	7.3	**United States**	12.9	15.9	12.7
Switzerland	10.0	21.9	8.1	**Belgium**	13.9	13.9	12.8
Luxembourg	8.6	7.2	8.4	**OECD average**	14.3	15.9	13.2
Norway	7.9	8.5	8.7	**Israel**	30.0	27.6	13.3
Sweden	10.5	9.1	8.9	**Hungary**	17.0	18.5	13.5
Germany	13.6	11.0	9.2	**Cyprus**	11.9	14.8	14.9
Slovenia	10.8	10.7	9.7	**Slovak Republic**	19.1	19.1	15.1
Japan	12.0	11.7	9.8	**Croatia**	15.8	19.1	15.6
Czech Republic	14.1	12.7	10	**France**	15.2	16.4	16.1
New Zealand	12.0	14.3	10.2	**Romania**	16.5	19.5	17.0
Lithuania	—	18.0	10.5	**Bulgaria**	23.9	24.7	18.1

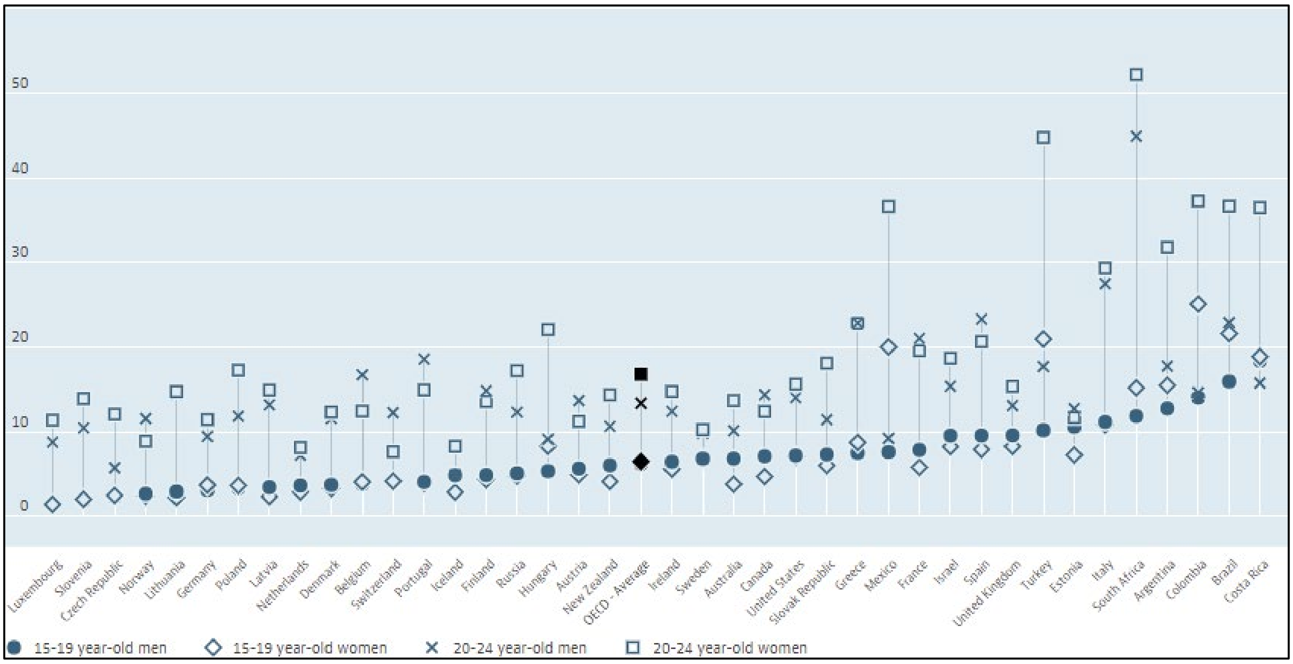
Australia	11.4	11.5	10.8	**Chile**	—	21.8	18.4
Denmark	6.2	11.0	10.8	**Spain**	15.9	24.3	19.1
Austria	12.0	10.3	11.1	**Mexico**	23.2	24.0	20.9
Latvia	14.4	19.6	11.2	**Greece**	16.7	21.6	21.5
Portugal	12.4	15.3	11.6	**Colombia**	—	20.1	22.7
Ireland	10.4	21.9	11.7	**Costa Rica**	—	20.1	23.1
Canada	12.0	13.4	11.9	**Italy**	20.1	23.2	23.9
Finland	10.4	11.8	11.9	**Brazil**	—	19.3	24.9
United Kingdom	15.1	15.5	12.6	**Turkey**	42.6	34.6	26.5

Source: OECD Family Database, Indicator CO3.5 "Young people not in education or employment", http://www.oecd.org/els/family/database.htm.
Notes: For 2011, data for Switzerland refer to 2009, for Lithuania to 2010, and for Colombia and Costa Rica to 2013. For 2018, data for Japan refer to 2014, and for Chile to 2017. The OECD average excludes Chile and Korea.

As shown in Figure 1, NEET rates are generally higher for young people in their 20s than for those in their teens. In the OECD countries, on average about 18 percent of those aged between 25 and 29 years old, compared to less than 6 percent of 15-19 year-olds, are NEET. This difference may be the result of the expansion of upper secondary education in many OECD countries. Furthermore, as the OECD reports, NEETs are less likely to live with their parents than non-NEETs. About 50 percent of NEETs, compared to about 75 percent of non-NEETs, live with their parents.

Caring for children and/or living with a partner can also make a substantial difference. About 26 percent of NEETs, but only 9 percent of non-NEETs, live with a partner and one or more children—an almost 3:1 ratio. The reason is likely that parenthood compels young people to devote their time and energy to childcare rather than education or working outside the home. Parenthood *with no partner* makes even more of a difference. Single (non-partnered) young women account for just 1 percent of non-NEETs, compared to 5 percent of NEETs—a 5:1 ratio versus 3:1. Caring for children, especially all by oneself, often forces a young person to stay at home instead of attending school or working outside (OECD, 2016).

Figure 1: NEET Rate by Age Group and Gender



Source: OECD (2019), Youth Not in Employment, Education or Training (NEET) Indicator. doi: 10.1787/72d1033a-en (accessed on December 20, 2019).

International Labour Organization (ILO) data allow us to enlarge our view to other regions of the world. ILO defines youth as "all persons between the ages of 15 and 24 (included)" and employees as "all persons of working age who during a specified brief period, such as one week or one day, were in the following categories: *a*) paid employment (whether at work or with a job, but not at work); or *b*) self-employment (whether at work or with an enterprise, but not at work)". People are defined as being in training if engaged "in a non-academic learning activity through which they acquire specific skills intended for vocational or technical jobs". Finally, vocational and technical training includes only programs that are solely school-based.

As Table 2 shows, nearly 22 percent of youth worldwide are NEET, about 77 percent of whom are women. This underscores the observation that deeply ingrained social norms drive the unequal labor market outcomes between men and women.[2]

[2] ILO (2017) analyzes in depth the drivers of gender disparities in educational attainment and labor market outcomes, and the constraints that influence these disparities.

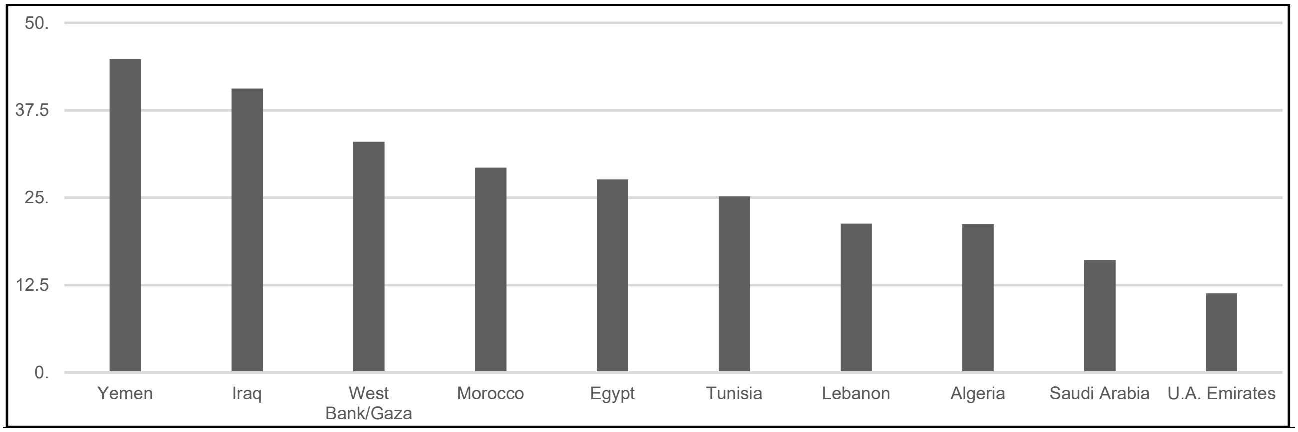
Table 2: NEET Rates for 15- to 24-Year-Olds, by Region

Region	NEET rates, latest years			Female share
	Total	Male	Female	
World	**21.8**	**9.8**	**34.4**	**76.9**
Developing countries	12.1	8.0	16.0	66.1
Emerging countries	25.2	9.6	41.8	80.3
Developed countries	13.1	11.3	14.9	55.7
Northern Africa	26.1	16.7	36.0	67.6
Sub-Saharan Africa	15.5	11.2	19.0	61.4
Latin America and the Caribbean	19.4	11.9	27.0	68.6
Northern America	16.3	14.1	18.6	55.8
Arab States	18.2	9.9	27.1	71.8
Eastern Asia	3.7	2.8	4.7	61.8
South-Eastern Asia and Pacific	18.0	13.4	22.6	61.5
Southern Asia	28.6	5.8	53.3	89.5
Northern, Southern and Western Europe	12.3	12.2	12.4	49.2
Eastern Europe	15.6	13.8	17.4	54.5
Central and Western Asia	23.4	14.8	32.1	67.5

Source: International Labour Organization, 2017.
Notes: the table shows the NEET rate in different regions of the world, using youth population-weighted averaging. The number of countries with available data in different regions are as follows: World (98), developing countries (12), emerging countries (46), developed countries (40), Northern Africa (3), Sub-Saharan Africa (16), Latin America and the Caribbean (16), North America (2), Arab states (5), Eastern Asia (4), South-Eastern Asia and the Pacific (8), Southern Asia (6), Northern, Southern and Western Europe (27), Eastern Europe (7), and Central and Western Asia (4). The most recent year is 2015, with 67 observations. There are 15 observations for 2014 and 16 observations for 2009–2013.

Figure 2 narrows the focus to Morocco and other Middle East and North Africa region countries. The MENA region, in particular the North African part, seems to perform worse than many other regions both in the developed and developing world. Although its peers are not doing particularly well, Morocco has even higher NEET rates than most. In 2017, Morocco was the worst performer among MENA countries that were not in a situation of conflict or state fragility (in other words, excluding the Republic of Yemen, Iraq and the West Bank and Gaza). Its NEET rate is two percentage points above that of the Arab Republic of Egypt, and four and five points higher than that of Tunisia and Algeria, respectively.

Figure 2: NEET Rates in MENA Countries



Source: ILOSTAT, https://ilostat.ilo.org/.

3. Research Findings on the Status of NEETs Worldwide

As mentioned in the introduction, a quantitative investigation of the condition and dynamics of NEETs in Morocco is rather new, compared to other parts of developing world where new studies have already become available. Employing longitudinal data, Ranzani and Rosati (2013) present evidence concerning the extent, characteristics, and evolution of the NEET phenomenon in Mexico over a 10-year period. In addition, they investigate the existence and extent of state dependence by disentangling unobserved heterogeneity from genuine state dependence. For example, they find that, compared to other NEETs, female and lower-educated youth are more likely to remain in this status than be employed.

Looking at Turkey, Bilgen Susanli (2016) examines the determinants of its NEET picture, drawing on data from the Household Labor Force Surveys over the 2004-2013 period. A logit analysis indicates that gender and educational attainment are key factors in explaining who is or is not in NEET. A greater number of household members who are in employment is associated with a lower likelihood of NEET. Transition matrixes analysis reveals that NEET status remains highly persistent despite the substantial fall over the sample period. In South Africa, Akinyemi and Mushunje (2017), investigating the determinants of rural youth participation in agricultural activities, show that 21 percent of youth are NEET, 77 percent of them in the 20–24 age bracket. Variables such as age, government funding and parent participation in farming increase the likelihood of young people's participation in agricultural activities. By contrast, being married, having young children, and receiving social grants reduce the likelihood.

Cabral (2018), focusing on Senegal, shows that about 40 percent of young people are NEET. In his analysis, the key factors affecting the probability of being NEET are the existence of a physical and mental disability, age and gender of the person, education, occupational and marital status of the household head, as well as household income.

Research by Abayasekara and Gunasekara (2019) using 2016 Labour Force Survey data reveals some of the risk factors that predispose young people to become NEET in Sri Lanka. Using binomial and multinomial logistic regression models, the results indicate that the risk factors center on being female, belonging to an ethnic and religious minority, being in the 20–24 age group, having very low or very high levels of education, being English-illiterate, belonging to a low-income household or to a male-headed household, having young children, and living in a more remote area. The authors also offer important policy recommendations for how to reduce Sri Lanka's NEET rate and engage more youth in education and in the labor force.

Looking at developed countries, Quintano, Mazzocchi and Rocca (2018) analyze the determinants of the NEET condition in Italy through a step-by-step procedure. They first determine the main characteristics of being NEET, then focus on specific homogeneous clusters of NEETs. The decomposition of the clusters into different probabilities of being NEET enables the effect of various personal characteristics to be verified. Using a bivariate selection probit model based on the propensity to look for a job against the condition of being inactive, the authors assess the influence of unobserved factors on the professional condition of young people. The results confirm the crucial role of education, as well as the importance of economic and social disparities between men and women in the Italian territorial districts.

4. Data and Methodology

1. Data and descriptive statistics

In this paper, we make use of the "*Enquête nationale sur l'emploi*", a nationally representative labor force survey conducted by the Moroccan *Haut-Commissariat au Plan* (HCP). Its main objective is identifying the volume of active population as well as the main demographic, cultural and socio-professional characteristics of workers. The data set may also be used to measure the Moroccan population's access to basic social services.

The survey has been conducted every year since 1999, using a comprehensive questionnaire covering both urban and rural areas. The sampling frame follows a two-stage stratification strategy in the country's urban and rural areas and regions, which in 2013 were consolidated into 12 from an original 16. On average, every year the sample comprises about 80,000 households, of which 60,000 reside in urban areas and 20,000 in rural areas. A team of HCP enumerators conducts each survey round through direct household interviews, using a computer-assisted personal interviewing (CAPI) technique. The survey also contains a rotating panel component that can be used to examine the persistence and dynamics of labor market status. This rotating panel component, however, is available only for about half of the sample for two adjacent years—specifically, 2010/2011 through to 2017/2018. In this paper, we focus our analysis on the period ranging from 2010 to 2018.[3]

Table 3 presents descriptive statistics of control variables for 2010 and 2018. We observe that between 2000 and 2018, the NEET rate remained high, hovering around 30 percent, with little sign of decline. In 2018, 28 percent of young Moroccans (about 2 million people) could be classified as NEET. The percentage of youth who have secondary education or are pursuing any type of education beyond high school has increased over time. In particular, secondary education moved from 23 to 30 percent between 2010 and 2018, with tertiary education rising from 6.7 percent in 2010 to 13.8 percent in 2018.

Table 3: Descriptive Statistics of Selected Control Variables (48,024 observations in 2010 and 55,280 in 2018)

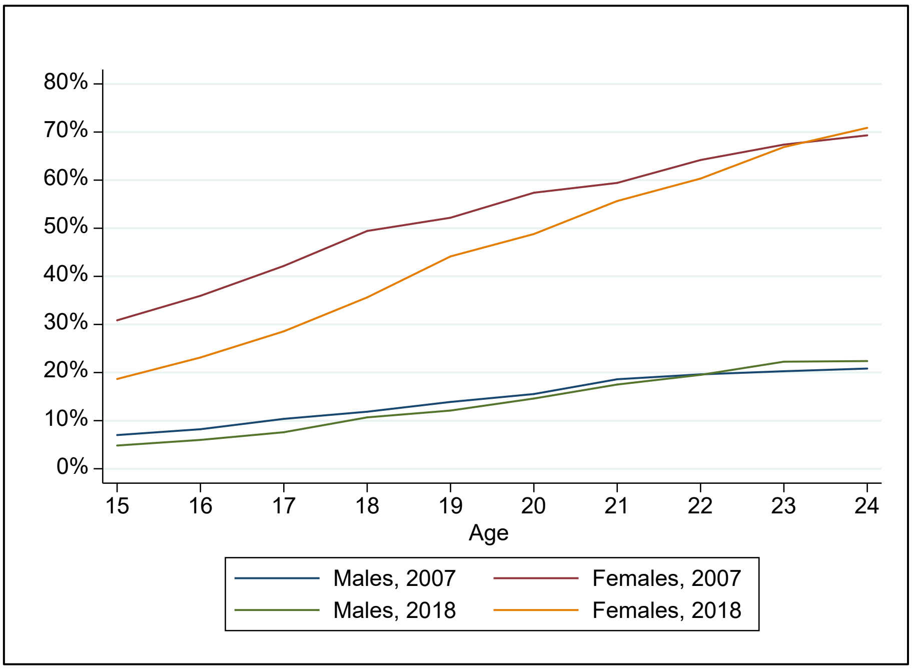
Variable	2010			2018		
	Mean	Min	Max	Mean	Min	Max
NEET (1 = yes)	32.4	0	1	28.4	0	1
HH member is female (1 = yes)	49.7	0	1	49.5	0	1
HH member is 20-24 years old (1 = yes)	55.7	0	1	54.2	0	1
HH member is single	87.8	0	1	88.3	0	1
HH member is married	11.8	0	1	11.2	0	1
HH member is widower\divorced	0.4	0	1	0.4	0	1
HH living in rural area	46.2	0	1	40.3	0	1
HH living in most developed regions	68.7	0	1	50.5	0	1
No education	12.5	0	1	5.1	0	1
Koranic school	1.3	0	1	0.7	0	1
Primary school	56.2	0	1	50.6	0	1
Secondary school	23.2	0	1	29.7	0	1
Tertiary education	6.7	0	1	13.8	0	1
Asset index (normalized)	37.4	0	1	43.6	0	1
HH living in rural accommodation (1 = yes)	35.8	0	1	26.9	0	1
HH living in villa (1 = yes)	1.3	0	1	1.3	0	1
HH living in apartment (1 = yes)	7.3	0	1	10.3	0	1
HH living in traditional house (1 = yes)	3.3	0	1	2.6	0	1
HH living in modern house (1 = yes)	47.3	0	1	55.5	0	1
HH living in shanty (1 = yes)	5.0	0	1	3.4	0	1

Source: authors' own elaboration based on the *Enquête nationale sur l'emploi* (ENE).

[3] We excluded 2016 from the sample because, in the available data set, we could not find a set of variables regarding family background that we could subsequently use in the econometric analysis. In any case, in 2016 the NEET rate was 29 percent, very similar to both previous and subsequent years.

Figure 3 shows that the age distribution of male NEETs did not change substantially between 2007 and 2018, as it did for females, especially for younger ones. The rapid increase in enrollment rates of young women in secondary and tertiary education explains this marked difference. However, when the same females approach the age at which they would normally be entering the labor market—their early 20s—this positive improvement they experienced in their early educational enrollment rates has all but been erased. The NEET rate for females age 23 to 24 is virtually the same in 2018 as it was in 2007, more than a decade earlier.

Figure 3: Percentage of the Moroccan Population Who are NEET: Males and Females by Age



Source: authors' own elaboration based on the *Enquête nationale sur l'emploi* (ENE).

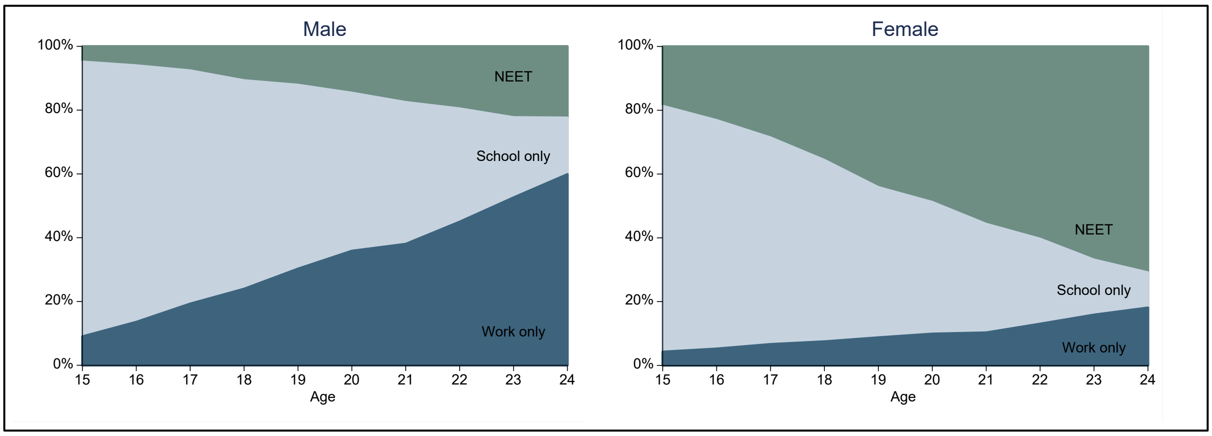
Figure 4 focuses on 2018 only but provides a more comprehensive snapshot of labor market outcomes by age and gender. We also represented the shares of those in education or working: the differences between men and women are quite striking. The disadvantaging of females starts very early on. In 2018, just 19 percent of girls aged 15 were NEET compared to more than 30 percent in 2007, a marked improvement. In 2018, of the remaining 81 percent of 15-year-old girls, 77 percent were in school and 4 percent were working. At 24 years old, however, more than 70 percent of women in 2018 were NEET, compared to just 19 percent of 15-year-olds.

By contrast, in 2018 about 5 percent of boys aged 15 were NEET—not much different from the 7 percent or so who were NEET in 2007. In comparative terms, that 5 percent figure for NEET young boys is not hugely different from the 19 percent of 15-year-old girls who were NEET in 2018. What is more significant is that when men reached 24 years old in 2018, about 21–22 percent of them were

NEET compared to more than 70 percent of their female counterparts—a very large difference that points to severe retrenchment on the women's side. It can be seen that, as age increases, the male-female gap widens markedly. Additionally, although this widening of the male-female gap holds both in 2007 and in 2018, in relative terms it is far worse in 2018 than in 2007, because of the great gains the girls made in early education but then lost as they entered their 20s. In 2018, about 10 percent of women aged 24 were in school, and fewer than 20 percent were working, compared to about 20 percent of their male counterparts in school and about 60 percent working.

Both Figures 3 and 4 portray a situation for Morocco not dissimilar from other MENA region countries, where the share of employed youth is higher among young men than young women, and the share of NEET is higher for young women. Interestingly, both in Morocco and in the rest of the region (Doss et al., 2018), when the NEET information is crossed with marital status, married women—either with or without children—represented a significant percentage of female NEETs. When this married group is removed from the NEET calculation, however, the share of female NEETs (for example, those who are neither married nor have children) becomes comparable to the share of NEET men.

Figure 4: School-to-Work Transition for Population Aged 15 to 24 years old, 2018



Source: authors' own elaboration based on the *Enquête nationale sur l'emploi* (ENE).

2. Logit regression

Following Bilgen Susanli (2016), we first estimate the probability of being NEET using a simple logit model based on a set of individual (e.g. age, gender, and level of education) and household characteristics, geographical location, and housing conditions.

$$logit(p_{it}) = \beta_t x_{it} + \varepsilon_{it}. \tag{1}$$

The model calculates the probability that the dependent variable acquires value 1:

$$E[Y_{ith} = 1 | X = x] = P(Y_{ith} = 1), \tag{2}$$

where $P(Y_{ith} = 1)$ represents the probability of observing the condition of success for the i-th individual given a particular value of X.

3. Synthetic panel

While the current panel data module allows the creation of year-by-year transition matrixes, any longer-term analysis of labor-force transition is not feasible. However, a majority of the analyses of the Moroccan labor market conducted so far (HCP-WB, 2017) indicate that the duration of inactivity or unemployment tends to be particularly long. The need for a longer-term perspective to gauge Moroccan labor market outcomes encouraged us to adapt a methodology originally developed for analyzing poverty dynamics, the so-called *synthetic panel* (Dang et al., 2014, and Dang and Lanjouw, 2013).[4] The *synthetic panel* approach, using repeated cross-sections, produces transition matrices the results of which tend not to be significantly different from those one might have produced by using a real panel.

The approach builds on the "out-of-sample" imputation methodology described in Elbers et al. (2003) for small-area estimation of poverty (often referred to as "poverty maps") which, for the first time in the literature, we adapt for analyzing movements in and out of the NEET condition. Following the approach employed by Dang et al. (2014), we adapt it to our analysis as follows:

- We estimate a logit model for a binary dependent variable (0 = non-NEET, 1 = NEET) in the first round of cross-sectional data (2010) using a specification which includes only time-invariant covariates.
- Parameter estimates from this model are then applied to the same time-invariant regressors in the second survey round (2018) to provide an estimate of the (unobserved) first period's NEET/non-NEET condition for the individuals surveyed in that second round.

[4] Synthetic panels differ from pseudo-panel data in two major ways: first, as few as two rounds of repeated cross-sections are required to construct the synthetic panels, and second, these panels are created at a more disaggregated level than pseudo-panels. They are broadly related to the literatures on survey-to-census imputation (for example, Elbers et al., 2003) and survey-to-survey imputation (see, for example, Dang et al., 2017). Recent applications and/or validations of synthetic panel methods against actual panel data include Bierbaum and Gassmann (2012), Ferreira et al. (2013), Martinez et al. (2013), Garbero (2014), Cancho et al. (2015), Dang and Ianchovichina (2018), Dang and Lanjouw (2018), Dang and Dabalen (2019) and Hérault and Jenkins (2019).

- We then conduct an analysis of transitions in and out of the NEET condition based on the NEET/non-NEET condition observed in the second round, along with the estimates from the first round.

This method produces lower- and upper-bound estimates of transitions in and out of the NEET condition that can be expected to sandwich *true* transition estimates obtained from actual panel data sets.[5]

More formally, the linear projection of the log-odds of the event that NEET equals 1 in each round is given by the following logit model, where x_{it} is a vector of time-invariant characteristics,[6] $logit(p_{it}) = \ln\left(\frac{p_{it}}{1-p_{it}}\right)$ – for $0 < p = Pr(\text{NEET} = 1) < 1$ – is the log-odds, ε_{it} denotes an error term and t runs from 1 to 2, representing the two rounds of cross-sectional surveys (that is, the 2010 and 2018 waves, respectively, of the *Enquête nationale sur l'emploi*):

$$logit\ (p_{it}) = \beta_t' x_{it} + \varepsilon_{it}. \tag{3}$$

Using model estimates, inferences on movements in and out of NEET are based on the directly observed condition of an individual in round 2, and the estimated condition for the same individual in round 1. For instance, the estimates of transitions in and out of the NEET condition are respectively given by:

$$Pr\left(N\hat{E}ET_1^2 = 0 \cap NEET_2 = 1\right) \tag{4}$$

and

$$Pr\left(N\hat{E}ET_1^2 = 1 \cap NEET_2 = 0\right), \tag{5}$$

where the superscript 2 denotes the estimated round 1 NEET/non-NEET condition for individuals sampled in the second round. By contrast, the fraction of individuals who are neither in education nor in employment or training in both survey rounds is given by:

$$Pr\left(N\hat{E}ET_1^2 = 1 \cap NEET_2 = 1\right), \tag{6}$$

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[5] It should be noted that the terms "lower bound" and "upper bound" do not refer to bounds on the proportions of NEETs, but to bounds on their mobility. This means that lower-bound estimates can indeed give higher proportions of NEETs than upper-bound estimates—which, instead, tend to understate mobility (Dang et al., 2014, p. 115). Therefore, in what follows, "lower" and "upper" will refer to the two bounds on mobility; for immobility, "lower" is the upper bound and "upper" is the lower bound.

[6] Given the data, the predictors that we include in the round 1 and 2 logit models are the ones that best adhere to the time invariance assumption: individual's sex, age, and relationship to the household head of the person.

whereas for individuals staying either in education or in employment or training in both rounds, the immobility probability can be written as:

$$Pr\left(\hat{NEET}_1^2 = 0 \cap NEET_2 = 0\right). \tag{7}$$

To use the proposed methodology, the following two assumptions need to be satisfied (Dang et al., 2014). In the first instance, the underlying population must be the same in all rounds of the survey; this assumption is necessary to justify the use of time-invariant individual characteristics to predict the NEET/non-NEET condition. Secondly, the correlation between the error terms of the logit model in the two rounds is assumed to be non-negative according to Dang et al. (2014), and this assumption can usually be made because negative correlation of the error terms is unlikely to happen on a large scale. In other words, although for particular individuals we might see some negative correlation, the kind of factors leading to such a correlation are unlikely to apply to an entire population all at the same time. Because NEET rates are calculated preferably for youth defined as persons aged 15 to 24, in our empirical analysis below these two assumptions will best be met by restricting the cross-sectional sample to individuals aged 15 to 24. This range refers to the age in round 1; the round 2 age range is adjusted upwards accordingly. The age-restricted sample size is 48,110 individuals for round 1 (that is, the 2010 wave); for round 2 (that is, the 2018 wave), the corresponding size is 47,186 individuals.

Based on these two assumptions, we estimate an upper bound on transitions in and out of NEET condition by assuming—as in Dang et al. (2014)—no correlation between the error terms in the two rounds. The practical implementation of the estimation of upper bounds proceeds along the following lines:

1. Using data from round 1, we estimate the logit model:

$$logit(p_{i1}) = \beta_1' x_{i1} + \varepsilon_{i1} \tag{8}$$

   and obtain the estimated coefficients $\hat{\beta}_1'$ and the predicted residuals $\hat{\varepsilon}_{i1}$.
2. For each individual in round 2, a random draw with replacement is taken from the empirical distribution of residuals $\hat{\varepsilon}_{i1}$, subsequently denoted $\tilde{\varepsilon}_{i1}^2$; the estimated NEET/non-NEET condition in the first round for each individual i in the second round is predicted through:[7]

$$\widehat{logit(p_{i1}^{2U})} = \hat{\beta}_1' x_{i1}^2 + \tilde{\varepsilon}_{i1}^2, \tag{9}$$

[7] The superscripts "U" and, later, "L" refer to upper- and lower-bound estimates, respectively, of transitions in and out of NEET condition.

from which we obtain:

$$\widehat{NEET}_{i1}^{2U} = \begin{cases} 0 \text{ if } \widehat{logit(p_{i1}^{2U})} < 0 \\ 1 \text{ if } \widehat{logit(p_{i1}^{2U})} \geq 0 \end{cases}. \tag{10}$$

3. Movements in and out of the NEET condition as well as immobility probabilities are calculated using (10) and the observed NEET/non-NEET condition of individuals in round 2 via Equations (4) to (7).

4. Steps 1 to 3 are repeated R times, and the average over all replications is taken.

Sensitivity analyses carried out using different numbers of replications suggested that precision gains beyond 50 replications are modest.[8] Therefore, for the following analysis, estimates are based on 50 replications.

A lower bound of mobility is provided by assuming perfect correlation between the error terms in the two rounds (Dang et al., 2014). Precisely, lower-bound estimates for transitions in and out of NEET condition are obtained as follows:

1. Using data from round 1, we estimate Equation (8) to obtain the predicted coefficients $\hat{\beta}_1'$.

2. Using data from round 2, we estimate the logit model:

$$logit(p_{i2}) = \beta_2' x_{i2} + \varepsilon_{i2} \tag{11}$$

   and obtain the predicted residuals $\hat{\varepsilon}_{i2}^2$.

3. The estimated NEET/non-NEET condition in round 1 for each individual in round 2 is predicted by using data from round 2, the predicted coefficients $\hat{\beta}_1'$ from round 1, and the individual's own residual in round 2, $\hat{\varepsilon}_{i2}^2$, via the equation:

$$\widehat{logit(p_{i1}^{2L})} = \hat{\beta}_1' x_{i1}^2 + \gamma \hat{\varepsilon}_{i2}^2, \tag{12}$$

   where scalar $\gamma = \frac{\hat{\sigma}_{\varepsilon_1}}{\hat{\sigma}_{\varepsilon_2}}$ is chosen to ensure the standard deviation of the imputed round 1 residuals distribution equals $\hat{\sigma}_{\varepsilon_1}$; from Equation (12), we obtain:

$$\widehat{NEET}_{i1}^{2L} = \begin{cases} 0 \text{ if } \widehat{logit(p_{i1}^{2L})} < 0 \\ 1 \text{ if } \widehat{logit(p_{i1}^{2L})} \geq 0 \end{cases}. \tag{13}$$

[8] The results of these analyses are not shown in the paper but are available upon request from the authors.

4. Movements in and out of NEET condition as well as immobility probabilities are calculated using (13) and the observed NEET/non-NEET condition of individuals in round 2 via Equations (4) to (7).

In this case, steps 1 to 3 do not have to be replicated since the prediction errors for each individual are used.

In summary, the only difference between the lower- and upper-bound estimates arises from the residual that is added to the prediction of the NEET/non-NEET condition, as can been seen by comparing Equations (9) and (12). The lower-bound estimate simply adds the same residual to the linear prediction that an individual has in round 2, thereby inducing perfect correlation between the residuals. The upper-bound estimate takes a random draw from all individual residuals in round 1, resulting in no correlation between the residuals in the first and second round.

5. Results

1. Characteristics of the NEET Category

Results of the logit regression analysis for all individuals in the age group 15-24 are presented in the following figures[9] and the marginal effects are presented in the Appendix. We estimate a logit model for the NEET binary dependent variable (NEET = 1, non-NEET = 0) assuming that the probability of a positive outcome is determined by the standard normal cumulative distribution function. Results show a clear profile of the NEETs, already provided in the descriptive analysis. In particular, the NEET category is composed mainly of young women 20 to 24 years old, with low levels of education, and typically married. This profile will be analyzed in greater detail when gender-specific results are presented.

With reference to Figure 5, results show that the likelihood of being a NEET increases with age because of the complexity of transitioning from school to the labor market that all too frequently leads

[9] For the logit regression model, we used the 2010, 2011, 2015, 2017 and 2018 survey rounds. The choice depended on whether of a complete set of data required to perform the analysis was available. Complete regression results are saved in the appendix. In the following graphs, significant results are those where the bar is away from the zero value and the symbol describing the confidence interval does not include the zero value. All the independent variables are dummies or categorical variables: female (1 = female, 0 = male); age group (1 = 19-24, 0 = 15-19); marital status (married or widower/divorced, with being single as the omitted reference case); education attainment (Koranic school, primary school, secondary school and tertiary education, with no-education as the omitted reference case); housing characteristics (villa, apartment, traditional Moroccan house, modern Moroccan house, with rural house as the omitted reference case) and two geographical areas, namely urban or rural regions (with urban as the omitted reference case), and macro-regions (less developed regions and more developed regions, with the former as the omitted reference case).

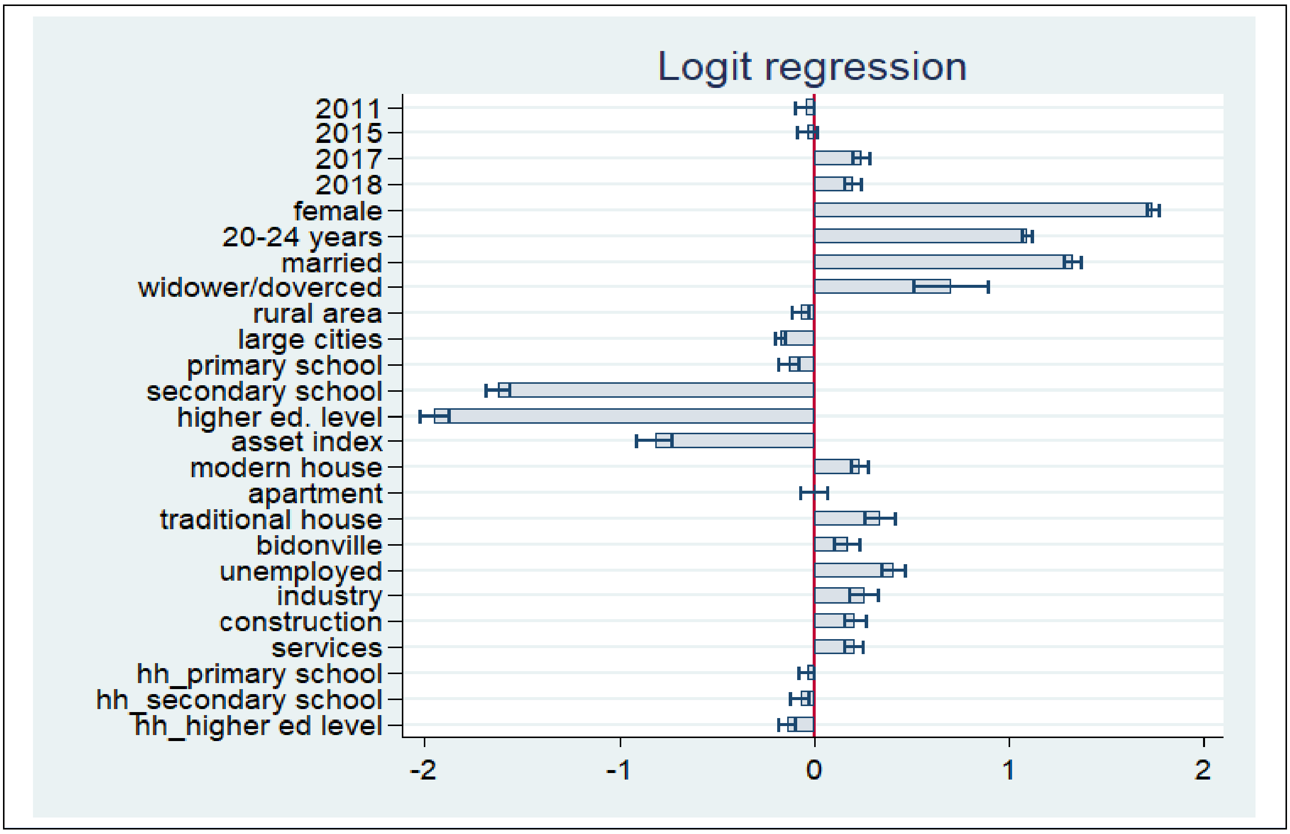
to unemployment as the person gets older. Moreover, the results confirm that the area of residence matters significantly; people living either in big towns or in rural areas are less likely to become NEET than those living in medium-sized towns. In big towns, there are many more chances to continue studying or to find a job, while in rural areas young people are often involved, depending on the season, in family-based farming activities.

The effect of education is as expected: all other things being equal, higher levels of education are associated with a lower probability of being NEET. This effect is particularly pronounced in the case of tertiary education (see also the marginal effects in the appendix). As expected, household well-being also matters substantially. The asset index constructed by aggregating various household assets[10] is also negatively associated with the probability of having a NEET in the household: the wealthier the household, the higher the chances are that young members will continue on to higher education or find a job. Coming from less affluent families, on the other hand, can in practice virtually preclude the possibility of continuing to study beyond a certain level, or may affect access to the jobs market.

Finally, the education level of the household head, and sector of activity, both significantly impact the probability of having NEETs in the family. Again, higher levels of household head education are negatively associated with the presence of NEETs at home. In addition, as previously discussed for rural areas, whenever the family (and household head) are active in agriculture, young members tend also to be active in that sector. This explains the negative and significant marginal effect of the variable household head employed in agriculture.

[10] With this asset index, suggested by Filmer and Pritchett (2001), principal-components analysis was used to calculate the weights of the index. The first principal component—the linear combination capturing the greatest variation among the set of variables—can be converted into factor scores, which serve as weights. The rationale for using this index is that it captures the household's permanent welfare dimension better than simple consumption data and can provide more reliable rankings among households.

Figure 5: Results of Logit Regression



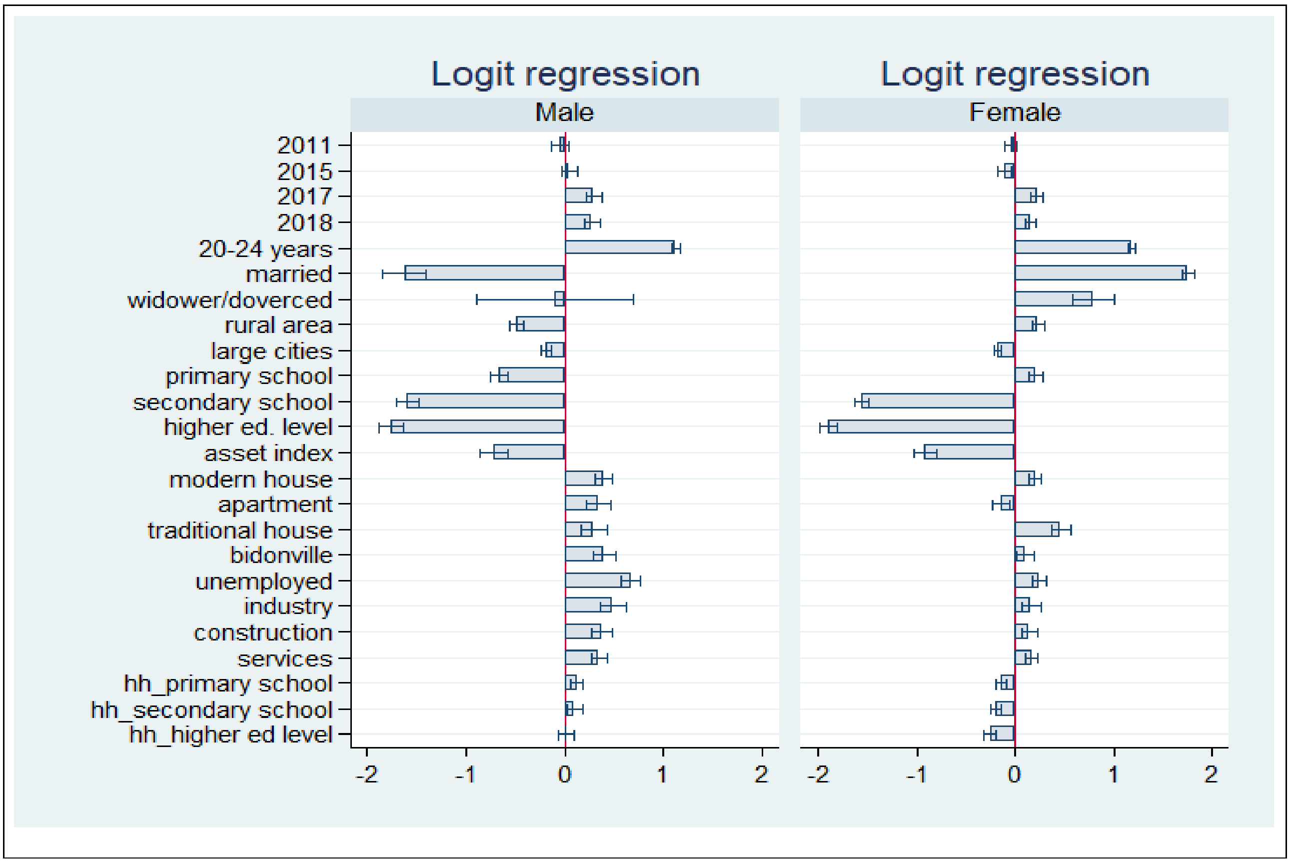
Source: authors' calculations using Labor Force Surveys 2010-2018.

Figure 6 shows the results by dividing the sample into males and females; we perform this analysis to understand whether specific individual characteristics affect the outcomes differently. Since the regressors are the same as those used in the whole sample, it is worth commenting only on the key aspects that differ in the two subgroups. The first point to mention is the difference in the impact of marital status between males and females: married men have a lower probability of being NEET, while the opposite can be observed for women. These results suggest that, once married, it is even harder for women to enter the labor market. They often must rely economically on their husbands' income.

Differences between men and women can also be found for other variables such as the educational level: all other things equal, education matters more for women than men in determining the risk of becoming NEET. Interestingly, the household head education variables remain significant and negative for women only, while for men they become insignificant, suggesting that family background matters more for women than for men. This is further confirmed by the size of the marginal effect of the asset index, as well as by most of the housing quality variables: in absolute value, they are bigger than those of men and always negative and significant.

Finally, results by area of residence show different effects for men and women. For men, this has the positive effect of reducing the probability of being NEET, while for women the effect is the opposite. This may be because in rural areas men can often find work in agriculture or undertaking jobs that require high levels of physical effort. This excludes many women from that labor market.

Figure 6: Logit Regression, by Gender



Source: authors' calculations using Labor Force Surveys 2010-2018.

2. Synthetic Panel and Transition Matrices

In the preceding section, we captured a static snapshot of the NEET condition, but it is also important to understand the dynamics of the phenomenon, especially the probability of moving in or out of NEET, remaining NEET, or remaining non-NEET, and for how long. As mentioned earlier, the lack of panel data that can cover a period longer than one year limits the possibility to undertake a meaningful analysis: one year is not enough, for example, to gauge whether or not a person is stuck in the NEET condition. A longer time span is clearly needed. The adaptation of a synthetic panel method to our analysis enabled us to overcome this limitation.

The following section will first present some validation results, notably showing that the estimated model can replicate observed transition matrixes. The section will then show the 2010-2018 transition matrix results, and finally, examine the performance of specific subsamples, such as men and women, and urban and rural.

Table 4 compares the percentages of NEETs in 2010 and 2018 derived from the cross-section data sets, the actual panel data tracking the same individuals in four survey rounds—notably 2010– 2011 and 2017–2018—and the synthetic panel based on cross-sectional data in 2010 and 2018. For 2010, there are no separate estimates of NEET rates based on the synthetic panel, because they are obtained using the share of individuals in the 2018 sample estimated from those who were NEET in 2010 and 2018, then adding the share of individuals falling into the NEET condition over the considered period.

Table 4: NEET Percentage Rates in 2010 and 2018: Comparison of Cross-Section, Actual Panel and Synthetic Panel Lower- and Upper-bound Estimates

Year	Lower-bound estimate	Cross-section	Actual panel	Upper-bound estimate
2010	-	31.41	31.82	-
		(30.96; 31.86)	(31.14; 32.51)	
2018	46.66	46.66	46.92	46.66
		(46.20; 47.12)	(46.33; 47.52)	

Notes: results are restricted to the sample of individuals aged 15 to 24 in 2010 and aged 23 to 32 in 2018. "Lower" is the upper bound and "Upper" is the lower bound. Synthetic panel upper-bound estimates are based on 50 replications. Individual-level sampling weights are applied; 95 percent confidence intervals are given in parentheses.

Two key elements emerge from this comparison. First, NEET rates for both 2010 and 2018 calculated on the cross-section and the actual panel data almost overlap. Second, the upper- and lower-bound estimates of the synthetic panel for 2018 are remarkably close to the NEET rates observed in both the cross-section and the actual panel. This represents an encouraging result that gives a positive first indication of the quality of the synthetic panel.

The next step is represented by the analysis of the transitions in and out of the NEET condition based on the 2010/2018 synthetic panel. For this purpose, a transition matrix was created. The rows in table 5 indicate the proportion of individuals in the 2018 sample estimated to be in one of four groupings: a. In NEET both in 2010 and 2018 (NEET, NEET); b. Moved out of NEET during that time period (NEET, non-NEET); c. Fell into the NEET condition (non-NEET, NEET); or d. Were never in NEET between 2010 and 2018 (non-NEET, non-NEET). These four options are exhaustive, and therefore each column adds up to 100 percent.

Table 5: Transition Matrix Based on the Synthetic Panel 2010/2018

Status in 2010, 2018	Lower-bound estimate (%)	Upper-bound estimate (%)
NEET, NEET	46.66	35.95
NEET, non-NEET	4.35	17.82
Non-NEET, NEET	0.00	10.71
Non-NEET, non-NEET	48.98	35.51

Notes: results are restricted to the sample of individuals aged between 15 and 24 in 2010 and between 23 and 32 in 2018. "Lower" and "Upper" refer to the two bounds on mobility; for immobility, "Lower" is the upper bound and "Upper" is the lower bound. Upper-bound estimates are based on 50 replications. Individual-level sampling weights are applied.

The estimated NEET rates for 2018 can be directly derived from the transition matrix by adding up the share of people in two groups: (NEET, NEET) and (non-NEET, NEET). For instance, the lower-bound estimate of the NEET rate in 2018 amounted to 46.66 percent, which is the estimate displayed in the respective cell in Table 4. Similarly, the upper-bound estimate consists of the chronically NEET (35.95 percent) and the (non-NEET, NEET) group (10.71 percent), resulting in the estimate displayed in the respective cell in Table 4 (46.66 percent).

The results suggest that the NEET condition tends to persist, as is hinted at in the paper's title. Comparing the share of NEET in both periods to those who were NEET in 2010, we found that those NEET in 2010 had a 70 to 90 percent probability of remaining NEET after 10 years, and only a 10 to 30 percent probability of escaping from the condition. This impression of substantial immobility is confirmed by the complementary results of the non-NEETs in 2010. The chances after 10 years of staying non-NEET are 80 to 100 percent; indeed, the risk of becoming NEET is between 0 and 20 percent. Ten years is quite a long period and yet we observed very little mobility during that time.

While it is beyond the scope of this paper to investigate the causes of this inertia, some indications can be already drawn from the results of the static analysis—notably, that the person's gender, the household head's level of education, and the well-being of households can all play a crucial role in explaining the labor market trajectory of young people. These initial conditions, we conjecture, tend to determine whether the young family member will start off as NEET—we can see this in the previous section—but they also can give some indication of his/her capacity to move or not move out of NEET.

To further explore the persistence and dynamics of the NEET condition in the Moroccan labor market, the same exercise is repeated for different population subgroups separately: male/female, wealthy and not, and levels of household head education (in Appendix). Table 6 summarizes NEET dynamics for males (left-hand side columns) and females (right-hand side columns). The share of NEET young women in 2010 is already four times bigger than that of young men. Therefore, since the labor market is particularly immobile, after 10 years these women have an 80 to 90 percent probability of remaining NEET, with little chance of improvement. The men's results confirm that for them is less of a problem: most of them are non-NEET in 2010 and remain that way after 10 years.

Table 6: Transition Matrix Based on the Synthetic Panel 2010/2018 by Gender

Status in 2010, 2018	*Male*		*Female*	
	Lower-bound estimate (%)	**Upper-bound estimate (%)**	**Lower-bound estimate (%)**	**Upper-bound estimate (%)**
NEET, NEET	18.31	3.20	74.23	67.75
NEET, non-NEET	0.14	14.69	8.45	20.90
Non-NEET, NEET	0.00	15.11	0.00	6.48
Non-NEET, non-NEET	81.55	67.01	17.32	4.87

Notes: results are restricted to the sample of individuals aged between 15 and 24 in 2010 and between 23 and 32 in 2018. "Lower" and "Upper" refer to the two bounds on mobility; for immobility, "Lower" is the upper bound and "Upper" is the lower bound. Upper-bound estimates are based on 50 replications. Individual-level sampling weights are applied.

We also divided the sample into two groups: those in the bottom 80 percent and those in the top 20 percent of the asset index distribution (Table 7). Here also, we noticed some differences between the two groups. First, as expected, there is a higher prevalence of NEETs among households in the bottom 80 percent than in the top 20. Second, among the top 20 percent, there is less persistence in the NEET condition, and there are fewer chances to become a NEET in 2018 if the person was non-NEET in 2010.

Table 7: Transition Matrix Based on the Synthetic Panel 2010/2018 for Top 20 Percent and Bottom 80 Percent Asset Index

Status in 2010, 2018	*Asset index < 80%*		*Asset index > 80%*	
	Lower-bound estimate (%)	**Upper-bound estimate (%)**	**Lower-bound estimate (%)**	**Upper-bound estimate (%)**
NEET, NEET	32.52	16.50	16.37	7.94
NEET, non-NEET	0.00	11.42	0.00	15.75
Non-NEET, NEET	0.00	16.02	0.00	8.44
Non-NEET, non-NEET	67.48	56.06	83.63	67.87

Notes: results are restricted to the sample of individuals aged between 15 and 24 in 2010 and between 23 and 32 in 2018. "Lower" and "Upper" refer to the two bounds on mobility; for immobility, "Lower" is the upper bound and "Upper" is the lower bound. Upper-bound estimates are based on 50 replications. Individual-level sampling weights are applied.

Some further validation checks were undertaken by means of comparison between transition matrices—both for the overall population and by population subgroups—using true panel data and the estimated synthetic panels for each of the consecutive year-pairs of data (2010/2011 to 2017/2018).[11] As we expected, the lower-bound estimates underestimate mobility—understating movements into and out of the NEET condition, and overstating the extent to which people remain NEET or non-NEET—while the upper-bound estimates overestimate mobility. Encouragingly, the "truth" (true rate) tends to lie about midway between these bounds. We find, thus, that our approach does indeed present bounds within which the "truth" can be observed.

6. Discussion and Conclusions

Several decades ago, Morocco embarked on a long-term process of political, social, economic, and environmental reforms, culminating in the adoption of the New Constitution in 2011. Because of these reforms, progress has been made, in particular, in the reduction of absolute poverty, better access to basic public services, and the considerable development of public infrastructures. The social landscape, however, remains marked by challenges yet to be met, particularly in terms of social cohesion. These challenges could pose the risk of exclusion of the most fragile components of Moroccan society, in particular women and young people. Young people unemployed, outside the school system and not undergoing any training—the so-called NEETs—form about 30 percent of the Moroccan population between ages 15 and 24. That number looks even grimmer when compared to NEET rates in the MENA region, already characterized by particularly high rates of NEETs (ILO, 2019).

Subsequent rounds of Moroccan labor force surveys have already presented the opportunity to develop a clearer profile of NEETs in the country. What is missing, however, are the data to examine how the circumstances of people in the NEET condition have evolved over a reasonably long period of time. Our adaptation of the synthetic panel methodology to this specific issue enables us to overcome the data limitations and to provide helpful insights into NEETs dynamics in the last decade.

The first part of our analysis showed the key determinants of the NEET condition. As expected, individual characteristics play an important role. The probability of becoming NEET is higher for

[11] For space considerations, we just summarize the findings here; the full set of results is provided in the Appendix.

women—particularly those married and/or with children—and for young men and women with lower levels of education. A higher concentration of NEETs is also more likely in medium-sized towns than in big towns or rural farming areas. In big towns, it is easier for young people to continue schooling or find a job, while in rural areas every household member is typically involved in some farming activities. The family context also influences the probability of being NEET. Higher parental education and better economic conditions tend—all other things being equal—to decrease the probability of young household members becoming NEET.

In the second part, we presented the results on NEET dynamics using a synthetic panel method, a primer in this literature. After validating the results using the available panel subsample in the data, we proceeded by estimating a transition matrix that tracks how those who were between ages 15 and 24 in 2010 evolved over a 10-year period. The results are far from encouraging: the vast majority of those who were in NEET in 2010 tended to remain outside both the labor market and education even after 10 years, with very little chance of moving out.

Likewise, those in non-NEET tended to remain as they were after 10 years, confirming not only a general impression of immobility within the Moroccan labor market, but also the crucial importance of initial conditions: to avoid the NEET condition in 2018, the best option is to have started in 2010 with a job or in school. While at first glance this might look like a tautological statement, it in fact is not. It confirms the importance of initial conditions—for example, being female, or coming from a relatively disadvantaged family—in determining future outcomes, and the profound effect of the lack of corrective mechanisms and interventions within the Moroccan political economy that might help to change these results along the line.

These preliminary results can already provide some initial suggestions for policy intervention.

On one side, the recommendation is to work on prevention since, as we have seen, initial conditions tend to largely condition a young person's future trajectory. For the young, prevention means improving the quality of education, reducing the likelihood of early dropouts, and financially supporting those whose initial disadvantaged background might preclude their continuing with formal academic studies or vocational skills training.

Ex-post interventions are likely to be more costly, but this does not lessen their urgency. In this regard, one important aspect we have stressed throughout the paper is the persistent disadvantaged position of women. This is true for those we analyzed as NEET (that is, between ages 15 and 24) but it also applies to those older than 24. According to the latest figures, more than 8 million Moroccan women are not active in the labor market. Among these, almost 2 million have more than a secondary level of education—truly a dramatic wastage and underutilization of human capital into which a costly educational investment has already been made. Developing incentives and providing services to encourage them to enter or remain in the labor market—and to undo the deeply entrenched social norms that undervalue women's education and their potential to contribute productively to the economy—should be a top priority in the country, and indeed, there are signs that this is becoming increasingly recognized as a matter of national urgency.

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Appendix A: Additional Tables

Table A.1: Marginal Effects of the Logit Model: Full, Male and Female Models

	N2010_2018 Total		M2010_2018 Male		F2010_2018 Female	
	coef	**se**	**coef**	**se**	**coef**	**se**
2011	-0.00719	0.00412	-0.00404	0.00378	-0.0117	0.00777
2015	-0.00546	0.00437	0.00472	0.00417	-0.0264**	0.0081
2017	0.0432***	0.00398	0.0290***	0.00378	0.0535***	0.00703
2018	0.0357***	0.004	0.0270***	0.00381	0.0385***	0.00709
Female	0.298***	0.0023				
20-24 years	0.182***	0.0023	0.102***	0.00217	0.278***	0.00423
Married	0.282***	0.00516	-0.0827***	0.00267	0.407***	0.00538
Widower\Divorced	0.143***	0.0222	-0.00879	0.0345	0.194***	0.0257
Rural area	-0.0112**	0.00366	-0.0446***	0.00339	0.0569***	0.00703
Large cities	-0.0297***	0.00242	-0.0175***	0.00223	-0.0444***	0.00445
Primary school	-0.0218***	0.00464	-0.0631***	0.00484	0.0517***	0.00854
Secondary school	-0.227***	0.00356	-0.118***	0.00348	-0.343***	0.00691
Higher education	-0.212***	0.00239	-0.0966***	0.00205	-0.367***	0.00574
Asset index	-0.140***	0.00774	-0.0654***	0.00683	-0.226***	0.0141
Modern house	0.0406***	0.00379	0.0362***	0.00382	0.0495***	0.00764
Apartment	0.0000634	0.00621	0.0354***	0.00687	-0.0369***	0.011
Tradition house	0.0639***	0.00768	0.0298***	0.00758	0.115***	0.0126
Bidonville	0.0308***	0.00652	0.0424***	0.00703	0.0260*	0.0118
HH characteristic						
Unemployed	0.0772***	0.00593	0.0784***	0.00714	0.0603***	0.0096
Industry	0.0475***	0.00756	0.0533***	0.00869	0.0403**	0.0125
Construction	0.0382***	0.00555	0.0402***	0.00629	0.0358***	0.00995
Services	0.0348***	0.00379	0.0308***	0.00368	0.0418***	0.00764
Primary school	-0.00594	0.0032	0.0115***	0.0031	-0.0351***	0.00622
Secondary school	-0.0115**	0.004	0.00971*	0.00391	-0.0485***	0.00755
Higher education	-0.0229***	0.00386	0.00105	0.00369	-0.0629***	0.00736

Table A.2: Transition Matrix: Synthetic vs. Actual Panel Data (2010/2011 through to 2017/2018)

Status in 2010, 2011	**Lower-bound estimate (%)**	**Actual panel (%)**	**Upper-bound estimate (%)**
NEET, NEET	33.81	24.52 (23.89; 25.15)	16.80
NEET, non-NEET	0.00	7.30 (6.93; 7.70)	11.36
Non-NEET, NEET	0.00	7.86 (7.47; 8.26)	17.02
Non-NEET, non-NEET	66.19	60.32 (59.60; 61.04)	54.82
Status in 2011, 2012	**Lower-bound estimate (%)**	**Actual panel (%)**	**Upper-bound estimate (%)**
NEET, NEET	33.88	24.11 (23.46; 24.77)	16.76
NEET, non-NEET	0.00	6.51 (6.13; 6.92)	10.68
Non-NEET, NEET	0.00	8.16 (7.76; 8.59)	17.12
Non-NEET, non-NEET	66.12	61.21 (60.45; 61.96)	55.44

Status in 2012, 2013	Lower-bound estimate (%)	Actual panel (%)	Upper-bound estimate (%)
NEET, NEET	33.21	21.70 (21.07; 22.34)	16.36
NEET, non-NEET	0.00	5.71 (5.37; 6.07)	10.82
Non-NEET, NEET	0.00	6.28 (5.93; 6.65)	16.85
Non-NEET, non-NEET	66.79	66.32 (65.59; 67.04)	55.97
Status in 2013, 2014	**Lower-bound estimate (%)**	**Actual panel (%)**	**Upper-bound estimate (%)**
NEET, NEET	32.75	24.41 (23.74; 25.09)	16.33
NEET, non-NEET	0.00	5.90 (5.53; 6.28)	10.97
Non-NEET, NEET	0.00	6.17 (5.80; 6.55)	16.42
Non-NEET, non-NEET	67.25	63.53 (62.76; 64.29)	56.28
Status in 2014, 2015	**Lower-bound estimate (%)**	**Actual panel (%)**	**Upper-bound estimate (%)**
NEET, NEET	32.48	23.56 (22.88; 24.26)	16.01
NEET, non-NEET	0.00	5.65 (5.29; 6.04)	10.73
Non-NEET, NEET	0.00	6.28 (5.90; 6.69)	16.47
Non-NEET, non-NEET	67.52	64.50 (63.69; 65.30)	56.79
Status in 2017, 2018	**Lower-bound estimate (%)**	**Actual panel (%)**	**Upper-bound estimate (%)**
NEET, NEET	32.17	24.30 (23.84; 24.78)	15.72
NEET, non-NEET	0.00	4.92 (4.69; 5.16)	10.53
Non-NEET, NEET	0.00	6.56 (6.29; 6.83)	16.45
Non-NEET, non-NEET	67.83	64.22 (63.69; 64.74)	57.30

Notes: for each year-pair of data, results are restricted to the sample of individuals age 15 to 24 in round 1; the round 2 age range is adjusted upwards accordingly. “Lower” and “Upper” refer to the two bounds on mobility; for immobility, “Lower” is the upper bound and “Upper” is the lower bound. Synthetic panel upper-bound estimates are based on 50 replications. Individual-level sampling weights are applied; 95 percent confidence intervals are given in parentheses.

Table A.3: Transition Matrix by Gender: Synthetic vs. Actual Panel Data (2010/2011 through to 2017/2018)

Status in 2010, 2011	***Male***			***Female***		
	Lower-bound estimate (%)	**Actual panel (%)**	**Upper-bound estimate (%)**	**Lower-bound estimate (%)**	**Actual panel (%)**	**Upper-bound estimate (%)**
NEET, NEET	13.41	6.12 (5.63; 6.66)	0.91	54.20	43.59 (42.57; 44.61)	32.64
NEET, non-NEET	0.00	6.64 (6.13; 7.19)	5.22	0.00	7.99 (7.45; 8.56)	17.46
Non-NEET, NEET	0.00	6.66 (6.14; 7.21)	12.50	0.00	9.10 (8.53; 9.71)	21.55
Non-NEET, non-NEET	86.59	80.58 (79.72; 81.41)	81.37	45.80	39.32 (38.32; 40.33)	28.34
Status in 2011, 2012	***Male***			***Female***		
	Lower-bound estimate (%)	**Actual panel (%)**	**Upper-bound estimate (%)**	**Lower-bound estimate (%)**	**Actual panel (%)**	**Upper-bound estimate (%)**
NEET, NEET	13.51	6.20 (5.71; 6.74)	0.92	54.30	42.43 (41.37; 43.50)	32.70
NEET, non-NEET	0.00	5.58 (5.07; 6.15)	5.18	0.00	7.46 (6.91; 8.05)	16.24
Non-NEET, NEET	0.00	6.68 (6.16; 7.25)	12.60	0.00	9.68 (9.07; 10.32)	21.60
Non-NEET, non-NEET	86.49	81.53 (80.65; 82.38)	81.31	45.70	40.43 (39.38; 41.49)	29.46
Status in 2012, 2013	***Male***			***Female***		
	Lower-bound estimate (%)	**Actual panel (%)**	**Upper-bound estimate (%)**	**Lower-bound estimate (%)**	**Actual panel (%)**	**Upper-bound estimate (%)**
NEET, NEET	14.03	5.83 (5.36; 6.35)	1.06	52.75	38.34 (37.30; 39.38)	31.87
NEET, non-NEET	0.00	4.69 (4.25; 5.17)	5.35	0.00	6.78 (6.27; 7.32)	16.37
Non-NEET, NEET	0.00	5.40 (4.94; 5.90)	12.97	0.00	7.20 (6.68; 7.75)	20.88
Non-NEET, non-NEET	85.97	84.08 (83.27; 84.85)	80.62	47.25	47.69 (46.64; 48.74)	30.88
Status in 2013, 2014	***Male***			***Female***		
	Lower-bound estimate (%)	**Actual panel (%)**	**Upper-bound estimate (%)**	**Lower-bound estimate (%)**	**Actual panel (%)**	**Upper-bound estimate (%)**
NEET, NEET	13.99	6.88 (6.34; 7.47)	1.19	51.65	42.81 (41.73; 43.89)	31.52
NEET, non-NEET	0.00	5.68 (5.18; 6.21)	5.62	0.00	6.13 (5.60; 6.70)	16.29
Non-NEET, NEET	0.00	5.46 (4.97; 6.00)	12.79	0.00	6.91 (6.38; 7.48)	20.12
Non-NEET, non-NEET	86.01	81.98 (81.10; 82.83)	80.39	48.35	44.16 (43.08; 45.24)	32.06

Status in 2014, 2015	Male			Female		
	Lower-bound estimate (%)	Actual panel (%)	Upper-bound estimate (%)	Lower-bound estimate (%)	Actual panel (%)	Upper-bound estimate (%)
NEET, NEET	14.33	6.56 (6.01; 7.17)	1.28	50.81	40.73 (39.65; 41.82)	30.81
NEET, non-NEET	0.00	4.84 (4.35; 5.38)	6.08	0.00	6.47 (5.95; 7.04)	15.52
Non-NEET, NEET	0.00	5.68 (5.15; 6.26)	13.05	0.00	6.89 (6.36; 7.47)	20.00
Non-NEET, non-NEET	85.67	82.91 (81.98; 83.81)	79.58	49.19	45.91 (44.81; 47.01)	33.67
Status in 2017, 2018	***Male***			***Female***		
	Lower-bound estimate (%)	**Actual panel (%)**	**Upper-bound estimate (%)**	**Lower-bound estimate (%)**	**Actual panel (%)**	**Upper-bound estimate (%)**
NEET, NEET	14.89	8.10 (7.69; 8.53)	1.59	49.66	41.13 (40.37; 41.90)	30.03
NEET, non-NEET	0.00	4.89 (4.56; 5.23)	6.78	0.00	4.96 (4.63; 5.31)	14.27
Non-NEET, NEET	0.00	6.16 (5.80; 6.54)	13.30	0.00	6.97 (6.59; 7.37)	19.63
Non-NEET, non-NEET	85.11	80.85 (80.24; 81.45)	78.33	50.34	46.94 (46.17; 47.72)	36.07

Notes: for each year-pair of data, results are restricted to the sample of individuals age 15 to 24 in round 1; the round 2 age range is adjusted upwards accordingly. “Lower” and “Upper” refer to the two bounds on mobility; for immobility, “Lower” is the upper bound and “Upper” is the lower bound. Synthetic panel upper-bound estimates are based on 50 replications. Individual-level sampling weights are applied; 95 percent confidence intervals are given in parentheses.

Table A.4: Transition Matrix by Education levels

Status in 2010, 2018	No education		Education	
	Lower-bound estimate (%)	Upper-bound estimate (%)	Lower-bound estimate (%)	Upper-bound estimate (%)
NEET, NEET	34.50	17.39	27.22	13.96
NEET, non-NEET	0.00	10.76	0.00	13.03
Non-NEET, NEET	0.00	17.11	0.00	13.26
Non-NEET, non-NEET	65.50	54.75	72.78	59.75

Notes: Results are restricted to the sample of individuals age 15 to 24 in 2010 and 23 to 32 in 2018. “Lower” and “Upper” refer to the two bounds on mobility; for immobility, “Lower” is the upper bound and “Upper” is the lower bound. Upper-bound estimates are based on 50 replications. Individual-level sampling weights are applied.