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The Dissertation of Arshad Mirza is
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For Rohani.

Dedicated to my wife and mother.

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Preface

This dissertation comprises of three original essays on different subjects, a culmination of six years of my graduate work. Two of the three chapters are co-authored with Prof. Nirvikar Singh, who is also one of my mentors on the dissertation committee.

In the first chapter, I present an analysis of the impact of the unconditional transfers intended for the elderly, the Indira Gandhi National Old Age Pensions program of India. I use the panel of individual-level data in the two waves of India Human Development Survey. Using propensity score matching techniques, I estimate the effect of these transfers on the labor supply of the beneficiary elderly and their household members. I find that the in the households of beneficiaries, the elderly retire or reduce work and the young adults are delaying entering the workforce.

The second chapter is a joint work of Prof. Singh and I. In this essay we present the results of our analysis of an original panel data of the richest persons in the USA based on the Forbes 400 list. We gathered twelve years of data, 2004-2015, across the financial crisis. In this panel, other than the Forbes' estimation of wealth and rank, we also have other characteristics of these individuals such as source of wealth, age, and education. We use this panel dataset to analyze the changing sources of wealth and the dynamics of wealth accumulation among the super-rich. We find that post-crisis the overall turnover in the list has reduced, indicating that the wealth is not changing hands as fast. Individuals with advanced degrees and those who have self-made wealth, were doing better in wealth generation before the crisis.

In the third chapter, also a joint work with Prof. Singh, we study the of mental health

care provision in India using secondary data, published research, and government policy and law documents. We structure this essay using seven question for which we provide partial answers. We find that while there are many new ideas in the policy and law that will make things better in the future, for the time-being, mental health care provision in India, both public and private, is in need of attention. We identify the areas that are especially neglected, and ideas from literature that can contribute to rapid improvements. We also identify areas where more information and research is needed.

Chapter 1

Unintended Consequences of Unconditional Transfers: Old-Age Transfers and the Labor Force Participation of Young Adults in India

Author: Arshad Mirza

1.1 Abstract

Indira Gandhi National Old-Age Pensions Scheme (IGNOAPS) is a large program that provides unconditional cash transfers to the elderly living close to the poverty line in India. I use propensity score matching to identify the impact of IGNOAPS on the labor outcomes of elderly beneficiaries and their households in the IHDS panel dataset. I find that the elderly in the households of the beneficiaries retire or decrease their labor hours and the young adults (ages 15-24) are delaying entering the work force. This delay is not due to education attainment.

Keywords: India, Indira Gandhi National Old Age Pension Scheme, Unconditional Cash Transfer, Welfare Programs, Retirement, Elderly, Young Adults.

JEL codes: H53, H55, H75, I38, J22, J26.

1.2 Introduction

The popularity of budget-financed income transfers such as social pensions and minimum pension guarantees is increasing world-wide. The main function of social pensions and other retirement income transfers is to prevent poverty during old age. India has one such cash transfer program aimed at the poorer elderly, the Indira Gandhi National Old-Age Pensions Scheme (IGNOAPS). In 2018, this program had a layout of about 18 billion USD (equiv. PPP) and provided an unconditional transfer to about 18 million of the 80 million elderly individuals in India. In this paper, I provide estimates of the impact of IGNOAPS transfers on the labor outcomes of the beneficiaries and their household members.

My estimates show that upon receiving old age transfers, the elderly in the household retire from work or reduced their work hours. There is also a significant effect on the labor outcomes of young adults (ages 15-24) in their households, they are delaying entering the work force and/or reducing their work hours as well. This in turn effects the household income. The income and consumption of the beneficiary households has not increased over and above the counterfactual group: the aim of these transfers at alleviating poverty have not been achieved.

Microeconomic theory does not assign the direction of labor change in response to transfers definitively. It is possible that cash transfers help the households escape the poverty trap problem; for example, as (Ardington, Case and Hosegood 2009) and Maluccio (2010) show, cash transfers to the poor may convert to productive assets and consequently increase household income in South Africa and Nicaragua respectively. But it is also possible that if the transfer income is not large enough or is given in small installments rather than lumpsum, a credit constrained household may not be able to convert it into capital[1]. Then it is treated as unearned income, which is spent on present consumption. Present consumption may include leisure, if leisure is a normal good. The retirement of the elderly on the receipt of transfers, then may be expected, but the delay of young adults' entering labor market is somewhat novel.

The inter-household effects of pensions and social transfers is evident in many stud-

[1]For example, in their experiments in Kenya, Haushofer and Shapiro (2016) find that smaller transfers to credit constrained household are used for present consumption, while lumpsum transfers are used for purchase of durables.

ies. Gustman and Steinmeier (2004) show how in USA the retirement of one household member effects the labor outcomes of spouse. In South Africa, large social cash transfers to old age persons leads to change in health and labor supply of other household members (Bertrand, Mullainathan and Miller 2003, Case and Deaton 1998, Duflo 2003). Ardington et al. (2009) point out that the transfers in South Africa lead to enough capital to allow prime-age adults to immigrate and look for labor opportunities elsewhere.

It is possible that the link between other household members and the elderly changes due to transfers to elderly. (Chen, Eggleston and Sun 2018) present the case of China where large social transfer to the elderly leads to weakened intergenerational transfers. In the case of IGNOAPS in India, there is no evidence to show that the relatively small IGNOAPS transfers are associated with changes in household arrangements. In these households, labor decisions of the young adults can plausibly be linked to intra-household exchange of transfer income.

In the following section I describe the origins and working of IGNOAPS in detail. In Section 1.4, I describe the challenges in estimation of treatment effects for IGNOAPS and how I plan to overcome these using propensity score matching. In Section 1.5, I describe the data I am using for my main results, and in Section 1.6 I present my results. I test the sensitivity of my results to the choices I make in the Section 1.7 and present my conclusions in Section 1.8.

1.3 National Old-Age Pensions Scheme

In the 2011 census India housed close to 66 million persons aged 65 and above[2], in 2018 this number is closed to 80 million. The largest old age social welfare scheme in India, IGNOAPS covers 18 million elderly with a 2018-19 budget layout of 18 billion USD[3].

Since most persons in India are employed in the informal sector most of these persons do not have access to any pensions and depend mostly on their family/household for their livelihoods. During the last two decades there have been many new initiatives for extending public social security to the elderly. The program was launched as National Old-Age Pensions Scheme (NOAPS) in 1995, to provide a monthly transfer of about USD 9[4] (INR 75) to persons aged 65 or above with little or no regular income or financial support from family members or other sources (Ministry of Rural Development, 2007). The NOAPS imposed a ceiling on the number of beneficiaries, covering half the elderly poor population in each state with an emphasis on covering all elderly persons with no income or family support.[5].

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[2] Data retrieved from `www.censusindia.gov.in` on 26 March 2019.

[3] INR 321 billion were sanctioned for IGNOAPS for the benefit of 18 million recipients in FY2018-19 (source: NSAP dashboard `http://nsap.nic.in`, retrieved on April 7, 2019.). Converted using 2017 (latest) PPP conversion rate of $\sim$18 INR/USD (source: World Bank Indicators).

[4] At 1995 PPP conversion rate of $\sim$8.5 INR/USD (Source: OECD data).

[5] In 1999, the government also added a program of monthly distribution of 10 kg of free food grains (rice or wheat) to elderly persons without any family support or income, via the Public Distribution System. In my analysis, I will control for this and any other govt. welfare programs.

In 2007, the program was rechristened Indira Gandhi NOAPS (IGNOAPS). The federal transfer amount under the program was raised to USD 20[6] (Rs. 200) per month and eligibility was extended to all persons aged 65 or above in households with incomes below the poverty line determined by the Government of India. Further, the federal government requested state governments to provide a matching monthly transfer. Response to federal government's request has varied across states. Twelve states/union territories did not provide any additional amount over the central transfer; 10 states/union territories provided an additional transfer ranging from USD equivalent of 3 to 14.5[7] per month; eight states/union territories had raised their contribution to USD 16.5 per month; and five states/union territories contributed between USD 21-66.5 in additional monthly transfers. There also was a large increase in number of beneficiaries from 2004-2005 to 2011-12, the years I am consider in this analysis.

There is a variation in state minimum age for eligibility the state pensions. While the central minimum age for transfer was 65 in both the periods under consideration, in 9 states, the age of eligibility for state transfer is 60 for both men and women. Elderly women in India are generally considered financially more insecure than men, and partly to reduce their vulnerability, in 7 states, the minimum age eligibility is 60 for women, but 65 for men; and in one state, Rajasthan, the minimum eligibility age is 55 for women and 58 for men. There also are many state-specific relaxations, for example in the state of Bihar, landless-labors or freed bonded-laborers have no age restrictions for selection into the scheme. As a result of these variations in pension amount and criterion for selection into the program, the transfer are different across age-state categories. Table

[6] At 1999 PPP conversion rate of ∼10 INR/USD.

[7] At 2007 PPP conversion rate of ∼12 INR/USD.

1.1 shows the transfer amounts and the age of eligibility for the transfers program in different states by years and gender.

The beneficiaries have to apply by filling out a simple form and provide documents to prove identity, age, and eligibility. These are to be submitted to the local Social Welfare Department officers. Jos, Murgai, Bhattacharya and Mehta (2015) report that the kind of documents that may be enough for the application can be a combination of AADHAR card (Indian national identity card), voter-card, birth-certificate, ration-card, utility bills, local officer certified letter for age, bank or post office account passbooks. The bank or post account information is needed because the IGNOAPS transfers the amounts directly to these.

Literature on the working of IGNOAPS finds that while there is friction in the application process and delays in the delivery, there are is low leakage in the transfers (Drèze and Khera 2017, Dutta, Howes and Murgai 2010, Dutta 2008, Garroway et al. 2013, Jos et al. 2015, Mishra and Kar 2017). The program is generally considered more successful than the other welfare schemes in India. A Task Force constituted to identify areas of improvements in the program has recommended scaling up the social pensions(Jos et al. 2015).

My goal for this paper is not to evaluate the working of the program, but limited only to estimating its effects on the labor outcomes of the beneficiary's households. I use the the India Human Development Survey (IHDS) (Desai and Vanneman 2015) panel dataset for this purpose. IHDS has granular data about individuals interviewed twice, in 2004-5 and 2011-12, separated by 6-8 years. These waves lie across the year 2007 in which the IGNOAPS was expanded, which makes this dataset well-suited for my analysis. Since the expansion occurred a few years after the first survey, the wave 1 data can be safely considered exogenous to the program expansion.

IHDS has information about work, migration, health, education, expenditures, consumption, and assets ownership. It is a randomly selected from the population to make a nationally representative sample. The datasets has the information regarding individuals and households in two one hour long interviews with detailed information about many topics including employment, economic status, health, education, and local infrastructure.

The first round data was collected in 2004-05 and includes randomly selected sample of 41,554 households in 1503 villages and 971 urban neighborhoods. In the second round, in 2010-11, all the round one households residing in the same village or urban neighborhood were re-interviewed. When households had divided, all split households were re-interviewed if located in the same village/neighborhood. I describe the part of the dataset I use for this analysis in detail in a later section 1.5[8].

1.4 Estimation Strategy

The goal of this analysis is to estimate how the unconditional IGNOAPS transfers effect the labor outcomes of the beneficiaries and their household members. Since the selection into the IGNOAPS is means-tested, this is not a straight-forward task. In this analysis I find a plausible counterfactual to the treatment group using propensity score matching, to estimate the average treatment effects.

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[8]More details are available at `www.ihds.info`.

1.4.1 Counterfactual Group Using Propensity Score Matching

Often when trying to evaluate labor market outcomes, randomization is not feasible, and thus matching based on observable characteristics is widely used in arriving at causal treatment effects estimates of labor market policies. The estimation of average treatment effect (ATE) requires a group that is similar to the treatment group in expectations. If we have reasons to believe that the group that is selected into the program is very different from the population, then we cannot ascribe the treatment effects on the treated as ATE since the outcomes of the persons not selected into the program may not present a good counterfactual. This problem is called Selection Bias. One way of reducing selection bias in estimation is to limit the control group to persons who are comparable to the treatment group in observable ways, a process described as Matching.

The approach of matching as an alternative for randomized control experiments has been developing since the 1970s, for example, the works of Rubin and others (Rubin 1973, Rubin 1974, Rubin 1979, Rosenbaum and Rubin 1983) and has been shown to produce comparable results for example Heckman, Ichimura and Todd (1997) and Dehejia and Wahba (2002). It is well understood and documented that matching is not a perfect replacement for randomization and it limited in its applications (Smith and Todd 2005).

Matching is based on characteristics that can be observed, say the questions answered in a survey interview, or the institutional data. It cannot account for unobservable characteristics that may separate the treatment group from the population, for instance in the case presented by Heckman et al. (1997), an individuals may have more information about their motivation or chances of getting a job after going through the job training, and may inform the effort they make in trying to get the benefits of the job training: the self-selection is based on their knowledge, something we cannot observe. Such biases cannot always be removed by finding a counterfactual group based on matching the observable characteristics such as gender, years of education, marital status, etc. I am convinced that in the case of IGNOAPS we may arrive at a plausible counterfactual based on the matching of observable characteristics using IHDS panel. The reasons for my conviction are as follows.

The implementation of IGNOAPS is done by the state, in other words the program makes a decision about the suitability of selecting the individual into the program. The program does not require institutional data such as tax returns for this process. The program coordinators, very likely, are looking for and are able to observe characteristics very similar to the ones available to us in the panel data I am using in this analysis. Moreover, I can also observe the characteristics by which the selected group is ultimately significantly different from the rest of the population of similar age, which I will use in the process of matching.

One major concern while matching is the exogeniety of the observable characteristics. Since I am working with a panel of individuals observed twice across the expansion of the program, I am able to overcome this large hurdle. Since the expansion happened in 2007, after the first survey in 2004-5, the wave 1 data can be safely considered exogenous to the program. As (Heckman et al. 1997) cautions, we have to be careful about the sources of the data for the control and treatment groups, the data I am using is gathered by the same organization IHDS, using a very similar questionnaire.

Based on both, the announced goals of the program and the observed differences between the beneficiaries and the population, we can match each individual in treatment group with someone similar to arrive at a control group. Matching by cells of all relevant covariates will require a very large dataset which I do not have. In these circumstances Rosenbaum and Rubin (1983) suggest use of scores, i.e. a function of the array of relevant variables (Z). One possible algorithm is called propensity score, i.e. the probability of being selected into the program conditional on Z such that the conditional distribution of baseline outcomes Y_0 given a score $e(Z)$ is independent of assignment into treatment (D):

$$Y_0 \amalg W \mid D.$$

Propensity score matching assumes that for all Z there is a positive probability of selection into the program ($D = 1$) or not ($D = 0$) and thus a match can be found for each person in treatment.

$$0 \leq Pr(D = 1 \mid Z) \leq 1$$

The values of the probability score for which there is support for both outcomes of D - 0 and 1, is called *common support*. In the following paragraphs I describe how I arrived at the algorithm I finally use for matching in this analysis.

1.4.2 Propensity Score Algorithm

I am limiting my analysis to the persons who were not themselves, nor anyone else in their household, age-eligible for IGNOAPS in the years 2004-5, but became eligible sometime later before 2011-12.[9] I also carefully eliminate any households who may receive transfer for other members at the baseline or endline. Also, if there are more than one persons from the same household, the person who does not receive transfer after are dropped, to avoid the same household from appearing both in treatment and control groups.

The treatment group are the individuals whose households received exactly one transfers when they were re-interviewed in 2011-12. For creating the control group by matching, my goal is to re-engineer the de-facto decision making process based on observed data and find those persons who were as likely to be selected into the program as the individuals in the treatment group.

As I described earlier I have a range of wave 1 variables that are very likely not influenced by the program. Many of these are possibly the same variables that were used by the IGNOAPS in making a decision about the suitability of the individual for being selected into the program[10]. After the expansion of the program in 2007 the literature of IGNOAPS describes the goal to extend the transfers to all persons aged 65 or above in households with incomes below the poverty line determined by the Government of India.

[9]The data for wave 1 of IHDS was collected in 2004-5 and the re-interview was in 2011-12. Throughout the paper, I refer to the year 2004-5 as wave 1 or baseline, and 2011-12 as the wave 2 or endline.

[10]It is possible that there were some large changes in the circumstances of these individuals and the wave 1 data differs widely from what IGNOAPS based the decision on. I am forced to assume that such cases conservative in nature: for each person whose circumstances improves, there is someone else whose circumstances have worsened and such changes are not driving my results.

The baseline comparison of the groups presented in Table 1.2 also sheds light on the selection process. We can see that the treatment group is more likely to be older than the rest. They are more likely to be employed at the baseline and earn less. They live in households with similar number of members but fewer earning ones. They are also less likely to suffer any major illness[11]. Perhaps only due to the nature of distribution of poverty[12] there are other covariates that also set the treatment group apart, such as caste[13], geographic situation: rural or urban residence, and type of dwelling. The treatment group is poorer in terms of household consumption and income, more likely to live in rural areas and to live in homes that are not permanent structures. Gender and religion are not significantly different.

To arrive at the propensity score algorithm, I tried many different variable that could represent the the announced criteria of the program and the differences highlighted in Table 1.2. My decision to keep a variable in the algorithm was based on two criteria: whether it is different from null at 5% level, and/or whether it increases the predictive

[11]List of illnesses considered major: cataract, tuberculosis, high blood pressure, heart diseases, leprosy, cancer, asthma, polio, paralysis, epilepsy, mental disorders, AIDS, and a category other based on reported major illness.

[12]Since many of these covariates were not significant when predicting selection into the program in the propensity score algorithm.

[13]For a detailed discussion on how caste can economic discrimination can depend on case, one can refer to one of the many works on the subject, e.g. Thorat and Neuman (2012) or Desai and Dubey (2012).

power (pseudo R^2) appreciably.

I start with the variables that translate the announced goal of the center: to serve all the age-eligible individuals who live below poverty line. The most obvious variable is age, which as expected is significant. Then, I included variables that may describe financial circumstances: personal income, household variables such as household income per capita (IPC) and consumption per capita (COPC), that are used for defining if a household is living below poverty line. IPC is very important in the prediction of selection into the program while COPC or its log transformation are not.

Years of education of the individual and religion effect the selection significantly and added to prediction. On the other hand, whether the person was working, personal income, gender, caste, and if the person had major illness[14], were not significant in the prediction, nor did these variables add to the pseudo R^2.

Before expansion of the program the announced goal was to give preference to the elderly who cannot depend on earning household members for financial support. Mishra and Kar (2017) and Jos et al. (2015) find that the number of earning members per household member are significant predictors of selection into IGNOAPS even after expansion[15]. I find that the neither the number of persons nor the earning persons in the household are significant for the selection algorithm.

[14]See footnote 11.

[15]Mishra and Kar (2017) studied IGNOAPS in Orissa in 2008 and Jos et al. (2015) studied three north Indian states, Delhi, Haryana, and Uttar Pradesh, in 2013.

Jos et al. (2015) also found such assets ownership to be predictors of inclusion into the program. IHDS asks about the household ownership of 33 difference assets such as bicycle, motorcycle, electric fan, television etc. I find this household asset ownership index to be significant predictors for selection. For the second wave, IHDS interviewed persons in the year 2011 or 2012. I tested this as a dummy for being interviewed in 2012, and it is not significant for predicting selection.

IGNOAPS requires documentation to certify age, income, and residency. Jos et al. (2015) describe how eligible persons may not be able to get transfers if they cannot provide the requisite documentation or, in extreme cases, get intimidated by the process and not apply at all. A Ration Card (RC) is a document issued under an order or authority of the State Government, as per the Public Distribution System, for the purchase of essential commodities at a subsidized rate from fair price shops. It has also become an important tool of identification now-a-days.[16] Families living below the poverty line are entitled to special BPL ration card. Some other demographic categories such as landless farm-labors also have special RC. In this data I can identify the persons who have any special RC, this may have been used as a form of identity while applying for IGNOAPS transfer and for evaluating if they meet the criteria. I tested the dummies for having a RC and if it marks a household for special-needs. I find that the set of dummies that represent having a RC and the type of RC are important predictors for selection algorithm.

Since the IGNOAPS is administered at the state-level and the generosity varies by

[16]More information about ration cards can be found at the government website: `https://archive.india.gov.in/howdo/howdoi.php?service=7`.

state (see Table 1.1), I tested dummies for states, which turns out to be very significant. The level of urbanization of the place of residence is de-facto important, and the labor markets can be very different by level of urbanization. I interact the state dummy with urban dummies, to create urban-state dummies, most of which are significant and jointly improve prediction by a large margin.

Finally, the propensity score algorithm uses the following baseline variables: age, dummy for Hindu religion, years of education, income per capita, assets ownership index, dummies for type of ration-cards, and urban-state dummies for place of residence. This probit regression is presented in Table 1.3.

1.5 Data

The dataset I am using for this analysis is the two waves panel of India Human Development Survey (IHDS). As I described in the previous section, I am using only the subset of individuals, who were not age-eligible in their respective states for being selected into the program when interviewed for the wave 1 (2004-5) and were above the eligible age when interviewed in wave 2 (2011-12). India has 35 states/union territories. The data I am using for matching are 5,653 individuals from the wave 2 of IHDS from the 27 states/territories of India where we have at least one IGNOAPS beneficiary.[17]

For each of these individuals I also have wave 1 characteristics that I will use for

[17] IHDS does not have data for Andaman & Nicobar or Lakshadweep Islands. IHDS data for following states/territory have no beneficiaries that match the criteria: Chandigarh, Daman & Diu, Meghalaya, Mizoram, Nagaland and Sikkim.

predicting the propensity score: age, years of education, per capita household income, dummy for Brahmin (caste), dummy for material of construction of roof, and dummies for urban-state residence. I convert all current currency amounts from Indian Rupees (INR) to U. S. Dollars using the purchase power parity (PPP) value of 11 INR/USD for years 2004 and 2005 and 15 for years 2011 and 2012[18].

I have chosen the sample based on three nearest neighbors, matched with replacement, for one treated individual. I am unable to find desirable balance on exogenous covariates based on one or two neighbors. The covariate balance these matched samples are shown in Tables 1.B.1 and 1.C.1, respectively. I also share the results for 1 and 2 nearest neighbors sample in the appendix Section 1.7 Tables 1.B.3-1.B.5, and Tables 1.C.3-1.C.8, respectively, to show how my results are not very sensitive to this choice.

A summary of the sample data of the beneficiaries: the 596 treated and 1003 matched individuals in Table 1.4. These individuals were not age eligible at baseline, with a mean age of 59, but were all age-eligible at the endline, when their mean age was 66. In means about 68% were working at baseline and 13% have retired at the endline. Of those that still worked, have reduced their hours to 60% of the baseline mean. Those that work still earn similar amounts as baseline.

Urbanization over 6-8 years has converted 2% rural to urban, based on the definitions used by the Census Bureau of India. The household sizes have reduced from about 6 persons to about 5. The transfers have increased the mean income by about 30% for the whole sample. The household incomes (curr. USD) have almost doubled in means, in

[18]Source is OECD data.

keeping with inflation[19]. While the material condition of these households seem to have improved slightly, about 8% more have roof made of permanent structures, based on IHDS assessment about the same number are still below poverty-line by consumption per capita.

I will also use the IHDS wave 1 and wave 2 data for the household members of the matched elderly individuals for cross-sectional and panel analysis. A summary of the sample labor outcomes of the household beneficiaries is presented in Table 1.7.

1.6 Results

As described in the previous section, I am basing my matching on those who became age-eligible for receiving the IGNOAPS transfers, in their respective states, sometime between wave 1 and wave 2 for 29 states/territories of India. I carefully exclude those households that may have received transfers at baseline or are receiving more than one transfer at the endline. I arrive at a propensity score based on a probit algorithm using many baseline (IHDS wave 1) characteristics of these individuals to predict whether they will receive IGNOAPS transfer at the endline (IHDS wave 2). Using these propensity score, I match the treatment group individuals to three nearest-neighbor individuals, with replacement, to form a control group. Table 1.4 shows the summary of the data set I used for the main results and was described in the earlier section. Table 1.5 presents the balance of exogenous covariates before and after matching.

[19]Based on World Bank Consumer Price Index data, between 2005 and 2012 the inflation is expected to be approx. 175%.

The Table 1.6 results are based on difference of the Outcome$_\triangle$ between the treatment group and the matched control group. This is called the difference-in-difference estimate, as suggested by Heckman et al. (1997) and Smith and Todd (2005). For each outcome I am interested in, first I estimate the difference in the outcome since the wave 1:

$$\text{Outcome}_{\triangle,i} = \text{Outcome}_{end,i} - \text{Outcome}_{base,i}.$$

I am interested in testing whether the labor and income outcomes of the individuals who receive the IGNOAPS, and members of their household, are significantly effected by these transfers. The regressions are of the form:

$$\text{Outcome}_{\triangle,i} \sim \text{Receiving transfer}_i \tag{1.1}$$

The lower panel of Table 1.6 results are based on age groups, in which case difference in difference will be difficult to interpret, and I am using difference estimator in the endline cross-sectional data:

$$\text{Outcome}_{hi} \sim \text{Receiving transfer}_i \tag{1.2}$$

I implemented the regression using the command *psmatch2* developed by Leuven and Sianesi (2003) in STATA. I estimate the standard error the standard as proposed by Abadie and Imbens (2006) by choosing the appropriate option in the implementation of *psmatch2*. The main results are reported in Table 1.6. In the following paragraphs I will describe the variables and the results from this table.

IHDS asks the individuals for a very granular measure of the hours worked. I use this to create two measures of work, first is if the persons works at all (more than zero hours) and the other is the hours worked last year. Based only on these results, we cannot reject the null hypothesis of no treatment effect on working at all last year (retiring) or difference in labor income, but the labor hours, the labor income (equiv. current PPP USD) of the treatment group is lesser than the counterfactual. The total income (labor income + transfer) is higher than the counterfactual. The amount of the transfer, about 260 USD in the mean, is meaningful for these individuals and has compensated for the loss of labor income due to the reduction in work hours, as both the means and DID of personal income (lab. inc. + tranfer) show. But at the same time, the amount is not comparable to the mean household income of $\sim$ 6500 of the counterfactual at the endline or the household income DID of about -1000 USD.

Among the household variables, the household income (including transfer) for the treatment group has reduced significantly. To check whether this result was driven by the size of the family, I compared the income per adult and find similar result. Since the total income of the beneficiaries has increased, while overall household income has decreased, this could only mean that the others in the household have experienced reduction in income.

To explore what is driving the reduction in the household income, I present the difference estimators for labor outcomes of other members of the family. Lower panel of the Table 1.6 shows a comparison of the household mean earning members by age groups. As expected more eldest persons in the treatment group have retired, but we can also see that fewer young adults (ages 15-24) in the treated group work.

These estimators are based only on the level of household. In the IHDS panel, I can observe the labor outcomes at the individual levels for each of the household members. Individual-level estimations allow me to control for heterogeneity that may be confounding the estimations due to old-age transfers: gender, urbanization, suffering for major illness, the year of interview, and the amount of other transfer. I present the individual fixed-effect estimations and cross-sectional estimations in the following sections, representatively.

1.6.1 Fixed-effects Regressions for All Household Members

To ascertain the findings about the household members from the matched regressions, I collected the individual data for prime age members and conducted individual fixed-effects regression for the labor outcomes in the endline. The individual fixed-effects regression have the most strict assumption and similar to difference in difference estimators. In these regressions I am able to capture the variation at the individual level rather than in the means, and I can also control for other characteristics that may effect labor outcomes. Especially, I am able to control for the household income from any major morbidities which can severly interfere with labor outcome.

As I had mentioned briefly in the introduction to the IGNOAPS, that the National Social Pensions Scheme is a collection of schemes, other than the old age pensions scheme there also is a scheme for transfer of grains to old age persons, transfers for widows, and disability pensions. In these regressions I am controlling for any other transfers to the household.

The models I estimate for this analysis is:

$$\text{Outcome}_{it} \sim \text{Receiving Transfer}_{ht} + controls_{it} \tag{1.3}$$

Where the subscript i represents individual, h household, and t time. Since the matching of the elderly was done with replacement, weights of households are important. I am controlling for age, education, if suffering major illness, urban dummy, and state-dummies. I cluster the standard errors at the state-level.

I present these estimates of weighted regressions estimates of model (1.3) in the columns 1-3 of Table 1.8. I also report the unweighted regressions for testing the sensitivity of my results in Table 1.A.1. The top panel is based on all individuals and the lower panel is based on grouping by age at the endline: young adults (15-24), prime-age adults (25-64), and the elderly (65+).

The loss of income is clearly driven by the young adults delaying their entry into labor force. It is possible that the household income, the income of the young members effects the selection into the program, and this bias is driving my results. Even if so, it is unlikely that this bias is proportional to the generosity in the state. I can test my hypothesis by utilizing the variation in the generosity by states. I conduct a regression on labor outcomes using the reported transfer incomes. The models I estimate for this analysis is:

$$\text{Outcome}_{it} \sim \text{Transfer Amount}_{ht} + controls_{it} \tag{1.4}$$

As before, I am controlling for age, education, if suffer major illness, any other govt. transfers to the household, year interviewed, and dummy for urban, and cluster the standard errors at the state-level.

These results for the weighted regressions estimates for model (1.4) based on reported transfers are presented in the columns 3-6 of Table 1.8. These results show that while there is no appreciable overall effect the transfers on the labor outcomes of the household, the work among the young adults is decreasing in transfer amounts, and further confirms that these labor outcomes are driven by the transfers.

The age group I am making claim about is 15-24 at the endline in 2011-12. At the baseline, in 2004-5 some of them were 7-9 years old. While fixed-effects regressions are most believable since we make the most strict assumption about the unobservable characteristics, the age at baseline may make this comparison implausible. Thus, to further confirm my findings, I am also presenting cross-sectional comparisons of the treated and control household members of the same age group.

1.6.2 Cross-section Regressions for All Household Members

As for the fixed-effects regressions presented in the previous section, in this section I show the cross-section regression for the endline labor outcomes of the members of the matched households. The models I estimate for this analysis are:

$$\text{Outcome}_i \sim \text{Receiving Transfer}_h + controls_i \tag{1.5}$$

$$\text{Outcome}_i \sim \text{Transfer Amount}_h + controls_i \tag{1.6}$$

Here also, the subscript i represents individual, h household, and t time. I am controlling for age[20], education, if suffer any major illness, any other govt. transfers to the household, year interviewed, dummy for urban, and state-dummies. I cluster the standard errors at the state-level. I present these results of estimates of model (1.5) in

[20] I control for second-degree polynomial of age when I regress all individuals, and first-degree when I regress by age groups.

the columns 1-3 and for model (1.6) in columns 4-6, respectively, of Table 1.9. As for the fixed-effects regression table, the top panel is based on all individuals and the lower panel is based on age-based groups.

In the cross section, we can again see that there is no significant overall effects on the labor outcomes of the household members. Comparison by age groups show that the elderly in the treated group reduce their work hours over the control group. Again the young adults are delaying their entry into labor force is the most significant difference between the groups and is probably driving the household income difference.

The age group 15-24 is often pursuing education, and there is perhaps a possible explanation for reduced labor that the treatment group is preparing itself for better career. If IGNOAPS transfers is associated with more enrolment in school or college that may be driving the reduced labor outcomes. In the following section I test this hypothesis using fixed-effects regressions.

1.6.3 Education of Young Adults

There is an alternative explanation for the reduction in work of the youngest age group: that they are spending their time pursuing more education in preparation for their career, rather than working. In the IHDS panel, I can observe the change in education over the years. Using the fixed-effects regressions I can estimate if difference-in-difference of education among the group that is 15-24 year old at endline is driven by the household receiving transfers or the transfer amount.

The models I estimate for this analysis are:

$$\text{Years of education}_{it} \sim \text{Receiving Transfer}_{ht} + controls_{it} \tag{1.7}$$

$$\text{Years of education}_{it} \sim \text{Transfer Amount}_{ht} + controls_{it} \tag{1.8}$$

Where the subscripts have the same meaning as the other models. I am controlling for urbanization, years passed, and if the individual suffers any major illness. These estimates of models (1.7) and (1.8) are presented in the Table 1.10.

In the summary table for households it can be seen that the young adults of the treated group are slightly more educated than the control group (4 years versus 3.5). But the individual fixed-effects model estimates in Table 1.10 make it clear that the DID in years of education is not associated with receiving transfer or the transfer amounts. In light of this evidence, the reduction in labor outcomes does not seem to be due to enrolment in school/college.

1.7 Sensitivity

It is well understood that the results from propensity score matching are sensitive to the choice of algorithm and the matching mechanism used (Smith and Todd 2005). I test and report the sensitivity of the results to some of the more important choices I have made in the analysis in the sections 1.10.1, 1.10.2, and 1.10.3. I find that the results do not change in direction due to my choices: in almost all cases the null hypothesis, that the young adults of the treated household have same labor outcomes as the control households, can be rejected at 5%. In the worst case, it can be seen that they work lesser (one-sided test) than the control group.

Since I matched beneficiaries with replacement, I have weighted all the main results for cross-section and fixed-effects results by weighted regressions. I cheked to see if the results are sensitive to weighting, and find that they are not. The results of unweighted cross-sectional results are reported in Tables 1.A.1 - 1.A.3.

Table 1.B.2 presents the matched DID and Diff estimators based on sample of 1 nearest neighbor matching (rather than 3 used for main results). I also show the results for household in the Tables 1.B.3 - 1.B.5. Similarly, Table 1.C.2 presents the matched DID and Diff estimators based on sample of 2 nearest neighbor matching and the results for household are presented in the Tables 1.C.3 - 1.C.8.

1.8 Discussion and Conclusion

By all accounts, a social security system for the poorest elderly in India is a very good idea. There is enough evidence to show all the benefits the elderly reap from IGNOAPS(Garroway et al. 2013, Mishra and Kar 2017, Drèze and Khera 2017, Dutta 2008, Dutta et al. 2010). There however are other consequences to the program.

In this paper, I presented the following discoveries: the elderly beneficiaries that receive the transfers reduce work. The reduction in their labor income is more than compensated by the transfers. Plausibly, the transfer of income allows persons of elderly age in the beneficiary households to retire. Yet, the households of these beneficiaries are earning lesser than their counterfactuals at the endline. I also present evidence that the youngest members of the treatment group work less often and/or lesser hours compared to the counterfactual group matched using exogenous wave 1 variables.

Usually when one working person of the family retires, the younger will enter the work force. It seems that the transfers due to the elderly allows the young adults in their households to delay entering the labor market. I also show that this delay is probably not because they are pursuing education.

As discussed in the introduction, the microeconomic theory is not clear on what to expect from transfers, if it is like lottery, unearned income it may be spent on leisure as Imbens, Rubin and Sacerdote (2001) find. It is also possible that cash transfers convert to capital and lead to more employment of prime-age adults as in South Africa (Ardington et al. 2009) or increased income as in Nicaragua (Maluccio 2010). Banerjee, Hanna, Kreindler and Olken (2017) assert that most cash transfer programs do not lead to reduced labor supply. Not withstanding which my findings are quite plausible.

While IGNOAPS transfers are not insignificantly small, but for a comparison they are not even as large as the per capita household income of the control households (see Table 1.4). It may not be large enough to form assets as in Nicaragua or South Africa. In fact the matched DID estimates show a small but significant decrease in assets ownership. Haushofer and Shapiro (2016) present evidence from randomized control trials in Kenya that households living near poverty line may experience problems in converting small periodic transfers into capital and such transfers are usually used for consumption.

In the matched DID results (Table 1.6), it is also apparent that the treatment groups have suffered a loss of assets. If these assets are related to employment, for example bicycle or motor vehicle that are major sources of locomotion on most rural parts, it may have something to do with labor outcomes of the young adults. Since IHDS offers granular information about assets ownership, it is possible to further analyse this.

In our data, while the govt. social security program provides cash transfers to widow and disabled persons, who are expected to be not working, the old age pensions have an impact on the labor outcomes of the elderly and the young adults. It would also be interesting to see the reserve wage for entering employment for the young adults in each of the treatment and control group is. Unfortunately in the IHDS data, the wage data is not directly provided. There may be a proxy though, as National Rural Employment Guarantee Act offers employment for anyone seeking employment at a minimum wage rate. It would also be interesting to see how the presence of such opportunity in the rural parts compared to urban parts explains the results.

I want to emphasize that since my analysis does not address the welfare effects of the IGNOAPS transfers and I cannot make any claim about the undesirability of these outcomes.

1.9 Figures and Tables

Table 1.1: IGNOAPS: Max. Transfer (Annual, Rs.) and Eligible Ages

State/ Union Territory	IHDS data round 1: 2005-'06	IHDS data round 2: 2010-'11	Age Eligibility Male	Age Eligibility Female
Andhra Pradesh	900	2400	65	65
Arunachal Pradesh	1800	2400	60	60
Assam	900	3000	65	60
Bihar	1200	2400	60	60
Chhattisgarh	1800	3300	65	65
Goa	9000	12000	60	60
Gujarat	3300	4800	60	60
Haryana	2400	3600	65	65
Himachal Pradesh	1800	2400	65	65
Jammu & Kashmir	900	2400	65	65
Jharkhand	1200	4800	65	65
Karnataka	1200	4800	65	60
Kerala	1320	2820	65	60
Madhya Pradesh	1800	3300	65	60
Maharashtra	3000	4500	65	60
Manipur	900	2400	65	60
*Meghalaya	1200	2400	65	60
*Mizoram	1200	3000	65	60
*Nagaland	1200	3600	65	60
Orissa	1200	2400	65	60
Punjab	2400	5400	65	60
Rajasthan	2400	4800	58	55
*Sikkim	2400	4800	65	65
Tamil Nadu	2400	4800	65	65
Tripura	1500	2400	65	65
Uttar Pradesh	1500	3600	65	65
Uttaranchal	1500	4800	65	65
West Bengal	3600	4800	65	65
*Andaman & Nicobar	900	6000	60	60
*Chandigarh	2400	2400	65	65
Dadra & Nagar Haveli	900	2400	65	65
*Daman & Diu	900	2400	60	60
Delhi	4200	7200	60	60
*Lakshadweep	1200	3600	60	60
Pondicherry	1500	7200	60	60

* Data from these states/territories is not considered in this analysis.

Table 1.2: Targeting by the IGNOAPS among those who became age eligible sometime between 2004-5 (baseline) and 2011-12 (endline)

At Endline:	Get Transfer (1) M_1	Not (2) M_2	Difference $M_1 - M_2$	S.E (Diff.)	T-value
	Unmatched sample, Baseline Characteristics				
Age	59.26	58.12	1.14	0.11	9.95
Hindu	0.88	0.82	0.06	0.01	3.80
Brahmin	0.03	0.08	-0.05	0.01	-5.40
Major illness: if any	0.14	0.17	-0.04	0.02	-2.40
Labor: If worked last year	0.66	0.64	0.02	0.02	0.99
Labor: Hrs. worked, yr.	695.38	726.84	-31.46	48.85	-0.64
Labor: Inc. (USD/yr.)	349.88	861.34	-511.46	59.09	-8.66
Household:					
Urban dummy	0.18	0.35	-0.17	0.02	-9.68
Assets: Index (scale: 1-33)	9.66	13.66	-4.00	0.23	-17.47
Annual income (USD)	3350.25	6492.20	-3141.95	259.02	-12.13
Annual income per cap. (USD)	930.66	1760.27	-829.61	59.43	-13.96
Cons. per cap.(USD)	802.34	1103.79	-301.45	40.24	-7.49
Below poverty line	0.26	0.18	0.08	0.02	4.37
No. persons	5.67	5.96	-0.29	0.13	-2.23
No. earning persons	1.28	0.96	0.32	0.05	6.15
No. of individuals	596	3864	Total: 4460		
No. of states	27				

Data from wave 1 IHDS, 2004-5.

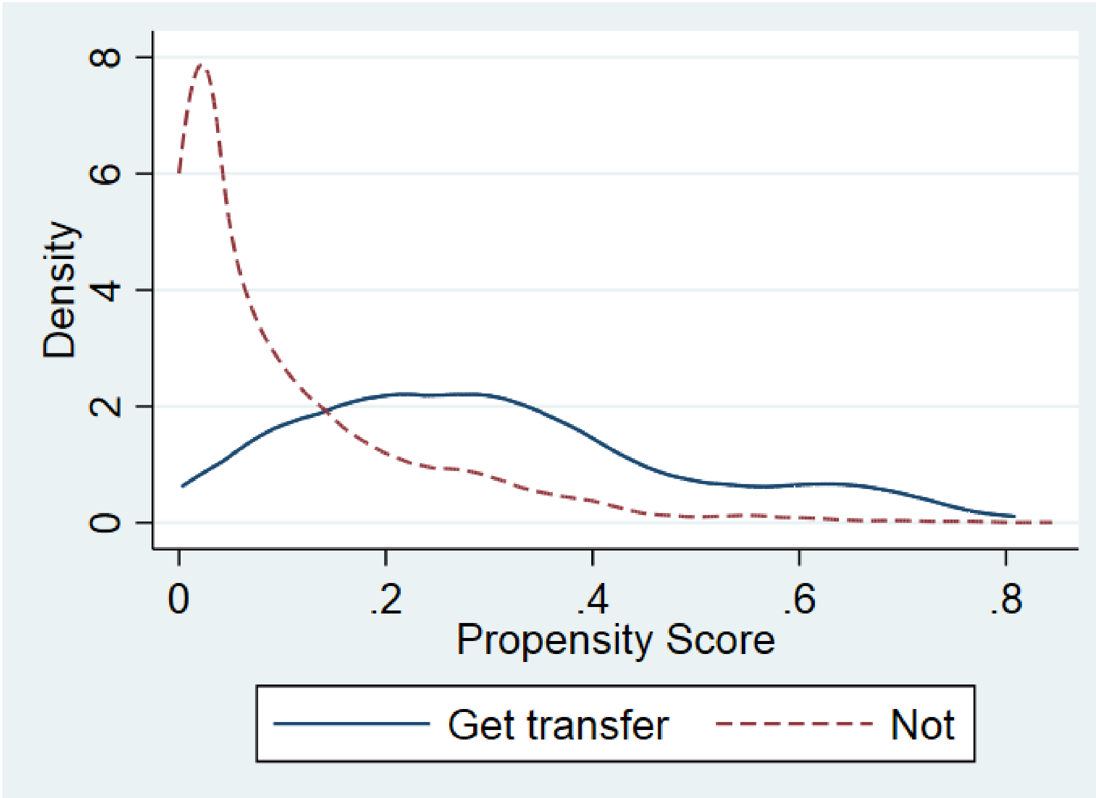

Figure 1.1: Distribution of Propensity Score for the Unmatched Sample

Table 1.3: Probit Regressions for Predicting Treatment at Endline Using Baseline Observable Characteristics

	(1)	(2)	(3)	(4)	(5)
	If reported old age transfer at endline				
Baseline Characteristics:					
Age	0.0360***	0.0363***	0.0370***	0.0372***	0.0383***
	(0.0127)	(0.0129)	(0.0129)	(0.0129)	(0.0130)
Hindu	0.204**	0.203**	0.214**	0.207**	0.210**
	(0.0849)	(0.0850)	(0.0852)	(0.0854)	(0.0854)
Years of Education	-0.0157**	-0.0154**	-0.0143*	-0.0143*	-0.0151*
	(0.00758)	(0.00773)	(0.00777)	(0.00777)	(0.00778)
Household: per cap. inc. ('000 USD)	-0.102***	-0.102***	-0.101***	-0.104***	-0.101***
	(0.0292)	(0.0292)	(0.0292)	(0.0293)	(0.0293)
Household: Asst. own. index (1-33)	-0.0403***	-0.0403***	-0.0395***	-0.0376***	-0.0379***
	(0.00739)	(0.00739)	(0.00741)	(0.00766)	(0.00767)
Ration Card: BPL	0.457***	0.457***	0.456***	0.455***	0.460***
	(0.0636)	(0.0636)	(0.0636)	(0.0637)	(0.0638)
Ration Card: Antodaya	0.461***	0.460***	0.461***	0.458***	0.463***
	(0.105)	(0.105)	(0.105)	(0.105)	(0.105)
Male		0.0140	0.0184	0.0104	0.00409
		(0.0918)	(0.0919)	(0.0923)	(0.0923)
Brahmin			-0.187	-0.186	-0.190
			(0.136)	(0.135)	(0.135)
Household: Dependence ratio				-0.0102	-0.0120
				(0.0106)	(0.0107)
If work					-0.102*
					(0.0618)
Constant	-0.0959	-0.132	-0.217	-0.171	-0.146
	(1.047)	(1.073)	(1.075)	(1.080)	(1.082)
Urban-State dummies	Yes	Yes	Yes	Yes	Yes
Observations	4424	4424	4424	4424	4424
Pseudo R^2	0.225	0.225	0.225	0.226	0.226

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Column 1 represents the algorithm finally used.

The base group for Ration Card dummies is above-poverty line (APL) which is omitted for this regression.
Note that we do not have any treated in some state-urban regions and thus the dummies predict failure completely. These urban-state regions and 36 individuals living here are ignored for the rest of the analysis.

Table 1.4: Summary of Individual Sample Data

Elderly by waves		
	Baseline	Endline
Age	59.11	66.13
Hindu	0.85	0.86
Brahmin	0.04	0.03
If reported old age pension	0.00	0.37
Major illness: if any	0.16	0.33
Labor: If worked last year	0.68	0.55
Labor: Hrs. worked, yr.	718.78	437.65
Labor: Inc. (USD/yr.)	403.36	441.76
Transfer (USD/yr.)	0.00	97.42
Lab. inc. + trans. (USD/yr.)	403.36	539.17
Household:		
Urban dummy	0.20	0.22
Household: Assets index (scale: 1-33)	9.97	12.71
Annual income (USD)	3466.32	6170.40
Annual income per cap. (USD)	964.05	1837.28
No. oth govt. transfer in HH	0.04	0.13
Oth. govt. tr., ann. (USD/yr.)	8.94	33.15
Cons. per cap.(USD)	812.00	1401.75
Below poverty line	0.26	0.23
No. persons	5.75	4.95
No. persons earning	1.16	1.14
No. persons age 15-24	0.82	0.49
No. prime-age adults	1.44	1.27
No. persons age 65-74	0.08	0.90
Observations	1599	1599

(Cont.) Summary of Individual Sample Data

Elderly by waves		
	Baseline	Endline
Age	59.11	66.13
Hindu	0.85	0.86
Brahmin	0.04	0.03
If reported old age pension	0.00	0.37
Major illness: if any	0.16	0.33
Labor: If worked last year	0.68	0.55
Labor: Hrs. worked, yr.	718.78	437.65
Labor: Inc. (USD/yr.)	403.36	441.76
Transfer (USD/yr.)	0.00	97.42
Lab. inc. + trans. (USD/yr.)	403.36	539.17
Household:		
Urban dummy	0.20	0.22
Household: Assets index (scale: 1-33)	9.97	12.71
Annual income (USD)	3466.32	6170.40
Annual income per cap. (USD)	964.05	1837.28
No. oth govt. transfer in HH	0.04	0.13
Oth. govt. tr., ann. (USD/yr.)	8.94	33.15
Cons. per cap.(USD)	812.00	1401.75
Below poverty line	0.26	0.23
No. persons	5.75	4.95
No. persons earning	1.16	1.14
No. persons age 15-24	0.82	0.49
No. prime-age adults	1.44	1.27
No. persons age 65-74	0.08	0.90
Observations	1599	1599

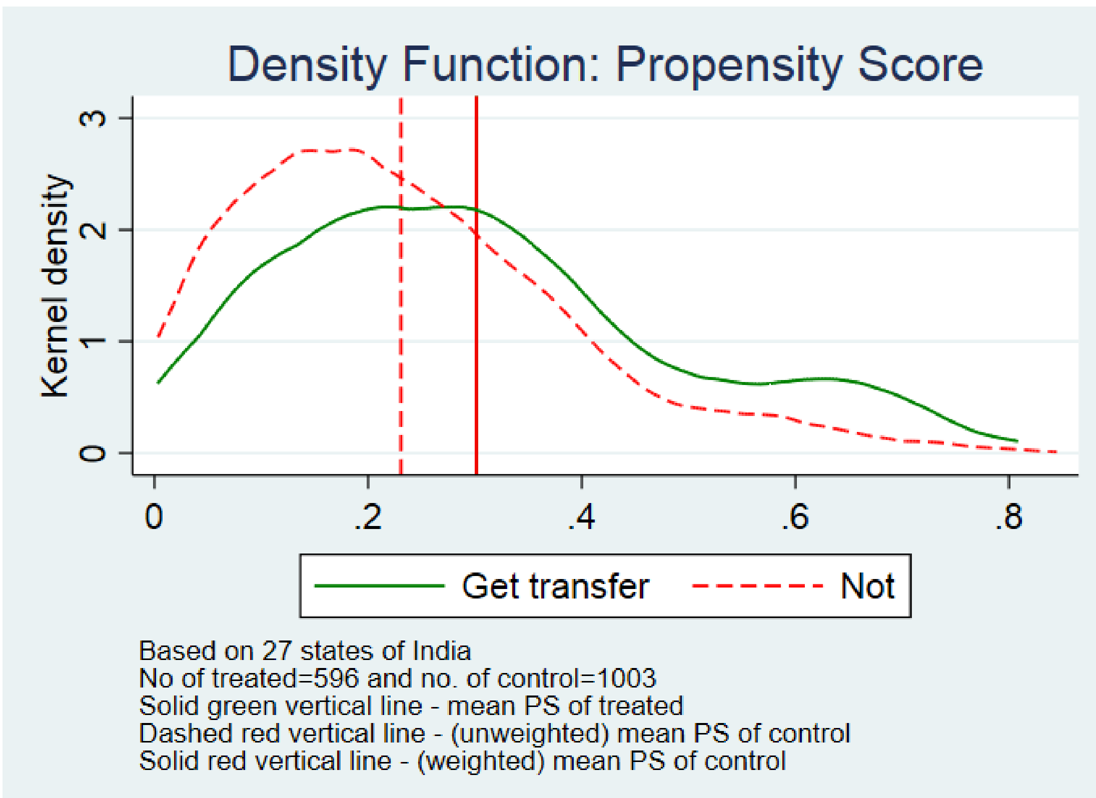

Figure 1.2: Distribution of Propensity Score: 3 Nearest Neighbor Matched Sample

Table 1.5: Exogenous Covariate Balance Before and After Matching: Three Nearest Neighbor Without Replacement

		Mean			% Reduction	t-Test		Variance Ratio
Variable		Treated	Control	% Bias	in Bias	t	p>t	V(T)/V(C)
Propensity Score	U	0.302	0.108	122.8		32.43	0	2.11*
	M	0.302	0.301	0.100	100	0.0100	0.993	1
Age	U	66.30	65.13	39.20		8.170	0	0.60*
	M	66.30	66.23	2.2	94.30	0.440	0.661	0.940
Hindu	U	0.876	0.819	15.70		3.390	0.00100	.
	M	0.876	0.859	4.8	69.20	0.880	0.378	.
Years of education	U	3.064	5.640	-57.50		-11.94	0	0.58*
	M	3.064	2.986	1.7	97	0.340	0.733	0.900
Brahmin	U	0.0319	0.0779	-20.30		-4.050	0	.
	M	0.0319	0.0464	-6.4	68.40	-1.290	0.196	.
Household:								
Urban	U	0.195	0.370	-39.60		-8.420	0	.
	M	0.195	0.193	0.4	99	0.0700	0.942	.
Assets index	U	12.11	15.97	-64.40		-13.96	0	0.77*
	M	12.11	12.50	-6.5	89.90	-1.160	0.245	0.860
Dependence Ratio	U	3.782	4.267	-19		-4.210	0	0.870
	M	3.782	3.702	3.2	83.40	0.550	0.581	0.910
HH: Per capita income	U	930.7	1746	-40.60		-7.400	0	0.14*
	M	930.7	918.7	0.6	98.50	0.210	0.834	1.070
Ration Card: BPL	U	0.597	0.278	67.80		15.94	0	.
	M	0.597	0.601	-0.8	98.80	-0.140	0.890	.
Ration Card: Antodaya	U	0.106	0.0410	25		6.790	0	.
	M	0.106	0.116	-4.1	83.60	-0.580	0.560	.

U: Unmatched; M: Matched

Table 1.6: Matching Estimates

N is 1599 after matching, 596 in treatment and 1003 in control groups from 27 states/territories

	Stars	DID	SE (DID)	t-value
Outcome$_{\triangle}$:				
Personal: If worked last year		0.0173	0.0312	0.556
Personal: Annual income (USD)		-118.8	80.22	-1.481
Personal: Hrs worked last year		-75.54	55.03	-1.373
Personal: Lab. inc. + transfer (USD)	*	142.6	80.92	1.762
Household: Income (USD)	**	-1119	513.5	-2.179
Household: Per capita income (USD)	**	-299.3	145.9	-2.051
Household: Consumption per capita (USD)		-66.93	73.67	-0.909
Household: Below poverty line		0.0129	0.0296	0.435
Household: Assets index (1-33)	**	-0.503	0.219	-2.296
	Stars	Diff	SE (Diff)	t-value
Mean for household by age group:				
15-24: Fraction earning	**	-0.0441	0.0199	-2.220
15-24: Mean yrs of educ.		0.535	0.378	1.418
15-24: Mean ann. lab. hrs.		162.2	146.0	1.111
Prime-age 25-64: Fraction earning		-0.0219	0.0248	-0.882
Prime-age 25-64: Mean ann. lab. hrs.		59.84	69.52	0.861
65-75: Fraction earning		-0.0411	0.0255	-1.611
65-75: Mean ann. lab. hrs.	***	-278.1	109.8	-2.532

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes:

(1) IHDS wave 2 data, restricted to individuals who became eligible sometime between wave 1 and wave 2, whose households were not receiving any transfer at baseline, and no other household members are getting transfers at endline.

(2) These include data from 25 states and 2 union territories: Andhra Pradesh, Arunachal Pradesh, Assam, Bihar, Chhattisgarh, Dadra & Nagar Haveli, Delhi, Goa, Gujarat, Haryana, Himachal Pradesh, Jammu & Kashmir, Jharkhand, Karnataka, Kerala, Madhya Pradesh, Maharashtra, Manipur, Orissa, Pondicherry, Punjab, Rajasthan, Tamil Nadu, Tripura, Uttar Pradesh, Uttarakhand, and West Bengal

(3) Propensity score algorithm uses the following wave 1 characteristics: age, hindu (religion) dummy, years of education, per capita HH income, per capita HH consumption, dummies for type of ration card, and urban-state dummies.

(4) Nearest (3) neighbour match with replacement.

(5) For DID estimates:

Outcome$_{\triangle,i}$ = (Outcome$_{end,i}$− Outcome$_{base,i}$).

Regression: Outcome$_{\triangle,i}$ $\sim$ Receive transfer$_i$.

(6) For Diff estimates:

Regression: Outcome$_h$ $\sim$ Receive transfer$_i$.

Table 1.7: Summary of Labor Outcomes for the Households by Age Groups

Household by waves						
	Work		Hrs.		Educ.	
Age	Baseline	Endline	Baseline	Endline	Baseline	Endline
15-24	0.146	0.513	76.50	532.4	3.179	3.674
N	705	705	641	531	705	705
25-64	0.672	0.676	777.9	878.1	3.762	4.252
N	2981	2981	2005	2239	2981	2981
65+	0.680	0.549	718.3	406.2	3.376	3.607
N	1498	1498	944	1025	1498	1498
Households at endline, by groups						
	Work		Hrs.		Educ.	
Age	Treatment	Control	Treatment	Control	Treatment	Control
15-24	0.448	0.547	466.7	569.9	4.075	3.466
N	241	464	193	338	241	464
25-64	0.692	0.667	872.4	881.4	4.222	4.270
N	1113	1868	820	1419	1113	1868
65-200	0.539	0.554	359.7	432.7	3.236	3.818
N	542	956	372	653	542	956

Table 1.8: Fixed-effects Panel Regressions (Weighted): Labor Outcome of Matched Households

	(1)	(2)	(3)	(4)
	If Work	Hrs.	If Work	Hrs.
	Regression for all individuals in HH			
If HH gets transfer	-0.0116	-88.79		
	(0.0201)	(58.40)		
Transfer, annual ('000 USD)			-0.0444	-37.14
			(0.0385)	(162.1)
Oth. govt. tr., ann. ('000 USD)	-0.0409	-344.2*	-0.0402	-296.1*
	(0.0747)	(171.6)	(0.0718)	(166.9)
Education years	-0.000449	-3.513	-0.000513	-3.787
	(0.00237)	(6.730)	(0.00234)	(6.675)
Urban dummy	-0.0714	-30.40	-0.0708	-42.20
	(0.0989)	(106.5)	(0.0980)	(105.9)
Age	-1.163***	354.4	-1.162***	11.91
	(0.126)	(396.7)	(0.145)	(457.2)
Major Illness: If any	-0.0782***	-129.0***	-0.0779***	-132.3***
	(0.0240)	(34.39)	(0.0241)	(34.05)
Constant	46.36***	-12843.2	46.31***	182.4
	(4.944)	(15125.5)	(5.686)	(17426.1)
Observations	10370	7387	10370	7387
No of Individuals	5185	4445	5185	4445

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Standard errors in parentheses, clustered at state-level.

For columns 1 and 2 I estimate

$$\text{Outcome}_{it} \sim \text{Receiving Transfer}_{ht} + controls_{it}$$

For columns 3 and 4 I estimate

$$\text{Outcome}_{it} \sim \text{Transfer Amount}_{ht} + controls_{it}$$

Controls: age, education years, if suffer major illness, HH income from other govt. transfers, dummy for year interviewed, urban dummy, and an intercept.

Regressions weighted by the same weights as used in matching for Table 1.6.

For comparison, see unweighted regression results in Table 1.A.1.

(Cont.) Fixed-effects Panel Regressions (Weighted): Labor Outcome of Matched Households

	(1)	(2)	(3)	(4)
	If Work	Hrs.	If Work	Hrs.
	Regression by age groups			
Coefficient for	*If HH gets transfer*		*Transfer amt*	
Age Groups				
15-24	-.126***	-221.941*	-.418**	-440.6
	(0.0506)	(119.0)	(0.184)	(354.9)
Obs	1410	1172	1410	1172
Ind	705	677	705	677
25-64	0.0240	-28.61	0.0640	115.0
	(0.0196)	(50.54)	(0.0674)	(156.8)
Obs	5962	4244	5962	4244
Ind	2981	2552	2981	2552
65+	-0.0140	-125.6	-0.0470	-20.12
	(0.0274)	(92.92)	(0.0739)	(329.0)
Obs	2996	1969	2996	1969
Ind	1498	1215	1498	1215

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Standard errors in parentheses, clustered at state-level.

For columns 1 and 2 I estimate

$$\text{Outcome}_{it} \sim \text{Receiving Transfer}_{ht} + controls_{it}$$

For columns 3 and 4 I estimate

$$\text{Outcome}_{it} \sim \text{Transfer Amount}_{ht} + controls_{it}$$

Controls: age, education years, if suffer major illness, HH income from other govt. transfers, dummy for year interviewed, urban dummy, and an intercept.

Regressions weighted by the same weights as used in matching for Table 1.6.

For comparison, see unweighted regression results in Table 1.A.1.

Table 1.9: Cross-Section Regressions (Weighted): Labor Outcomes of the Matched Households

	(1) If Work	(2) Hrs.	(3) If Work	(4) Hrs.
	Regression for all individuals in HH			
If HH gets transfer	-0.0272	-68.05		
	(0.0187)	(41.35)		
Transfer, annual ('000 USD)			-0.0508	-26.72
			(0.0351)	(136.8)
Oth. govt. tr., ann. ('000 USD)	-0.138***	-120.1	-0.0866**	-56.13
	(0.0365)	(93.44)	(0.0408)	(121.0)
Age	0.0353***	72.84***	0.0344***	73.15***
	(0.00312)	(7.071)	(0.00345)	(6.322)
Age^2	-0.000418***	-0.923***	-0.000408***	-0.925***
	(0.0000362)	(0.0781)	(0.0000396)	(0.0686)
Male dummy	0.0316	-63.15	0.0151	-80.71**
	(0.0287)	(41.72)	(0.0247)	(38.85)
Education years	-0.0122***	-25.07***	-0.0118***	-25.49***
	(0.00162)	(4.106)	(0.00187)	(3.898)
Major Illness: If any	-0.0901***	-160.7***	-0.0822***	-160.6***
	(0.0116)	(39.15)	(0.0124)	(37.40)
Year interviewed	0.00596	24.50	0.0362	167.8***
	(0.0191)	(53.60)	(0.0427)	(52.26)
Urban dummy	-0.148***	181.2***	-0.151***	207.2***
	(0.0196)	(58.32)	(0.0234)	(59.00)
Constant	-11.88	-49493.9	-72.76	-337854.7***
	(38.42)	(107828.7)	(85.91)	(105117.1)
Observations	5185	3796	5185	3796

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Standard errors in parentheses, clustered at state-level.

For columns 1 and 2 I estimate

Outcome$_i$ $\sim$ Receiving Transfer$_h$ $+$ $controls_i$

For columns 3 and 4 I estimate

Outcome$_i$ $\sim$ Transfer Amount$_h$ $+$ $controls_i$

Controls: f(age), male dummy, years of education, if suffer major illness, HH income from other govt. transfers, year interviewed, urban dummy, state dummies, and an intercept.

Regressions weighted by the same weights as used in matching for Table 1.6.

For comparison, see unweighted regression results in Table 1.A.2.

(Cont.) Cross-Section Regressions (Weighted): Labor Outcomes of the Matched Households

	(1) If Work	(2) Hrs.	(3) If Work	(4) Hrs.
	Regression by age groups			
Coefficient for Age Groups	*If HH gets transfer*		*Transfer amt*	
15-24	-.139***	-228.523*	-.324*	-134.9
	(0.0527)	(131.2)	(0.169)	(369.4)
Obs	705	531	705	531
25-64	0.00700	-0.895	0.0550	64.33
	(0.0205)	(57.09)	(0.0380)	(134.3)
Obs	2981	2239	2981	2239
65+	-0.0340	-111.314***	-0.0980	-29.80
	(0.0273)	(38.12)	(0.0602)	(133.1)
Obs	1498	1025	1498	1025

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Standard errors in parentheses, clustered at state-level.

For columns 1 and 2 I estimate

$\text{Outcome}_i \sim \text{Receiving Transfer}_h + controls_i$

For columns 3 and 4 I estimate

$\text{Outcome}_i \sim \text{Transfer Amount}_h + controls_i$

Controls: f(age), male dummy, years of education, if suffer major illness, HH income from other govt. transfers, year interviewed, urban dummy, state dummies, and an intercept.

Regressions weighted by the same weights as used in matching for Table 1.6.

For comparison, see unweighted regression results in Table 1.A.2.

Table 1.10: Fixed-effects Panel Regressions (Weighted): Education of Young Adults

Dependent Variable	Years of Education	Years of Education
	Age group 15-24	
If HH gets transfer	-0.186	
	(0.209)	
Transfer, annual ('000 USD)		-0.697
		(0.531)
Urban dummy	-0.612	-0.569
	(1.037)	(1.041)
Year interviewed	0.0958***	0.0947***
	(0.0268)	(0.0252)
Major Illness: If any	0.142	0.142
	(0.426)	(0.428)
Constant	-189.1***	-187.0***
	(53.72)	(50.57)
Observations	1410	1410
No of Individuals	705	705

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Standard errors in parentheses, clustered at state-level.

I estimate:

Years of Education$_{it}$ $\sim$ Receiving Transfer$_{ht}$ + $controls_{it}$ for column 1, and

Years of Education$_{it}$ $\sim$ Transfer Amount$_{ht}$ + $controls_{it}$ for column 2.

Controls: urban, if suffer major illness, year of interview (years passed), and an intercept.

Regressions weighted by the same weights as used in matching for Table 1.6.

For comparison, see unweighted regression results in Table 1.A.3.

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1.10 Appendices to Chapter 1

1.10.1 Appendix A: Sensitivity to Weighting

Table 1.A.1: Fixed-effects Panel Regressions (Unweighted): Labor Outcome of Matched Households

	(1) If Work	(2) Hrs.	(3) If Work	(4) Hrs.
	Regression for all individuals in HH			
If HH gets transfer	-0.00754	-107.2		
	(0.0189)	(63.30)		
Transfer, annual ('000 USD)			-0.0342	-107.4
			(0.0377)	(163.0)
Oth. govt. tr., ann. ('000 USD)	0.00512	-204.8	0.00496	-165.4
	(0.0532)	(131.3)	(0.0529)	(127.7)
Education years	-0.00172	-0.592	-0.00175	-1.124
	(0.00241)	(6.212)	(0.00241)	(6.410)
Urban dummy	-0.0583	-79.39	-0.0579	-82.84
	(0.0814)	(106.8)	(0.0811)	(110.1)
Age	-0.530^{***}	66.93	-0.526^{***}	-197.8
	(0.117)	(319.1)	(0.126)	(381.0)
Major Illness: If any	-0.0870^{***}	-156.5^{***}	-0.0869^{***}	-158.7^{***}
	(0.0222)	(34.81)	(0.0222)	(34.78)
Constant	21.48^{***}	-1883.1	21.30^{***}	8145.7
	(4.595)	(12096.3)	(4.933)	(14447.4)
Observations	10370	7387	10370	7387
No of Individuals	5185	4445	5185	4445

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Standard errors in parentheses, clustered at state-level.

For columns 1 and 2 I estimate

$$\text{Outcome}_{it} \sim \text{Receiving Transfer}_{ht} + controls_{it}$$

For columns 3 and 4 I estimate

$$\text{Outcome}_{it} \sim \text{Transfer Amount}_{ht} + controls_{it}$$

Controls: age, education years, if suffer major illness, HH income from other govt. transfers, dummy for year interviewed, urban dummy, and an intercept.

1.10.2 Appendix B: Results for One Nearest Neighbor Matching without Replacement

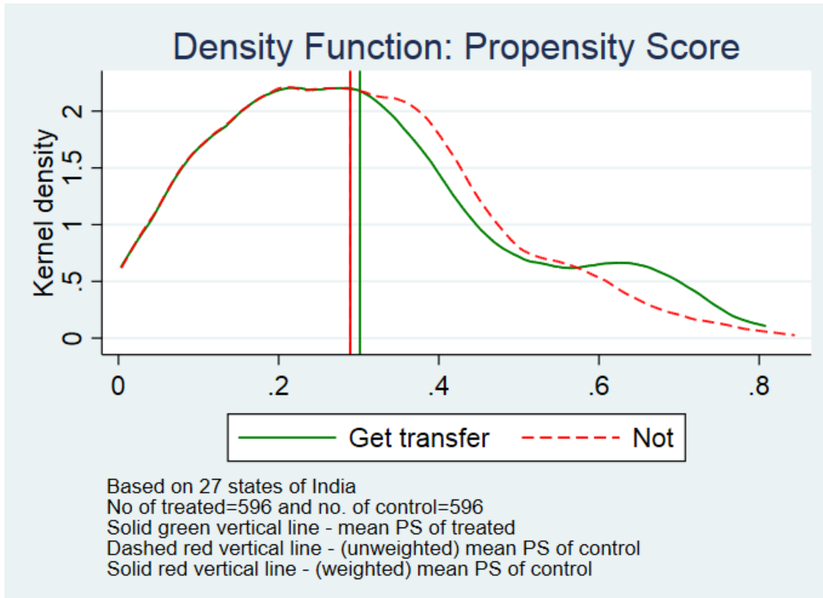

Figure 1.B.1: Distribution of Propensity Score: 1 Nearest Neighbor Matched Sample

(Cont.) Fixed-effects Panel Regressions (Unweighted): Labor Outcome of Matched Households

	(1)	(2)	(3)	(4)
	If Work	Hrs.	If Work	Hrs.
	Regression by age groups			
Coefficient for	*If HH gets transfer*		*Transfer amt*	
Age Groups				
15-24	-.098*	-117.7	-.346*	-208.6
	(0.0520)	(116.1)	(0.206)	(305.5)
Obs	1410	1172	1410	1172
Ind	705	677	705	677
25-64	0.0170	-103.321*	0.0520	-94.63
	(0.0176)	(56.90)	(0.0603)	(156.4)
Obs	5962	4244	5962	4244
Ind	2981	2552	2981	2552
65+	-0.00400	-109.3	-0.0260	-30.18
	(0.0273)	(87.24)	(0.0745)	(318.8)
Obs	2996	1969	2996	1969
Ind	1498	1215	1498	1215

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Standard errors in parentheses, clustered at state-level.

For columns 1 and 2 I estimate

$$\text{Outcome}_{it} \sim \text{Receiving Transfer}_{ht} + controls_{it}$$

For columns 3 and 4 I estimate

$$\text{Outcome}_{it} \sim \text{Transfer Amount}_{ht} + controls_{it}$$

Controls: age, education years, if suffer major illness, HH income from other govt. transfers, dummy for year interviewed, urban dummy, and an intercept.

Table 1.A.2: Cross-Section Regressions (Unweighted): Labor Outcomes of the Matched Households

	(1) If Work	(2) Hrs.	(3) If Work	(4) Hrs.
	Regression for all individuals in HH			
If HH gets transfer	-0.0109	-45.60		
	(0.0160)	(42.34)		
Transfer, annual ('000 USD)			-0.0398	-16.47
			(0.0296)	(118.4)
Oth. govt. tr., ann. ('000 USD)	-0.133**	-100.3	-0.0837*	-53.15
	(0.0502)	(134.4)	(0.0465)	(135.6)
Age	0.0335***	74.36***	0.0327***	75.24***
	(0.00308)	(7.299)	(0.00352)	(6.511)
Age^2	-0.000394***	-0.928***	-0.000385***	-0.936***
	(0.0000337)	(0.0799)	(0.0000384)	(0.0701)
Male dummy	0.0466*	-68.88	0.0303	-92.14**
	(0.0241)	(44.62)	(0.0263)	(41.96)
Education years	-0.0126***	-22.83***	-0.0125***	-22.50***
	(0.00148)	(3.628)	(0.00175)	(3.175)
Major Illness: If any	-0.0916***	-180.8***	-0.0861***	-184.7***
	(0.0110)	(37.44)	(0.0115)	(34.96)
Year interviewed	0.0106	17.07	0.0257	127.3**
	(0.0107)	(66.47)	(0.0395)	(53.72)
Urban dummy	-0.140***	189.5***	-0.149***	213.8***
	(0.0180)	(57.53)	(0.0220)	(55.80)
Constant	-21.12	-34606.1	-51.49	-256426.3**
	(21.47)	(133718.4)	(79.53)	(108050.5)
Observations	5185	3796	5185	3796

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Standard errors in parentheses, clustered at state-level.

For columns 1 and 2 I estimate

$$\text{Outcome}_i \sim \text{Receiving Transfer}_h + controls_i$$

For columns 3 and 4 I estimate

$$\text{Outcome}_i \sim \text{Transfer Amount}_h + controls_i$$

Controls: f(age), male dummy, years of education, if suffer major illness, HH income from other govt. transfers, year interviewed, urban dummy, state dummies, and an intercept.

(Cont.) Cross-Section Regressions (Unweighted): Labor Outcomes of the Matched Households

	(1)	(2)	(3)	(4)
	If Work	Hrs.	If Work	Hrs.
	Regression by age groups			
Coefficient for Age Groups	*If HH gets transfer*		*Transfer amt*	
15-24	-.088*	-98.13	-.324*	-134.9
	(0.0508)	(117.9)	(0.169)	(369.4)
Obs	705	531	705	531
25-64	0.0210	1.034	0.0550	64.33
	(0.0196)	(57.90)	(0.0380)	(134.3)
Obs	2981	2239	2981	2239
65+	-0.0280	-97.164***	-0.0980	-29.80
	(0.0233)	(31.31)	(0.0602)	(133.1)
Obs	1498	1025	1498	1025

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Standard errors in parentheses, clustered at state-level.

For columns 1 and 2 I estimate

$$\text{Outcome}_i \sim \text{Receiving Transfer}_h + controls_i$$

For columns 3 and 4 I estimate

$$\text{Outcome}_i \sim \text{Transfer Amount}_h + controls_i$$

Controls: f(age), male dummy, years of education, if suffer major illness, HH income from other govt. transfers, year interviewed, urban dummy, state dummies, and an intercept.

Table 1.A.3: Fixed-effects Panel Regressions (Unweighted): Education of Young Adults

Dependent Variable	Years of Education	Years of Education
	Age group 15-24	
If HH gets transfer	-0.0480	
	(0.274)	
Transfer, annual ('000 USD)		-0.349
		(0.717)
Urban dummy	-0.195	-0.176
	(0.861)	(0.848)
Year interviewed	0.0739^{**}	0.0757^{**}
	(0.0303)	(0.0273)
Major Illness: If any	0.0647	0.0636
	(0.301)	(0.302)
Constant	-145.0^{**}	-148.6^{**}
	(60.83)	(54.88)
Observations	1410	1410
No of Individuals	705	705

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Standard errors in parentheses, clustered at state-level.

I estimate:

Years of Education$_{it}$ $\sim$ Receiving Transfer$_{ht}$ $+ \, controls_{it}$ for column 1, and

Years of Education$_{it}$ $\sim$ Transfer Amount$_{ht}$ $+ \, controls_{it}$ for column 2.

Controls: urban, if suffer major illness, year of interview (years passed), and an intercept.

Table 1.B.1: Exogenous Covariates Balance Before and After Matching: One Nearest Neighbor Without Replacement

		Mean			% Reduction	t-Test		Variance Ratio
Variable		Treated	Control	% Bias	in Bias	t	p>t	V(T)/V(C)
Propensity Score	U	0.30154	0.10846	122.8	0	32.43	0	2.11*
	M	0.30154	0.28943	7.7	93.7	1.2	0.231	1.23*
Age	U	66.302	65.129	39.2	0	8.17	0	0.60*
	M	66.302	66.237	2.2	94.5	0.42	0.671	0.93
Hindu	U	0.87584	0.81949	15.7	0	3.39	0.001	
	M	0.87584	0.85235	6.6	58.3	1.18	0.237	
Years of education	U	3.0638	5.6398	-57.5	0	-11.94	0	0.58*
	M	3.0638	3.2148	-3.4	94.1	-0.66	0.512	0.88
Brahmin	U	0.03188	0.07785	-20.3	0	-4.05	0	
	M	0.03188	0.04195	-4.4	78.1	-0.92	0.357	
Urban	U	0.19463	0.36964	-39.6	0	-8.42	0	
	M	0.19463	0.18624	1.9	95.2	0.37	0.713	
Asset index	U	12.112	15.975	-64.4		-13.96	0	0.77*
	M	12.112	12.387	-4.6	92.9	-0.82	0.413	0.89
Dependence ratio	U	3.7822	4.267	-19		-4.21	0	0.87
	M	3.7822	3.6513	5.1	73	0.91	0.361	0.98
HH: Per capita income	U	930.66	1746	-40.6		-7.4	0	0.14*
	M	930.66	904.64	1.3	96.8	0.46	0.647	1.07
Ration Card: BPL	U	0.59732	0.27847	67.8	0	15.94	0	
	M	0.59732	0.61409	-3.6	94.7	-0.59	0.554	
Ration Card: Antodaya	U	0.1057	0.04101	25	0	6.79	0	
	M	0.1057	0.10738	-0.6	97.4	-0.09	0.925	

U: Unmatched; M: Matched

Table 1.B.2: Matching Estimates

N is 1192 after matching, 596 in treatment and 596 in control groups from 27 states/territories

	Stars	DID	SE (DID)	t-value
Outcome$_{\triangle}$:				
Personal: If worked last year		-0.00671	0.0326	-0.206
Personal: Annual income (USD)	*	-159.8	84.08	-1.901
Personal: Hrs worked last year	**	-116.2	50.82	-2.286
Personal: Lab. inc. + transfer (USD)		101.6	84.74	1.199
Household: Income (USD)		-923.2	790.7	-1.168
Household: Per capita income (USD)	**	-334.2	163.7	-2.042
Household: Consumption per capita (USD)		-53.21	66.92	-0.795
Household: Below poverty line		-0.00671	0.0319	-0.210
Household: Assets index (1-33)	***	-0.520	0.219	-2.377
	Stars	**Diff**	**SE (Diff)**	**t-value**
Mean for household by age group:				
15-25: Fraction earning		-0.0250	0.0167	-1.500
15-25: Mean ann. lab. hrs.		225.6	163.0	1.385
15-25: Mean yrs of educ.		0.553	0.391	1.415
Prime-age: Fraction earning		-0.00672	0.0249	-0.269
Prime-age: Mean ann. lab. hrs.		25.00	75.73	0.330
65-75: Fraction earning	**	-0.0453	0.0231	-1.965
65-75: Mean ann. lab. hrs.	**	-255.2	115.4	-2.212

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes:

(1) IHDS wave 2 data, restricted to individuals who became eligible sometime between wave 1 and wave 2, whose households were not receiving any transfer at baseline, and no other household members are getting transfers at endline.

(2) These include data from 25 states and 2 union territories: Andhra Pradesh, Arunachal Pradesh, Assam, Bihar, Chhattisgarh, Dadra & Nagar Haveli, Delhi, Goa, Gujarat, Haryana, Himachal Pradesh, Jammu & Kashmir, Jharkhand, Karnataka, Kerala, Madhya Pradesh, Maharashtra, Manipur, Orissa, Pondicherry, Punjab, Rajasthan, Tamil Nadu, Tripura, Uttar Pradesh, Uttarakhand, and West Bengal

(3) Propensity score algorithm uses the following wave 1 characteristics: age, hindu (religion) dummy, years of education, per capita HH income, per capita HH consumption, dummies for type of ration card, and urban-state dummies.

(4) Nearest (1) neighbour match without replacement.

(5) For DID estimates:

Outcome$_{\triangle,i}$ = (Outcome$_{end,i}$ − Outcome$_{base,i}$).

Regression: Outcome$_{\triangle,i} \sim$ Receive transfer$_i$.

(6) For Diff estimates:

Regression: Outcome$_h \sim$ Receive transfer$_i$.

Table 1.B.3: Fixed-effects Panel Regressions: Labor Outcome of Matched Households

	(1) If Work	(2) Hrs.	(3) If Work	(4) Hrs.
	Regression for all individuals in HH			
If HH gets transfer	-0.0133	-97.81		
	(0.0192)	(58.46)		
Transfer, annual ('000 USD)			-0.0443	-41.18
			(0.0345)	(150.9)
Oth. govt. tr., ann. ('000 USD)	0.0135	-168.5	0.0151	-115.0
	(0.0688)	(167.9)	(0.0691)	(161.4)
Education years	0.00112	3.374	0.00106	2.888
	(0.00247)	(5.549)	(0.00245)	(5.442)
Urban dummy	-0.0675	-78.84	-0.0671	-91.80
	(0.108)	(122.9)	(0.107)	(122.5)
Age	-0.946***	-1616.8***	-0.953***	-2011.0***
	(0.145)	(424.9)	(0.165)	(519.0)
Major Illness: If any	-0.0838***	-135.1***	-0.0836***	-138.3***
	(0.0256)	(38.57)	(0.0256)	(38.11)
Constant	37.89***	62232.6***	38.17***	77231.4***
	(5.692)	(16166.5)	(6.465)	(19752.4)
Observations	7610	5478	7610	5478
No of Individuals	3805	3287	3805	3287

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Standard errors in parentheses, clustered at state-level.

For columns 1 and 2 I estimate

$$\text{Outcome}_{it} \sim \text{Getting Transfer}_{ht} + controls_{it}$$

For columns 3 and 4 I estimate

$$\text{Outcome}_{it} \sim \text{Transfer Amount}_{ht} + controls_{it}$$

Controls: age, education years, if suffer major illness, HH income from other govt. transfers, dummy for year interviewed, urban dummy, and an intercept.

(Cont) Fixed-effects Panel Regressions: Labor Outcome of Matched Households

	(1)	(2)	(3)	(4)
	If Work	Hrs.	If Work	Hrs.
	Regression by age groups			
Coefficient for	*If HH gets transfer*		*Transfer amt*	
Age Groups				
15-24	-0.0710	-129.7	-0.271	-195.2
	(0.0562)	(131.2)	(0.204)	(322.7)
Obs	1048	888	1048	888
Ind	524	508	524	508
25-64	0.0180	-65.98	0.0560	46.22
	(0.0161)	(53.79)	(0.0568)	(158.9)
Obs	4316	3072	4316	3072
Ind	2158	1856	2158	1856
65+	-0.0330	-168.087*	-0.0890	-107.1
	(0.0310)	(95.94)	(0.0827)	(334.7)
Obs	2246	1518	2246	1518
Ind	1123	923	1123	923

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Standard errors in parentheses, clustered at state-level.

For columns 1 and 2 I estimate

$$\text{Outcome}_{it} \sim \text{Getting Transfer}_{ht} + controls_{it}$$

For columns 3 and 4 I estimate

$$\text{Outcome}_{it} \sim \text{Transfer Amount}_{ht} + controls_{it}$$

Controls: age, education years, if suffer major illness, HH income from other govt. transfers, dummy for year interviewed, urban dummy, and an intercept.

Table 1.B.4: Cross-Section Regressions: Labor Outcomes of the Matched Households

	(1) If Work	(2) Hrs.	(3) If Work	(4) Hrs.
	Regression for all individuals in HH			
If HH gets transfer	-0.0274	-90.43**		
	(0.0178)	(33.67)		
Transfer, annual ('000 USD)			-0.0531	-61.68
			(0.0324)	(138.3)
Oth. govt. tr., ann. ('000 USD)	-0.154***	-161.8	-0.0931*	-101.4
	(0.0432)	(131.7)	(0.0461)	(142.0)
Age	0.0380***	81.18***	0.0373***	80.64***
	(0.00314)	(7.287)	(0.00350)	(6.466)
Age^2	-0.000443***	-1.008***	-0.000434***	-1.000***
	(0.0000347)	(0.0795)	(0.0000381)	(0.0696)
Male dummy	0.0460	-53.34	0.0288	-73.10*
	(0.0322)	(46.34)	(0.0265)	(40.42)
Education years	-0.0115***	-23.14***	-0.0111***	-23.18***
	(0.00203)	(4.227)	(0.00217)	(4.000)
Major Illness: If any	-0.0983***	-194.8***	-0.0898***	-190.5***
	(0.0129)	(36.78)	(0.0129)	(32.14)
Year interviewed	0.00336	-3.683	0.0364	135.6*
	(0.0204)	(130.8)	(0.0451)	(66.44)
Urban dummy	-0.151***	164.8**	-0.154***	224.4***
	(0.0239)	(62.45)	(0.0248)	(57.69)
Constant	-6.733	7054.2	-73.19	-273292.0*
	(41.11)	(263101.8)	(90.81)	(133623.7)
Observations	3805	2802	3805	2802

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Standard errors in parentheses, clustered at state-level.

For columns 1 and 2 I estimate

$$\text{Outcome}_i \sim \text{Receiving Transfer}_h + controls_i$$

For columns 3 and 4 I estimate

$$\text{Outcome}_i \sim \text{Transfer Amount}_h + controls_i$$

Controls: f(age), male dummy, years of education, if suffer major illness, HH income from other govt. transfers, year interviewed, urban dummy, state dummies, and an intercept.

(Cont.) Cross-Section Regressions: Labor Outcomes of the Matched Households

	(1) If Work	(2) Hrs.	(3) If Work	(4) Hrs.
	Regression by age groups			
Coefficient for	*If HH gets transfer*		*Transfer amt*	
Age Groups				
15-24	-.082*	-153.6	-.283**	-254.6
	(0.0429)	(107.7)	(0.140)	(365.1)
Obs	524	412	524	412
25-64	-0.00400	-51.69	0.0240	1.837
	(0.0223)	(52.83)	(0.0460)	(143.6)
Obs	2158	1609	2158	1609
65+	-0.0370	-112.989**	-0.0900	-18.66
	(0.0232)	(51.40)	(0.0677)	(185.8)
Obs	1123	781	1123	781

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Standard errors in parentheses, clustered at state-level.

For columns 1 and 2 I estimate

$$\text{Outcome}_i \sim \text{Receiving Transfer}_h + controls_i$$

For columns 3 and 4 I estimate

$$\text{Outcome}_i \sim \text{Transfer Amount}_h + controls_i$$

Controls: f(age), male dummy, years of education, if suffer major illness, HH income from other govt. transfers, year interviewed, urban dummy, state dummies, and an intercept.

Table 1.B.5: Fixed-effects Panel Regressions: Education of Young Adults

Dependent Variable	Years of Education	Years of Education
	Age group 15-24	
If HH gets transfer	-0.0198	
	(0.286)	
Transfer, annual ('000 USD)		-0.274
		(0.614)
Urban dummy	-0.506	-0.477
	(0.872)	(0.861)
Year interviewed	0.0721**	0.0751***
	(0.0325)	(0.0264)
Major Illness: If any	-0.0418	-0.0443
	(0.470)	(0.473)
Constant	-141.3**	-147.4**
	(65.20)	(53.03)
Observations	1048	1048
No of Individuals	524	524

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Standard errors in parentheses, clustered at state-level.

I estimate:

Years of Education$_{it}$ $\sim$ Receiving Transfer$_{ht}$ $+ \, controls_{it}$ for column 1, and

Years of Education$_{it}$ $\sim$ Transfer Amount$_{ht}$ $+ \, controls_{it}$ for column 2.

Controls: urban, if suffer major illness, year of interview (years passed), and an intercept.

1.10.3 Appendix C: Results for Two Nearest Neighbor Matching with Replacement

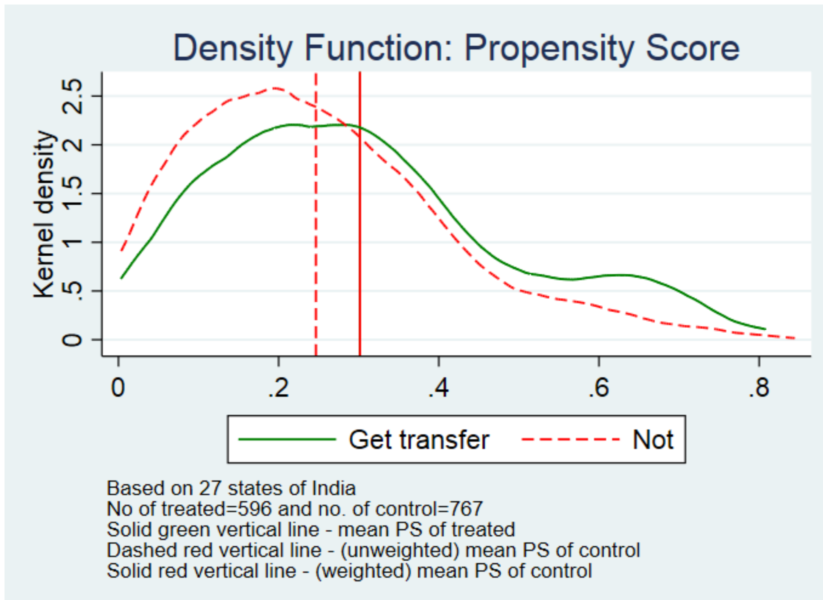

Figure 1.C.1: Distribution of Propensity Score: 2 Nearest Neighbor Matched Sample

Table 1.C.1: Exogenous Covariates Balance Before and After Matching: Two Nearest Neighbors With Replacement

		Mean			% Reduction	t-Test		Variance Ratio
Variable		Treated	Control	% Bias	in Bias	t	p>t	V(T)/V(C)
Propensity Score	U	.30154	.10846	122.8		32.43	0.000	2.11*
	M	.30154	.30161	-0.0	100.0	-0.01	0.994	1.00
Age	U	66.302	65.129	39.2		8.17	0.000	0.60*
	M	66.302	66.272	1.0	97.4	0.20	0.844	0.93
Hindu	U	.87584	.81949	15.7		3.39	0.001	.
	M	.87584	.86326	3.5	77.7	0.64	0.519	.
Years of education	U	3.0638	5.6398	-57.5		-11.94	0.000	0.58*
	M	3.0638	3.0629	0.0	100.0	0.00	0.997	0.91
Brahmin	U	.03188	.07785	-20.3		-4.05	0.000	.
	M	.03188	.04279	-4.8	76.3	-0.99	0.321	.
Urban	U	.19463	.36964	-39.6		-8.42	0.000	.
	M	.19463	.19631	-0.4	99.0	-0.07	0.942	.
Asset index	U	12.112	15.975	-64.4		-13.96	0.000	0.77*
	M	12.112	12.522	-6.8	89.4	-1.22	0.222	0.88
Dependence ratio	U	3.7822	4.267	-19.0		-4.21	0.000	0.87
	M	3.7822	3.7137	2.7	85.9	0.47	0.641	0.89
HH: Per capita income	U	930.66	1746	-40.6		-7.40	0.000	0.14*
	M	930.66	898.48	1.6	96.1	0.57	0.570	1.09
Ration Card: BPL	U	.59732	.27847	67.8		15.94	0.000	.
	M	.59732	.60822	-2.3	96.6	-0.38	0.701	.
Ration Card: Antodaya	U	.1057	.04101	25.0		6.79	0.000	.
	M	.1057	.12164	-6.2	75.4	-0.87	0.386	.

U: Unmatched; M: Matched

Table 1.C.2: Matching Estimates

N is 1363 after matching, 596 in treatment and 767 in control groups from 27 states/territories

	Stars	DID	SE (DID)	t-value
Outcome$_{\triangle}$:				
Personal: If worked last year		0.0151	0.0321	0.471
Personal: Annual income (USD)	*	-129.1	78.37	-1.647
Personal: Hrs worked last year	*	-94.99	53.00	-1.792
Personal: Lab. inc. + transfer (USD)	*	132.3	79.17	1.671
Household: Income (USD)	**	-1199	607.4	-1.973
Household: Per capita income (USD)	*	-350.2	178.9	-1.957
Household: Consumption per capita (USD)		-99.35	78.98	-1.258
Household: Below poverty line		0.0302	0.0310	0.975
Household: Assets index (1-33)	***	-0.555	0.237	-2.346
	Stars	Diff	SE (Diff)	t-value
Mean for household by age group:				
15-24: Fraction earning	*	-0.0418	0.0218	-1.917
15-24: Mean ann. lab. hrs.	*	260.9	152.9	1.707
15-24: Mean yrs of educ.	**	0.793	0.377	2.102
prime-age 25-64: Fraction earning		-0.0228	0.0264	-0.866
Prime-age 25-64: Mean ann. lab. hrs.		80.46	74.21	1.084
65-75: Fraction earning		-0.0298	0.0260	-1.145
65-75: Mean ann. lab. hrs.	**	-254.1	116.9	-2.175

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes:

(1) IHDS wave 2 data, restricted to individuals who became eligible sometime between wave 1 and wave 2, whose households were not receiving any transfer at baseline, and no other household members are getting transfers at endline.

(2) These include data from 25 states and 2 union territories: Andhra Pradesh, Arunachal Pradesh, Assam, Bihar, Chhattisgarh, Dadra & Nagar Haveli, Delhi, Goa, Gujarat, Haryana, Himachal Pradesh, Jammu & Kashmir, Jharkhand, Karnataka, Kerala, Madhya Pradesh, Maharashtra, Manipur, Orissa, Pondicherry, Punjab, Rajasthan, Tamil Nadu, Tripura, Uttar Pradesh, Uttarakhand, and West Bengal

(3) Propensity score algorithm uses the following wave 1 characteristics: age, hindu (religion) dummy, years of education, per capita HH income, per capita HH consumption, dummies for type of ration card, and urban-state dummies.

(4) Nearest (3) neighbour match with replacement.

(5) For DID estimates:

Outcome$_{\triangle,i}$ = (Outcome$_{end,i}$− Outcome$_{base,i}$).

Regression: Outcome$_{\triangle,i}$ $\sim$ Receive transfer$_i$.

(6) For Diff estimates:

Regression: Outcome$_h$ $\sim$ Receive transfer$_i$.

Table 1.C.3: Fixed-effects Panel Regressions (Weighted): Labor Outcome of Matched Households

	(1)	(2)	(3)	(4)
	If Work	Hrs.	If Work	Hrs.
	Regression for all individuals in HH			
If HH gets transfer	-0.00684	-78.09		
	(0.0213)	(55.73)		
Transfer, annual ('000 USD)			-0.0317	-15.57
			(0.0429)	(148.9)
Oth. govt. tr., ann. ('000 USD)	0.00783	-247.0	0.00754	-204.7
	(0.0735)	(189.6)	(0.0714)	(186.7)
Education years	-0.000257	-6.952	-0.000299	-7.310
	(0.00233)	(8.517)	(0.00232)	(8.490)
Urban dummy	0.00195	24.30	0.00257	10.53
	(0.110)	(109.4)	(0.110)	(107.2)
Age	-0.200	-27.03	-0.194	-347.4
	(0.133)	(456.6)	(0.144)	(518.0)
Major Illness: If any	-0.0827***	-140.9***	-0.0825***	-143.4***
	(0.0268)	(41.58)	(0.0268)	(40.84)
Constant	8.490	1693.0	8.247	13866.9
	(5.230)	(17360.0)	(5.667)	(19700.5)
Observations	8764	6294	8764	6294
No of Individuals	4382	3771	4382	3771

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Standard errors in parentheses, clustered at state-level.

For columns 1 and 2 I estimate

$$\text{Outcome}_{it} \sim \text{Receiving Transfer}_{ht} + controls_{it}$$

For columns 3 and 4 I estimate

$$\text{Outcome}_{it} \sim \text{Transfer Amount}_{ht} + controls_{it}$$

Controls: age, education years, if suffer major illness, HH income from other govt. transfers, dummy for year interviewed, urban dummy, and an intercept.

Regressions weighted by the same weights as used in matching for Table 1.C.2.

For comparison, see unweighted regression results in Table 1.C.4.

(Cont.) Fixed-effects Panel Regressions (Weighted): Labor Outcome of Matched Households

	(1)	(2)	(3)	(4)
	If Work	Hrs.	If Work	Hrs.
	Regression by age groups			
Coefficient for Age Groups	*If HH gets transfer*		*Transfer amt*	
15-24	-.122**	-213.942*	-.412**	-426.5
	(0.0569)	(125.0)	(0.194)	(354.7)
Obs	1174	1003	1174	1003
Ind	587	570	587	570
25-64	0.0210	-10.10	0.0580	143.8
	(0.0191)	(56.49)	(0.0680)	(181.0)
Obs	5032	3593	5032	3593
Ind	2516	2159	2516	2159
65+	-0.00300	-137.6	-0.0220	-50.32
	(0.0303)	(94.18)	(0.0753)	(330.6)
Obs	2556	1696	2556	1696
Ind	1278	1041	1278	1041

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Standard errors in parentheses, clustered at state-level.

For columns 1 and 2 I estimate

$$\text{Outcome}_{it} \sim \text{Receiving Transfer}_{ht} + controls_{it}$$

For columns 3 and 4 I estimate

$$\text{Outcome}_{it} \sim \text{Transfer Amount}_{ht} + controls_{it}$$

Controls: age, education years, if suffer major illness, HH income from other govt. transfers, dummy for year interviewed, urban dummy, and an intercept.

Regressions weighted by the same weights as used in matching for Table 1.C.2.

For comparison, see unweighted regression results in Table 1.C.4.

Table 1.C.4: Fixed-effects Panel Regressions (Unweighted): Labor Outcome of Matched Households

	(1) If Work	(2) Hrs.	(3) If Work	(4) Hrs.
	Regression for all individuals in HH			
If HH gets transfer	-0.00730	-112.3*		
	(0.0208)	(62.28)		
Transfer, annual ('000 USD)			-0.0318	-99.05
			(0.0417)	(158.0)
Oth. govt. tr., ann. ('000 USD)	-0.00227	-150.6	-0.00230	-101.8
	(0.0500)	(132.5)	(0.0502)	(126.1)
Education years	-0.00211	-2.016	-0.00214	-2.764
	(0.00229)	(6.486)	(0.00229)	(6.698)
Urban dummy	-0.0269	19.14	-0.0264	7.031
	(0.105)	(125.5)	(0.105)	(129.2)
Age	-0.260*	-55.80	-0.256*	-393.2
	(0.140)	(388.8)	(0.146)	(457.3)
Major Illness: If any	-0.0858***	-155.3***	-0.0856***	-156.8***
	(0.0250)	(38.80)	(0.0251)	(38.80)
Constant	10.89*	2788.4	10.74*	15587.3
	(5.508)	(14752.7)	(5.729)	(17357.8)
Observations	8764	6294	8764	6294
No of Individuals	4382	3771	4382	3771

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Standard errors in parentheses, clustered at state-level.

For columns 1 and 2 I estimate

$$\text{Outcome}_{it} \sim \text{Receiving Transfer}_{ht} + controls_{it}$$

For columns 3 and 4 I estimate

$$\text{Outcome}_{it} \sim \text{Transfer Amount}_{ht} + controls_{it}$$

Controls: age, education years, if suffer major illness, HH income from other govt. transfers, dummy for year interviewed, urban dummy, and an intercept.

(Cont.) Fixed-effects Panel Regressions (Unweighted): Labor Outcome of Matched Households

	(1)	(2)	(3)	(4)
	If Work	Hrs.	If Work	Hrs.
	Regression by age groups			
Coefficient for	*If HH gets transfer*		*Transfer amt*	
Age Groups				
15-24	-.099**	-172.9	-.347*	-333.8
	(.0498)	(125.9)	(0.191)	(337.6)
Obs	1174	1003	1174	1003
Ind	587	570	587	570
25-64	0.0170	-82.06	0.0510	-22.67
	(0.0185)	(63.56)	(0.0590)	(171.0)
Obs	5032	3593	5032	3593
Ind	2516	2159	2516	2159
65+	-0.00600	-132.9	-0.0290	-60.82
	(0.0308)	(82.50)	(0.0796)	(307.7)
Obs	2556	1696	2556	1696
Ind	1278	1041	1278	1041

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Standard errors in parentheses, clustered at state-level.

For columns 1 and 2 I estimate

$$\text{Outcome}_{it} \sim \text{Receiving Transfer}_{ht} + controls_{it}$$

For columns 3 and 4 I estimate

$$\text{Outcome}_{it} \sim \text{Transfer Amount}_{ht} + controls_{it}$$

Controls: age, education years, if suffer major illness, HH income from other govt. transfers, dummy for year interviewed, urban dummy, and an intercept.

Table 1.C.5: Cross-Section Regressions (Weighted): Labor Outcomes of the Matched Households

	(1)	(2)	(3)	(4)
	If Work	Hrs.	If Work	Hrs.
	Regression for all individuals in HH			
If HH gets transfer	-0.0187	-60.84		
	(0.0184)	(40.19)		
Transfer, annual ('000 USD)			-0.0381	-2.500
			(0.0362)	(127.2)
Oth. govt. tr., ann. ('000 USD)	-0.132**	-22.19	-0.0826	4.031
	(0.0486)	(122.4)	(0.0609)	(159.2)
Age	0.0385***	76.22***	0.0378***	76.06***
	(0.00349)	(7.808)	(0.00372)	(7.254)
Age^2	-0.000452***	-0.958***	-0.000444***	-0.955***
	(0.0000414)	(0.0874)	(0.0000438)	(0.0802)
Male dummy	0.0406	-57.54	0.0244	-78.36*
	(0.0309)	(46.33)	(0.0267)	(44.97)
Education years	-0.0123***	-24.05***	-0.0117***	-24.52***
	(0.00168)	(4.071)	(0.00188)	(3.889)
Major Illness: If any	-0.0954***	-172.2***	-0.0874***	-170.5***
	(0.0119)	(36.41)	(0.0121)	(32.47)
Year interviewed	-0.00567	16.14	0.0295	148.8**
	(0.0167)	(98.05)	(0.0384)	(69.98)
Urban dummy	-0.134***	201.1***	-0.139***	231.8***
	(0.0204)	(62.66)	(0.0235)	(60.84)
Constant	11.43	-32759.8	-59.23	-299752.3**
	(33.67)	(197266.3)	(77.32)	(140784.4)
Observations	4382	3231	4382	3231

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Standard errors in parentheses, clustered at state-level.

For columns 1 and 2 I estimate

$\text{Outcome}_i \sim \text{Receiving Transfer}_h + controls_i$

For columns 3 and 4 I estimate

$\text{Outcome}_i \sim \text{Transfer Amount}_h + controls_i$

Controls: f(age), male dummy, if suffer major illness, HH income from other govt. transfers, years of education, year interviewed, urban dummy, state dummies, and an intercept.

Regressions weighted by the same weights as used in matching for Table 1.C.2.

For comparison, see unweighted regression results in Table 1.C.6.

(Cont.) Cross-Section Regressions (Weighted): Labor Outcomes of the Matched Households

	(1)	(2)	(3)	(4)
	If Work	Hrs.	If Work	Hrs.
	Regression by age groups			
Coefficient for Age Groups	*If HH gets transfer*		*Transfer amt*	
15-24	-.109*	-180.7	-.258*	-189.5
	(0.0569)	(135.5)	(0.156)	(394.5)
Obs	587	461	587	461
25-64	0.00400	-11.75	0.0370	40.90
	(0.0191)	(57.78)	(0.0392)	(129.9)
Obs	2516	1888	2516	1888
65+	-0.0130	-84.196*	-0.0880	-29.15
	(0.0333)	(50.60)	(0.0570)	(144.7)
Obs	1278	881	1278	881

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Standard errors in parentheses, clustered at state-level.

For columns 1 and 2 I estimate

$\text{Outcome}_i \sim \text{Receiving Transfer}_h + controls_i$

For columns 3 and 4 I estimate

$\text{Outcome}_i \sim \text{Transfer Amount}_h + controls_i$

Controls: f(age), male dummy, if suffer major illness, HH income from other govt. transfers, years of education, year interviewed, urban dummy, state dummies, and an intercept.

Regressions weighted by the same weights as used in matching for Table 1.C.2.

For comparison, see unweighted regression results in Table 1.C.6.

Table 1.C.6: Cross-Section Regressions (Unweighted): Labor Outcomes of the Matched Households

	(1) If Work	(2) Hrs.	(3) If Work	(4) Hrs.
	Regression for all individuals in HH			
If HH gets transfer	-0.0143	-62.84		
	(0.0172)	(42.63)		
Transfer, annual ('000 USD)			-0.0439	-40.76
			(0.0303)	(119.5)
Oth. govt. tr., ann. ('000 USD)	-0.143***	-17.71	-0.101**	19.92
	(0.0317)	(107.1)	(0.0415)	(122.2)
Age	0.0365***	76.04***	0.0359***	76.43***
	(0.00295)	(8.003)	(0.00326)	(7.270)
Age^2	-0.000425***	-0.947***	-0.000418***	-0.950***
	(0.0000325)	(0.0892)	(0.0000358)	(0.0801)
Male dummy	0.0406	-76.21	0.0247	-98.59**
	(0.0294)	(44.70)	(0.0268)	(41.93)
Education years	-0.0134***	-23.12***	-0.0129***	-22.85***
	(0.00154)	(3.620)	(0.00176)	(3.298)
Major Illness: If any	-0.0938***	-184.5***	-0.0871***	-181.8***
	(0.0107)	(40.69)	(0.00973)	(36.84)
Year interviewed	-0.00922	-39.86	0.0275	105.2**
	(0.0131)	(85.02)	(0.0436)	(49.51)
Urban dummy	-0.128***	208.4***	-0.137***	247.8***
	(0.0185)	(60.94)	(0.0229)	(57.89)
Constant	18.62	79901.9	-55.30	-212024.7**
	(26.35)	(171058.6)	(87.67)	(99590.4)
Observations	4382	3231	4382	3231

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Standard errors in parentheses, clustered at state-level.

For columns 1 and 2 I estimate

$\text{Outcome}_i \sim \text{Receiving Transfer}_h + controls_i$

For columns 3 and 4 I estimate

$\text{Outcome}_i \sim \text{Transfer Amount}_h + controls_i$

Controls: f(age), male dummy, if suffer major illness, HH income from other govt. transfers, years of education, year interviewed, urban dummy, state dummies, and an intercept.

(Cont.) Cross-Section Regressions (Unweighted): Labor Outcomes of the Matched Households

	(1)	(2)	(3)	(4)
	If Work	Hrs.	If Work	Hrs.
	Regression by age groups			
Coefficient for Age Groups	*If HH gets transfer*		*Transfer amt*	
15-24	-0.0680	-116.5	-.258*	-189.5
	(0.0527)	(123.7)	(0.156)	(394.5)
Obs	587	461	587	461
25-64	0.0140	-17.18	0.0370	40.90
	(0.0206)	(57.69)	(0.0392)	(129.9)
Obs	2516	1888	2516	1888
65+	-0.0280	-105.578***	-0.0880	-29.15
	(0.0228)	(39.06)	(0.0570)	(144.7)
Obs	1278	881	1278	881

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Standard errors in parentheses, clustered at state-level.

For columns 1 and 2 I estimate

Outcome$_i$ $\sim$ Receiving Transfer$_h$ $+ \, controls_i$

For columns 3 and 4 I estimate

Outcome$_i$ $\sim$ Transfer Amount$_h$ $+ \, controls_i$

Controls: f(age), male dummy, if suffer major illness, HH income from other govt. transfers, years of education, year interviewed, urban dummy, state dummies, and an intercept.

Table 1.C.7: Fixed-effects Panel Regressions (Weighted): Education of Young Adults

Dependent Variable	Years of Education	Years of Education
	Age group 15-24	
If HH gets transfer	-0.0918	
	(0.206)	
Transfer, annual ('000 USD)		-0.420
		(0.568)
Urban dummy	-0.974	-0.947
	(0.948)	(0.952)
Year interviewed	0.0840^{**}	0.0847^{***}
	(0.0313)	(0.0298)
Major Illness: If any	0.270	0.269
	(0.476)	(0.477)
Constant	-165.3^{**}	-166.8^{**}
	(62.77)	(59.86)
Observations	1174	1174
No of Individuals	587	587

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Standard errors in parentheses, clustered at state-level.

I estimate:

Years of Education$_{it}$ $\sim$ Receiving Transfer$_{ht}$ $+ \, controls_{it}$ for column 1, and

Years of Education$_{it}$ $\sim$ Transfer Amount$_{ht}$ $+ \, controls_{it}$ for column 2.

Controls: urban, if suffer major illness, year of interview (years passed), and an intercept.

Regressions weighted by the same weights as used in matching for Table 1.C.2.

For comparison, see unweighted regression results in Table 1.C.8.

Table 1.C.8: Fixed-effects Panel Regressions (Unweighted): Education of Young Adults

Dependent Variable	Years of Education	Years of Education
	Age group 15-24	
If HH gets transfer	0.132	
	(0.262)	
Transfer, annual ('000 USD)		0.151
		(0.660)
Urban dummy	-0.593	-0.589
	(0.772)	(0.759)
Year interviewed	0.0501	0.0556**
	(0.0300)	(0.0262)
Major Illness: If any	0.222	0.219
	(0.358)	(0.354)
Constant	-97.16	-108.2*
	(60.19)	(52.47)
Observations	1174	1174
No of Individuals	587	587

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Standard errors in parentheses, clustered at state-level.

I estimate:

Years of Education$_{it}$ $\sim$ Receiving Transfer$_{ht}$ + $controls_{it}$ for column 1, and

Years of Education$_{it}$ $\sim$ Transfer Amount$_{ht}$ + $controls_{it}$ for column 2.

Controls: urban, if suffer major illness, year of interview (years passed), and an intercept.

Chapter 2

The 0.0003 Percent: Sources of Extreme Wealth in America

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2.1 Abstract

This paper documents the changing sources of wealth among the Forbes 400 list of the wealthiest individuals in the United States, using annual data for 12 years spanning each side of the financial crisis of 2008-9. We examine mobility in and out of this group of the extremely wealthy, the impact of age and having an advanced degree, and whether individuals were "self-made" or not. We find that turnover in the Forbes 400 was higher in the period prior to the financial crisis, that individuals with advanced degrees did better than their counterparts without that education in this earlier period, and those who we classified as self-made also did better before the financial crisis, relative to their counterparts.

JEL Codes: J11, I24.

Key Words: Forbes 400, Great Recession, Income Inequality, Wealth Inequality, Higher Education.

2.2 Introduction

Recent trends in income and wealth distributions in advanced economies, as well as work by economists (e.g., Piketty (2014)) have refocused attention on increasing inequality. One slice of this picture of inequality is the extreme inequality of wealth in America, evidenced by the status of a few hundred individuals annually listed in the Forbes 400[1]. This number makes up about 0.0003 percent of the number of US households, or a tiny fraction of the top 1 percent of households by wealth. One important conceptual issue in determining social attitudes to such extreme wealth is the question of how that wealth was generated. Recent work has examined the roles played by inheritance, innovation, technology and education in the process of wealth generation, and stressed the importance of human capital and technological change. This paper extends such work, to examine further the proposition that technological progress has become a more important driver of new wealth creation over the last decade-and-a-half. The paper also examines the impact of business cycle effects, as captured in differences in the characteristics of this extreme group befoe and after the financial crisis.

Our main contribution in this paper is to provide an econometric analysis of panel data constructed from the Forbes 400 annual lists. Econometric analysis through panel regressions allows us to identify business cycle effects, as well as their interaction with the individual characteristics of those in the list, such as age, being "self-made" and educational attainment in the form of advanced degrees. We also analyze the persistence of individuals in the list, how it changes over time and how it is related to individual characteristics such as education. We employ a recent econometric innovation to estimate the

[1]This data source and the data are described in Section 3.

covariation of wealth with time-invariant characteristics, such as educational attainment, while accounting for the intermittent absence of some individuals from the list due to the rank cutoff. This issue of truncation in the panel is handled with an adaptation of Heckman's two-step method.

Several authors have used the Forbes 400 data to examine aspects of economic inequality in the US. For example, Piketty (2014) focuses on increasing global inequality in income and wealth, but for the United States specifically, he uses the Forbes 400 list to document increasing wealth concentration over the previous three decades. According to the list, the share of billionaires wealth rose from 0.4 percent in 1987 to 1.5 percent in 2012 (Piketty 2014, 432–36). Also for the US, Saez and Zucman (2016) show that wealth inequality has increased dramatically at the top of the distribution over the last three decades. This conclusion is based on wealth estimates constructed from administrative income data. A similar conclusion is reached from data on Forbes magazines annual list of the 400 wealthiest Americans. Kaplan and Rauh (2013a), which is closest to the current paper, use this data at 10 year intervals from 1982 to 2011, to examine the characteristics of individuals in this set of the extremely wealthy. They find that over this period, the percentage of the Forbes 400 that inherited wealth declined, and that more of them had a college education. Their analysis shows that the Forbes 400 were more likely to be in technology, finance or mass retailing,in 2011 as compared to 1982. Our approach differs from that of Kaplan and Rauh in using annual data, allowing us to examine short run changes and business cycle effects, the latter especially on either side of the financial crisis. The annual data also allows us to explore short-term mobility and persistence of membership in the Forbes 400.[2]

[2]The general literature on wealth inequality is large, and includes, for example, the early analysis of

Our analysis of turnover or mobility over short spans of years and its relation to the business cycle is also quite different than the approach of Arnott et al. (2015). Those authors estimate that the wealth of the individuals in the Forbes 400 rose from 13,800 times US per capita GDP in 1982 to 108,000 times US per capita GDP in 2014, but they mostly emphasize the long run turnover in the list, “Instead, we find huge turnover in the names on the list: only 34 names on the inaugural 1982 list remain on the 2014 list, and only 24 names have appeared on all 33 lists.” They go on to estimate that only 39 percent of the wealth of the original 1982 Forbes 400 list is represented in the 2014 list, so that 61 percent is “new money.” However, this neglects the wealth that does not show up on the list, so that it could be that some of that “new money” existed before those individuals made it on to the list[3]. Arnott et al. argue that dynastic wealth is less important than entrepreneurial wealth, including[4] over the period of the three decades of existence of the Forbes 400 list, as well as over longer periods, but, unlike Kaplan and Rauh, they do not provide any quantitative analysis of the sources of new wealth. In any case, our analysis is more short term, and we cannot shed as much light on longer run phenomena in the generation of large fortunes.

In the next section, we provide a detailed overview of the Forbes 400 data used

Thurow (1971), as well as more recent contributions such as Alvaredo et al. (2013), Kaplan and Rauh (2013b), and Wolff and Gittleman (2014).

[3]Thus, Donald Trump was wealthy before he made it on to the Forbes 400, so not all of his fortune once he appeared on the list was “new money”.

[4]For earlier periods, they use figures constructed by Phillips (2002).

in this paper. We first confirm and extend the results of Klass et al. (2006) and Nagayama (2013) that show increasing wealth inequality even among this group of the very richest Americans. Then, we document trends in the number of the Forbes 400 with advanced degrees of any kind (master's, doctorates and professional degrees). This analysis extends the focus of Kaplan and Rauh (2013a), which examines the increased presence of college graduates among the group. We show that the number of those with advanced degrees does not follow a smooth trend in our sample period. In fact, the Great Recession falls roughly in the middle of our sample period, and there appear to be differences in trends of those with advanced degrees, those who are self-made (defined in the next section) and in the relative presence of individuals whose fortunes are attributable to particular sectors. As one example of such sectoral differences, the share of wealth associated with real estate rises rapidly during the boom in the first part of the sample, and falls after the financial crisis, while the share of technology and telecom as a sector has the opposite pattern. Several such aspects of the data are discussed in the data overview section, and we believe this kind of analysis has not been conducted previously for the Forbes 400.

Our analysis then turns to a consideration of mobility, both within the Forbes 400, and in terms of entry and exit. We document changes in entry and exit over the sample period, including differences in these patterns before and after the financial crisis (boom vs. recession). We distinguish differences in patterns for those with and without advanced degrees, and also consider annual patterns of entry, including those who are new entrants, those who are self-made, and those who have both or neither characteristic. This analysis can be seen as complementing that of Arnott et al. (2015), since we examine more recent data, and are able to discuss features of the data that they cannot examine, such as what happens to individuals with advanced education. Broadly, the rates of attrition and persistence in our 12 year period are similar to those documented by Arnott et al. (2015) over about three decades, although we must repeat the caveat that those dropping out of the list are most unlikely to be moving into poverty! In this section, we also provide a regression analysis of persistence in the Forbes 400 list, which is an innovation over previous analyses.

Our analysis is rounded out by a detailed econometric analysis of our panel data, using the growth rate of wealth as the dependent variable, and allowing for a range of possible specification issues. In particular, we adapt the method of Kripfganz and Schwarz (2013) to deal with non-normality and time-invariant characteristics. Furthermore, we innovate in simultaneously dealing with truncation through an adaptation of the Semykina and Wooldridge (2010) correction for selection bias for panel data in the presence of endogeneity. Our results for the overall panel suggest mild wealth convergence among the group, business cycle effects in terms of the GDP growth rate, and also some additional positive boom-year impacts of being self-made and having an advanced degree. However, these results are not always robust to disaggregation by sectors, which suggests that wealth dynamics are quite complex, partly as a result of different sectors having different sensitivity to the business cycle, and to the overlay of longer term trends. In particular, the technology and telecom sector differs in these patterns from the finance sector. We hope our analysis will point the way to further investigation of these complex dynamics at the very top of the wealth distribution.

2.3 Data Overview

We use annual data taken from Forbes magazine, which lists and ranks the magazine's determination of the 400 richest persons in the United States of America. This list appears in October every year, and we have compiled data manually for a dozen years, from 2004 to 2015. There are 722 individuals who appear at least once in the Forbes list over these 12 years. Some information, namely wealth and rank, of these persons is only available if they are in the list for the year in question: thus, we have only 4800 observations out of a potential 8664 (722x12) observations. There are other variables that are invariant over time, such as gender, education, and whether the individual was "self-made", in a sense to be made precise later in the paper. In some cases, more than one individual may be listed in one of the 400 positions (e.g., a couple may be listed together), and we treat these cases as one individual or observation, using the characteristics of the member of the couple or family group that we identify as the "main" wealth generator. There are is a relatively small number of such cases, and our results are robust to their exclusion.

Data on education, one of our main characteristics of interest, is not consistently available in the Forbes 400 lists, and we have compiled the data on education manually from a variety of sources. In some cases, the information was not available or reliable, and so our annual totals do not always equal 400, because we omit such observations. Of course, many individuals appear repeatedly in the list, and, as noted, there are a total of 722 distinct individuals in our 12-year data set. When individuals for whom we were not able to find the education levels, are excluded, our analysis is based on a remaining sample of 696 distinct individuals.

Since data on each individual's wealth in a particular year is only available if they happen to be in the top 400 in that year, observations for some individuals are not available for all 12 years. This kind of truncation in the panel data is an important issue that we will deal with in our empirical analysis.

In the rest of this section, we describe the data and its properties in some detail, highlighting some of the features and patterns that can be observed. This exploratory data analysis provides some motivation for the subsequent formal analysis. We explore individual characteristics such as age in the first year of our sample, having an advanced degree (anything beyond a bachelor's degree), the sector that is the source of wealth, being "self-made", and being a new entrant.

2.3.1 Wealth Inequality among the Wealthiest

We begin with a description of the distribution of wealth among the Forbes 400. It is standard to use a Pareto function to model this distribution at the very top end of the wealth spectrum. Using this model, Klass et al. (2006) demonstrated increasing wealth inequality at the very top. Nagayama (2013) extended this kind of analysis to 2012, and we provide a similar analysis for our sample period, which extends to 2015.

The model uses a Pareto function of the wealth and rank, as follows:

$$W_R = AR^{-\frac{1}{\alpha}}.$$

Here, W_R stands for the wealth (in current USD), while R is the rank of that person. Taking a log transformation on both sides, we get:

$$\log W_R = \log A - \frac{1}{\alpha} \log R.$$

$$\implies \log R = \alpha \log A - \alpha \log W_R.$$

We plot linear log transformation of rank vs. wealth for the first and last years of our sample in Figure 1. The α is estimated as the slope of the estimated least-squares line and reported below the scatter plots. A lower (higher) α indicates more (less) inequality in the distribution.

In Figure 1, the scatter plot shifts to the right over the period, simply reflecting increasing nominal wealth. The relative slopes are not apparent from the plots, but the estimated α, as reported in the lower box, did decrease, implying increased inequality over the sample period, consistent with the earlier results of Klass et al. and Nagayama.

Figure 2 plots the estimated α for each year of the sample. From 2004-2007 there was a slight reduction in the inequality of wealth among this rarefied set of the extremely wealthy, but post-crisis the inequality measure increased every year till 2013. In the last two years the trend did reverse. In this paper we will explore some of the underlying characteristics of those who make up these distributions, how their wealth changed over the sample period, what kind of turnover there was in the composition of the sample over the years, and so on.

2.3.2 Advanced Degrees

As discussed in the introduction, one of the characteristics we examine is the importance of education in this sample of the extremely wealthy. Kaplan and Rauh (2013a) had documented the increased number of the Forbes 400 with college degrees over a period of three decades. We examine the more recent data for importance of education beyond the bachelor's level, i.e., advanced degrees of any type. US data (Table 2.1) shows that the earlier US trend of increasing proportions of college graduates has been reinforced by acquisition of graduate or advanced degrees (i.e., masters, professional, and doctoral degrees of any kind) at a higher rate as well.

Whereas the national data displays a relatively steady increase in the total numbers (about 700,000 per year) and percent (about 0.22 percentage points per year) of the US population with advanced degrees from 2000 to 2015, the pattern of change in the Forbes 400 is different. Figure 2.4 shows a sizable increase in the number of listed individuals with advanced degrees from 2004 to 2007, but the number levels off and even declines slightly thereafter. The percentage of individuals in the Forbes 400 goes from about 35 percent in 2004 to 42 percent in 2007, or almost a 20 percent increase in the proportion. This is much more rapid than the national trend in acquisition of advanced degrees. The right panel in Figure 2.4 illustrates a similar pattern over time, but in terms of the fraction of wealth among the Forbes 400 held by those with advanced degrees, rather than just numbers. The fraction of wealth levels off, but does not decline from the 2007 peak in the manner that the number of individuals does. This suggests that the individuals with advanced degrees who are remaining in the Forbes 400 are doing relatively better after 2007.

Next, Figure 2.5 plots the mean and median wealth for individuals in the Forbes 400, with and without an advanced degree, by year. Since the distribution of wealth among the Forbes 400 is itself very skewed (a small number of exceptionally wealthy individuals among the mere billionaires), the mean is greater than the median for both groups. However, for those with an advanced degree, after 2008, the mean becomes higher than that for their less educated counterparts. On the other hand, the median for the more educated stays slightly lower than the median for the less educated group. This implies that the wealthier individuals with advanced degrees are driving the comparison. This is consistent with the earlier comparison in Figure 2.4.

2.3.3 Sector

We now consider the industries or sectors in which the Forbes 400 can be found. We essentially use the classification of sectors in the lists themselves, and largely are able to assign individuals to their respective insustries based on the information in the lists. Recall that Kaplan and Rauh (2013a) find, in going from 1982 to 2011, increased numbers in Finance, Technology and Retailing.

Table 2.2 lists the classification of sectors we are using in this analysis, sorted by the number of unique individuals. It also shows those with advanced degrees by sector. It is indeed the case that Finance and Technology (including Telecoms) have the highest representation in the sample of individuals. Retail comes further down the list in terms of numbers. Interestingly, manufacturing is slightly more common as the sector of these extremely wealthy individuals, more so than several service sectors. Note that Diversified Investments and Inheritance are not really sectors or industries, but represent how the wealth was acquired, or where it is invested. There are some clear, and mostly obvious patterns with respect to the sectors in which individuals with advanced degrees are more likely to be. Compared to the sample average, these sectors are Finance, Technology and Telecom, Healthcare and Medicine, and Diversified Investments.

While Table 2.2 represents counts of individuals who are in the sample at least once over the whole 12 year period, Figure 2.6 shows how the proportion of wealth of the 400 held within each sector or sector changes over the sample period. Correspondingly,

Figure 2.7 shows how the number of individuals in each sector changes over the sample period. In order to highlight the impact of the financial crisis on trends in the concentration of wealth, these figures include linear fits for 2004-08 and 2010-15, with 2009 not included in either sub-period. This choice is also based on the direct observation from the plots that the most marked changes are around 2009. While the differences in trends before and after 2009 and across sectors may not be reflective of what was happening in each sector, they are still useful in suggesting further investigations about the structure of the economy and how it responds to business cycles. Perhaps the most obvious feature of these plots is the real estate boom that occurred prior to the financial crisis and recession. Finance, Diversified Investments, and Hospitality also share some of this feature. Unlike the longer term trends noted by Kaplan and Rauh, considering annual data on either side of a major turning point in the economy provides insight into cyclical factors rather than clear long run trends.

2.3.4 Being "Self-Made"

An important aspect of American ideology (or mythology) is the notion that anyone can become successful through their own efforts. The main argument of Arnott et al. (2015) is that inherited wealth dissipates relatively rapidly, and that the large fortunes we see at present have been created in the recent past.

In line with the conceptual importance of personal success versus inheritance, the Forbes list reports a "self-made" score on a scale of 1-10. The scoring system is described in detail in a Forbes Magazine article by Fontevecchia (2014). The scoring uses information on whether, and to what extent, individuals were the beneficiaries of substantial inherited wealth. Of course, this does not distinguish among those who might still have come from wealthy or educated families, those from comfortable backgrounds (e.g., "upper middle class"), and those who may have started without any advantages in their socio-economic background.

We use a simpler version of their score, a binary variable which takes the value 1 for anyone with the score 6 or more, and 0 for others. By this classification, of the 696 unique individuals, there are 497 self-made and 199 who are not. Note that the set of individuals who are not self-made by this measure is smaller than the set of individuals whose wealth is not attributed to inheritance, in Table 2.2. Using this definition, as shown in Figure 2.8, the proportion of the self-made in the Forbes list is high and it increased slightly over the dozen years of our sample. The increase coincided with the boom years prior to the financial crisis. The proportion of the Forbes 400 who were self-made by our binary classification stabilized at around 70% from 2009 on. The share in wealth of the self-made relative to the total wealth of the Forbes 400 displays a similar pattern, leveling at about 65% since 2009. The lower share of wealth as compared to the share of individuals reflects the fact that self-made individuals were slightly less wealthy on average than others in the list.

The pattern of increase in the first years of our sample, and stabilization thereafter, in the number of the self-made in the Forbes 400 is similar to that of those holding advanced degrees. In fact, self-made individuals are somewhat more likely to hold an advanced degree: among the 497 unique self-made individuals in the panel, 41% hold an advanced degree, while among the not self-made 199, only 32% do. The lower panel in Figure 2.8 divides the self-made into the two groups, those holding advanced degrees and others, and plots them separately. This figure shows that much of the increase in the number and share in wealth of the self-made in the early part of the sample is due to an increase in the number of the self-made who have advanced degrees.

Table 2.2 shows the proportion of self-made individuals by sector. As expected, human-capital intensive industries with likely low barriers to entry, such as Finance and Technology, have the highest rates of self-made rich, while more capital intensive industries such as Hospitality and Agriculture have less than 50%.

2.3.5 Age

There are two perspectives we can take on age, which is calculated from the reported year of birth for each individual. We can look at the age profile of the individuals in our sample, irrespective of which years they appear in the list, and we can also examine the age profile of each year's list. The connection between the two depends on entry and exit, which is discussed in the next section. For example, a simple t-test over unique individuals shows that the younger individuals are more likely to have advanced degrees, and this will be related to the increased presence of the latter characteristic over the first years of the sample. The source of year of birth is the Forbes list, or other news articles where needed.

Figure 2.9 relates being self-made to the year of birth, rounded to the nearest 5 years. The fraction of unique individuals who are self-made, calculated for each 5-year interval, tends to be higher among younger individuals, although there is considerable variation around the line of best fit.

In Figure 2.10, we plot the proportion of unique individuals with advanced degrees by year of birth. Among those born up until 1970, we see a steady increase in the fraction with advanced degrees, This pattern reverses for the younger cohorts in our sample of individuals. To check whether there was a difference between the self-made and others in this regard, we plotted the fraction of graduates by self-made in the right panel. The difference between the self-made and others is quite pronounced. For the self-made, the pattern is quite similar to the whole sample. The reversal for younger cohorts is now clearly attributed to them: those not self-made are all born before 1980s. There is a large pronounced increase in the proportion with advanced degrees in the younger cohorts among the ones not self-made.

Next, we turn to the second perspective on age, by examining the age profile of individuals in each of the annual lists. The 400 does not age all that much over the sample period (see Figure 2.11). The group with advanced degrees is younger than their less educated counterparts, but the average age of this group increases slightly faster than their counterparts. This could be due to the mobility of those with advanced degrees, if they persist longer in the list before dropping off; but more likely this is due to the fact that there is an influx of new entrants without advanced degrees. The right hand panel of the figure displays a different pattern for new entrants: their average age declines over the sample period, though there is again convergence in the average age of those with and without advanced degrees.

Turning to the age profile of just the self-made over the sample period, in Figure 2.12, one sees that the average age of the self-made is increasing at about the same rate as for the overall sample, shown in the previous figure. The differences between those with and without advanced degrees for the self-made subsample are fairly similar to those in the whole sample. This similarity also hold for new entrants, as shown in the right hand panel of the figure.

2.4 Mobility: Entry and Exit

In this section, we analyze mobility or turnover within the Forbes 400, an issue explored by Arnott et al. (2015) in a somewhat different manner. While we have annual data, it is easier to observe noticeable changes at periods longer than a year, so we divide our sample into two periods, from 2004 to 2009, and 2009 to 2015. Thus, the two sub-periods are slightly unequal in length. The first sub-period includes the years up to and including the financial crisis, while the second period is one of slow recovery from the crisis. Our division of the sample period allows us to examine possible business cycle effects in the process of turnover among the Forbes 400.

2.4.1 New Entrants

Figure 2.13 provides different views of trends with respect to annual new entrants into the Forbes 400 over the sample period. In the top panels, the left hand plot displays the fraction of the Forbes 400 who are new entrants for each year. These vary considerably from one year to the next, but the fitted lines on either side of 2009 suggest that entry goes down after the financial crisis. The right-hand panel displays the proportion of the wealth of the Forbes 400 held by new entrants. This is smaller than the fraction of the 400 who are new entrants because, on average, the new entrants are less wealthy than the rest. The fraction of wealth does not seem to vary as much as the numbers.

The middle panels compare new entrants with and without advanced degrees. Interestingly, after the financial crisis, the number of new entrants with advanced degrees trends down, while the number without advanced degrees does not display this trend.

The bottom left panel plots the mean wealth for new entrants with and without advanced degrees. The mean wealth of the former group is always lower than the mean wealth of the latter group. The right hand panel displays the same patterns, but in this case for the per person average proportion of total wealth in each group.

Table 2.3 extends the breakdown of new entrants to examine whether they are self-made or not. Numbers are reported for each year. Most new entrants are self-made, but this is especially true of the boom years earlier in the sample period. In parallel, the number of self-made also increases in these boom years.

2.4.2 Turnover

Table 2.4 shows the pattern of turnover within the entire Forbes 400 for both the two chosen sub-periods (2004-09 and 2009-15). The data are aggregated by quartile, so that we capture movement between quartiles, as well as entry into and exit from the Forbes 400. Quartile 1 represents the richest quarter of individuals, quartile 2 the next richest group, and so on. The numbers do not equal 100 for each quartile because of ties in estimated wealth, and there are also some missing observations, because we have omitted those for whom we do not have education data. The table can be read as follows. There are 383 individuals included in 2004 (505 minus 122 who are not in the 2004 list). Out of these, 115 were no longer in the list in 2009 (the sum of the first column):

20 of these because of death. Out of the 101 in the top quartile in 2004, 67 remained in that quartile in 2009. A total of 16 individuals dropped out of the list entirely, over the five year period. On the other hand, as one would expect, erosion was much higher at the lower end of the distribution: 50 out of 77 in the bottom quartile in 2004 had dropped out in 2009. Of the 107 individuals in the top quartile in 2009, 17 were new entrants. The numbers of new entrants were much higher in the other three quartiles (27, 43, 35). We can also observe movement within the list. Thus, 14 people went from the top quartile in 2004 to the second quartile in 2009, whereas 17 people made the reverse move between these years, climbing from quartile 2 to the top quartile. If we look at the bottom half of Table 2.4, we can see similar patterns for the second sub-period, from 2009 to 2015.

Table 2.5 presents the data in an identical format, but restricted to individuals with advanced degrees. In 2004, 142 (202 minus 60 in the final column) of the 383 individuals included in Table 2.4 had advanced degrees. The number with advanced degrees in 2009 was somewhat higher, at 164 (202 minus 38). There was a net increase of 22 in the number of individuals with advanced degrees in the Forbes 400 list, with 60 entering and 38 leaving. Since 3 exits were due to death, if we exclude these, there was a net increase of 25 individuals with advanced degrees. This pattern was not replicated in the second sub-period, after the financial crisis, with a net decrease of 3: 42 individuals entering and 45 leaving (6 due to death, implying a net increase of 3 excluding those cases)the list between 2009 and 2015. The numbers who dropped out because of death were relatively small, so most of the turnover was from other causes.

In Table 2.6, we present the same data for the remainder of the list, those without an advanced degree. This designation therefore lumps together college graduates and those without college degrees. We can see that among this subset, there is very small net addition in the first sub-period of 2 people, if deaths are excluded (62 minus 77, adjusted for 17 deaths). But in the second sub period there is an appreciable addition of 35 (82 minus 74, adjusted for 27 deaths).

Comparing the groups with and without advanced degrees, the patterns of turnover are fairly similar for each of the two sub-periods. However, the proportion dropping out due to death is quite a bit higher among those without advanced degrees.

The most notable feature of the comparisons across level of education for each sub-period is that the period 2004-09 is different, because the number of individuals with advanced degrees increases over those years. But whether this is a transitory phenomenon, or a specific feature of the business cycle of that time, or something that reflects underlying trends in the relationship between higher education and extreme wealth (extending Kaplan and Rauhs observations) cannot be determined with this sample. These possibilities certainly deserve further investigation.

2.4.3 Keeping Wealth: Mobility Regressions

Table 2.7 presents the results of regressions to test the hypothesis that persistence in the list is related to having an advanced degree or being self-made.

In the first two columns, the observations are the 696 unique individuals, for whom we have education data. The dependent variable is the number of times each individual appears on the list in the 12 year period 2004-2015. The right hand side variable of interest is a dummy variable for whether the individual has an advanced degree. Column 1 reports the results of a simple regression, while column 2 controls for age as well as sector and year fixed effects. In either case, those who have advanced degrees appear significantly more often than those who do not, while self-made individuals appear less often.

In the next two columns the dependent variable is the probability of persisting in the list after being in it the previous year. In all these regressions we account for persons who have been dropped from the list after their death by including the dummy for deceased as an explanatory variable.

Specifically, in columns 3 and 4, if a person was on the list in 2004, and is still the list in 2005, $Stay$ assumes value 1 for 2005. If the person is not on the list any more, $Stay$ takes value 0. If a person was not on the list in the previous year, the value is unassigned. The variable $Stay$ cannot be estimated for the year 2004.[5]

In columns 5 and 6, we present a test of the hypothesis that self-made or persons with advanced degrees improve their ranks more than their counterparts without advanced degrees. The dependent variable is a dummy for improvement of rank, which we explain with an example. Suppose a person appears in the list in the previous year, say 2004 at a rank say 100. If in the next year, 2005, their rank is below 100 the dummy takes the value 1. If they stay at the same rank or slide down below 100 or drop out, the dummy takes the value 0. If a person is not in the list in the initial year (2004 in our example), the value for the dummy is unassigned or 'missing'. Like $Stay$, we can only estimate

[5]Thus, the number of observation in the estimation panel is much smaller than in the entire panel.

this variable for the years 2005-2015.

Since the dependent variables for these regressions are dummy variables we estimate panel probit models with random effects. While persons with advanced degrees are significantly more likely to appear on the list over the period of twelve years (columns 1 and 2), when examined year-by-year, columns 3-6 show that, the difference is not different from null at the 5% level. However, individuals with advanced degrees are more likely to improve their rank within the list than their counterparts without advanced degrees. About self-made, the columns 3 and 4 confirm as the columns 1 and 2 suggested, that year after year being self-made is associated with less persistence. However, those that do persist in the list, rise up the ranks faster than the not self-made, thus being self-made is associated with an improvement of rank.

2.5 Wealth Dynamics

In this section, we first describe the basic econometric approach to examining how the wealth of those in our sample evolves over the sample period. Then we present the initial regression results. Next, we extend the analysis to take account of possible estimation biases due to truncation, since some individuals may drop out of the sample in particular years because they no longer meet the ranking criterion for inclusion. Finally, we consider specific sectors in isolation, to examine how different parts of the economy have different dynamics of wealth for this sample.

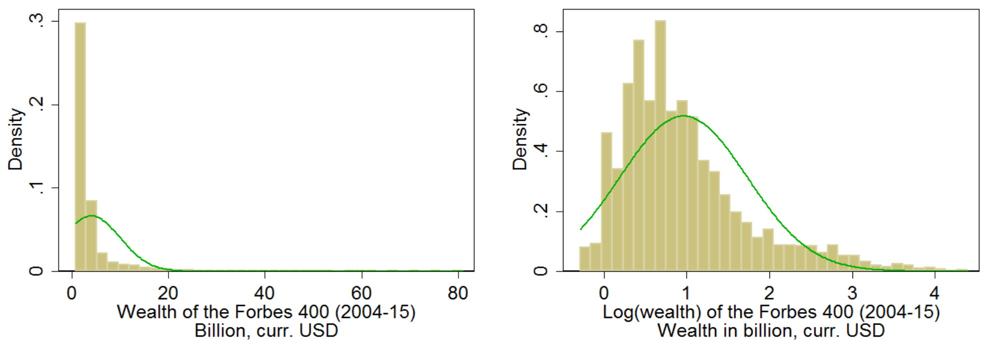
2.5.1 Econometric Modeling Approach

The subscript i indicates an individual and t the year. For example, W_{it} indicates wealth of one person in a particular year, say, the wealth of Bill Gates in 2008. Lower case, w_{it}, represents the log of wealth. Information about whether a person is self-made, or their education level, does not change over time, so we drop t, Self-Made$_i$ and Adv. Deg$_i$.

The figure 2.1 shows the distribution wealth (W_{it}), which is very skewed, as noted earlier, and the log of wealth (w_{it}). We will use the log transformation as the dependent variable for the rest of the analysis.

Figure 2.1: Distribution of the Variables Wealth and log(Wealth), 2004-15

Smooth line is the normal distribution with same mean and deviation, for comparison



Let us say that wealth depends on an array of independent variables X_{it}. In a panel of data, wealth in this period will be heavily dependent on wealth in the last period, as in the following equation:

$$w_{it} = \beta_0 + \beta_1 w_{it-1} + \beta_2 X_{it} + u_{it} \tag{2.1}$$

However, it is more useful to estimate the equation in terms of the change in log wealth, which is the growth rate of wealth:

$$\Delta w_{it} = \beta_0 + \beta_1 w_{it-1} + \beta_2 X_{it} + u_{it}. \tag{2.2}$$

If we divide the variables X_{it} into those that are time-invariant – such as being self-made, having advanced degrees, and sector – and those that are not, the above model can be rewritten:

$$\Delta w_{it} = \beta_0 + \beta_1 U_i + \beta_2 V_{it} + u_{it}. \tag{2.3}$$

Generally, two kinds of methods are employed to estimate such a model, depending on the assumptions: random-effects or fixed-effects (Wooldridge 2010).

Random-effect models assume that there are no individual related-effects in the panel, that all the unobserved characteristics are unrelated to the error term. In our case, this assumption is likely to be violated: individuals have many characteristics that contribute to wealth generation, other than the ones we have measured.

If there is a clear case for time-invariant individual effects in the panel, we can employ fixed-effect methods, in which we essentially remove the time-invariant individual fixed effects. This can be done by taking first differences, or alternatively by demeaning all the variables (Arellano and Bond 1991). Subtracting the mean removes the time-invariant individual fixed effects, so we will not be able to estimate the effect of time-invariant characteristics such as having advanced degrees or being self-made.

There however, are some hybrid models[6] such as one proposed by Allison (2009) for estimating the within-effects in the random effects model. These could be suitable for our analysis, other than the complication that we have time-persistence in our model, so we will have to modify these methods for our purpose.

---

[6]Summarized by Schunck et al. (2013).

In the hybrid method proposed by Allison, we can decompose the time varying variables into two parts: $V_{it} - \overline{V_i}$ and $\overline{V_i}$. Our model 2.3 can be rewritten as:

$$\begin{aligned} & \Delta w_{it} && = \beta_0 + \beta_1 U_i + \beta_2 (V_{it} - \overline{V_i}) + \beta_3 \overline{V_i} + u_{it}. \\ \implies & \Delta w_{it} && = \beta_0 + \beta_1 U_i + \beta_2 V_{it} + (\beta_3 - \beta_2)\overline{V_i} + u_{it}. \\ \implies & \Delta w_{it} && = \beta_0 + \beta_1 U_i + \beta_2 V_{it} + \beta_4 \overline{V_i} + u_{it}. \end{aligned}$$

For implementation, we would include the means of time-varying terms for each individual as explanatory variables on the right-hand side and estimate this model with the random-effects assumption:

$$\Delta w_{it} = \beta_0 + \beta_1' U_i' + \beta_2 V_{it} + u_{it}. \tag{2.4}$$

Where, $U_i' = U_i + \overline{V_i}$.

A further issue is that the panel data has AR(1) errors, and lagged wealth is an explanatory variable, so the random-effects assumption that the error term u_{it} is uncorrelated with unobserved individual fixed-effects does not hold. To overcome this problem we implement the hybrid model in STATA through a two stage method proposed by Kripfganz and Schwarz (2013), using the command xtseqreg developed by Kripfganz. Very briefly, one estimates the GMM coefficients of the time-varying variables at the first-stage. At the second-stage, residuals from the first-stage analysis are used to estimate the coefficients of the time-invariant variables, with corrected standard-errors.

2.5.2 Estimation Results

The results of the different regressions are displayed in Table 2.8. In each case, the dependent variable is the growth rate of wealth, measured as the difference of log wealth. In all the methods, the coefficient of lagged wealth is negative, indicating some convergence. However, in the random effects and sequential Kripfganz-Schwarz methods, the magnitude of the coefficient is much smaller, and more plausible. In general, as one would expect, the results for the random effects and hybrid models are closer to those of our preferred method, the two-stage or sequential K-S method, than the fixed effect estimates.

In all cases, the estimates display a strong business cycle effect, in that the GDP growth rate has a large and significant effect on the growth rate of wealth. Indeed, a one point increase in the GDP growth rate translates into over 3 points of growth in the wealth of those in the Forbes 400. At the aggregate economy level, this should not be surprising, although we will observe differences across sectors in disaggregated estimations in section 4.4.

There are some additional differences in the period before the onset of the financial crisis. Focusing on the results of the sequential K-S method, in column 4, the dummy associated with the pre-crisis period is negative, but interactions of this dummy with indicators for being self-made and having an advanced degree both have positive coefficients, which are also similar in magnitude. In other words, this was a period in which individuals with these two characteristics were doing better in terms of growth in wealth than their counterparts without advanced degrees or those who were not self-made. However, the results for the second stage, in which time-invariant effects are estimated, show that the positive impact of being self-made on the growth of wealth continued after 2008, albeit at a lower level, while the impact of having an advanced degrees no longer was positive.

2.5.3 Dealing with Truncation

We also estimate a modified version of the two-stage Kripfganz method, which deals with the truncation issue arising from the data being restricted to the 400 wealthiest individuals in each year. Truncation leads to a potential selection bias, which is dealt with by methods based on Heckman (1979) seminal approach. Semykina and Wooldridge (2010) provide a method for estimation of the part of the error that is allowed to be systematically correlated with selection. With some simplifying assumptions, these can be obtained and included in the primary equation to give consistent estimates of the primary regression coefficients. This extra term is the inverse Mills ratio.

Here we innovate by combining the methods of Semykina and Wooldridge (2010) and Kripfganz and Schwarz (2013). First we estimate the inverse Mills ratios following the technique of Semykina and Wooldridge (2010), and then we use these inverse Mills ratios as an explanatory variable along with the other variables, using the STATA implementation created by Kripfganz.

The results for our modification of the sequential K-S method are presented in the first column of Table 2.9. They are very similar to those in column 4 of Table 2.8, suggesting that the truncation problem is not a serious one. However, we provide further estimates to examine the robustness of the results to selection bias due to truncation. Column 2 of Table 2.9 applies the K-S method, but without the correction for selection, to a sample restricted to individuals who are in the Forbes 400 for each of the 12 years. Hence, there is no issue of individuals dropping out of the sample in some years due to their rank falling below 400. The results are broadly similar to those of the two-stage K-S method, with and without the truncation correction.

Results of a further robustness check are reported in Table 2.10. Column 1 of the table applies the K-S method to the top 300 of our sample, excluding data for those individuals who remain in the top 400 in some years. Column 2 applies the selection correction to this sub-sample, as was done for the full sample in Column 1 of Table 2.9. The next two columns use the top 300 individuals, but we now include data for these individuals for years in which their rank is between 301 and 400, since this data is available to us. The idea here is that the truncation issue will be partially attenuated in this data set. Column 3 estimates the regression using the 2-stage K-S method, and column 4 further applies the truncation correction. Comparing across all four columns, we see that the impact of missing data is not severe, and the truncation correction does not change the results appreciably.

2.5.4 Sectoral Results

In this section, we examine how our results change when we restrict attention to sector-specific subsets of the Forbes 400. The group is spread across more than a dozen sectors (Table 2.2, so the numbers are relatively small for individual sectors, and there are no obvious cases for further combinations of sectors, beyond what we have done (Technology and Telecom, Healthcare, and Medicine). Therefore, we estimate the model for just the three most highly represented sectors, in terms of numbers of individuals. The results are reported in Table 2.11.

In none of the three top sectors is there any statistically significant evidence of convergence, since the coefficient of lagged wealth is statistically insignificant, even though it remains negative. In the case of Finance, only the impact of being self-made remains significant, although that is no longer true of any additional pre-2008 effect. The impact of the business cycle, as captured by the coefficient of the GDP growth rate, is positive, but no longer significant when the truncation correction is applied. For Technology and Telecom, the pre-2008 effect of having an advanced degree remains significant, but the impact of GDP growth changes sign when the truncation correction is applied. The case of Diversified Investments, which is not really a sector in the sense of the others, but represents the best description of the source of wealth of individuals in this category, has the most robust results with respect to GDP growth and the pre-2008 impact of having an advanced degree, but the other coefficients are no longer statistically significant.

At this stage, the best we can conclude from these sectoral results may be that wealth dynamics differ across sectors, and additional disaggregated analysis would be helpful. To do such analysis a longer sample might be useful, in making it easier to disentangle longer-term trends (such as might be overwhelming business cycle impacts for Technology and Telecom in our results), although longer samples would also introduce more challenges in terms of assumptions of parameter stability.

2.6 Conclusion

By analyzing annual panel data for the Forbes 400, covering 12 years spanning either side of the financial crisis, we are able to observe some interesting characteristics of the dynamics of membership in this group of the extremely wealthy. In particular, in the boom years leading up to the financial crisis, there was greater mobility in this group, and increased entry by those with advanced degrees and those who could be characterized as “self-made”. In these boom years, there is evidence that having an advanced degree and being self-made also contributed positively to the growth of wealth for these selected individuals. We find evidence of business cycle effects in the growth of wealth, which should not be surprising, but these are less clear when the analysis is restricted to individuals in particular sectors of the economy. It is possible that other, longer-term trends are being reflected in these differences across sectors.

For the average super-rich person over the entire time-span, the rate of growth of wealth was slightly negatively related to the previous year’s wealth, implying a mild degree of convergence. While the rate of growth of wealth slowed down after 2008, as would be expected, the growth rate of wealth for this group was considerably higher than the GDP growth rate, by a factor of about three. However, the rate of growth of wealth was higher for the self-made in this group of the extremely wealthy, relative to their counterparts, and was even higher before 2008. We also found that the self-made were more likely to improve their ranking within the group, conditional on staying in the list. The dynamics of inequality and its interaction with the growth of non-dynastic self-made wealth also deserves further investigation over a longer time span.

Our results for the overall panel found business cycle effects in terms of the relationship between the GDP growth rate and the growth of wealth for the group, as well as positive boom-year impacts of being self-made and having an advanced degree. However, these results are not always robust to disaggregation by sectors, which suggests that wealth dynamics are quite complex, partly as a result of different sectors having different sensitivity to the business cycle, and partly due to the overlay of longer term trends on short term fluctuations. In particular, the technology and telecom sector differs in these patterns from the finance sector. On the other hand, the group whose wealth is in diversified investments displayed wealth growth patterns more like the overall sample. We hope our analysis will point the way to further investigation of these complex dynamics at the very top of the wealth distribution.

2.7 Figures and Tables

Figure 2.2: Forbes 400 Rank vs. Curr. Wealth in Log-Log Scale

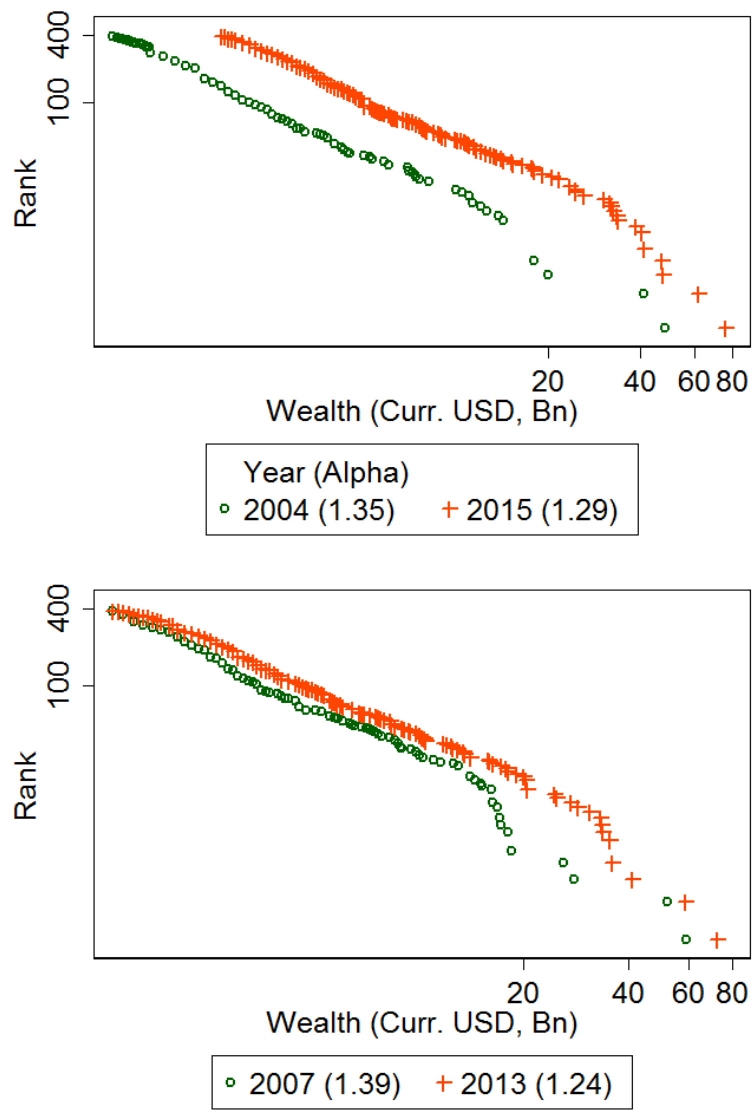


Figure 2.3: Time Series of α, 2004-2015

Table 2.1: Number and Percent of US Population 25 and Over with Advanced Degrees

Year	Number ('000s)	Percent
2000	15,006	8.6
2001	15,728	8.7
2002	16,414	9.0
2003	17,169	9.3
2004	17,983	9.7
2005	18,121	9.6
2006	18,567	9.7
2007	19,184	9.9
2008	20,228	10.3
2009	20,938	10.6
2010	21,056	10.5
2011	22,057	10.9
2012	22,730	11.1
2013	23,931	11.6
2014	24,623	11.9
2015	25,445	12.0

Figure 2.4: Forbes 400: Individuals with Advanced Degrees

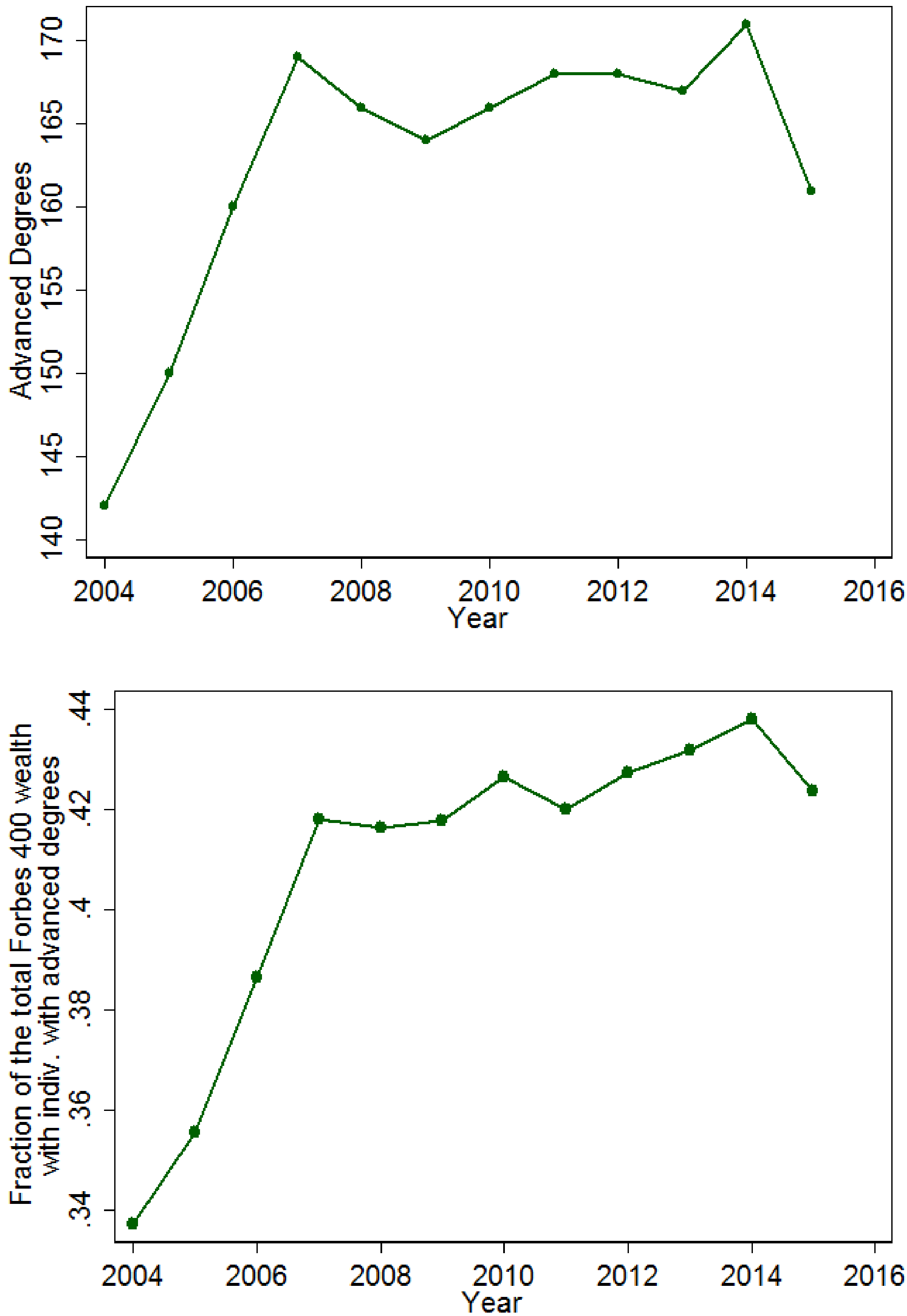


Figure 2.5: Wealth by Advanced Degrees

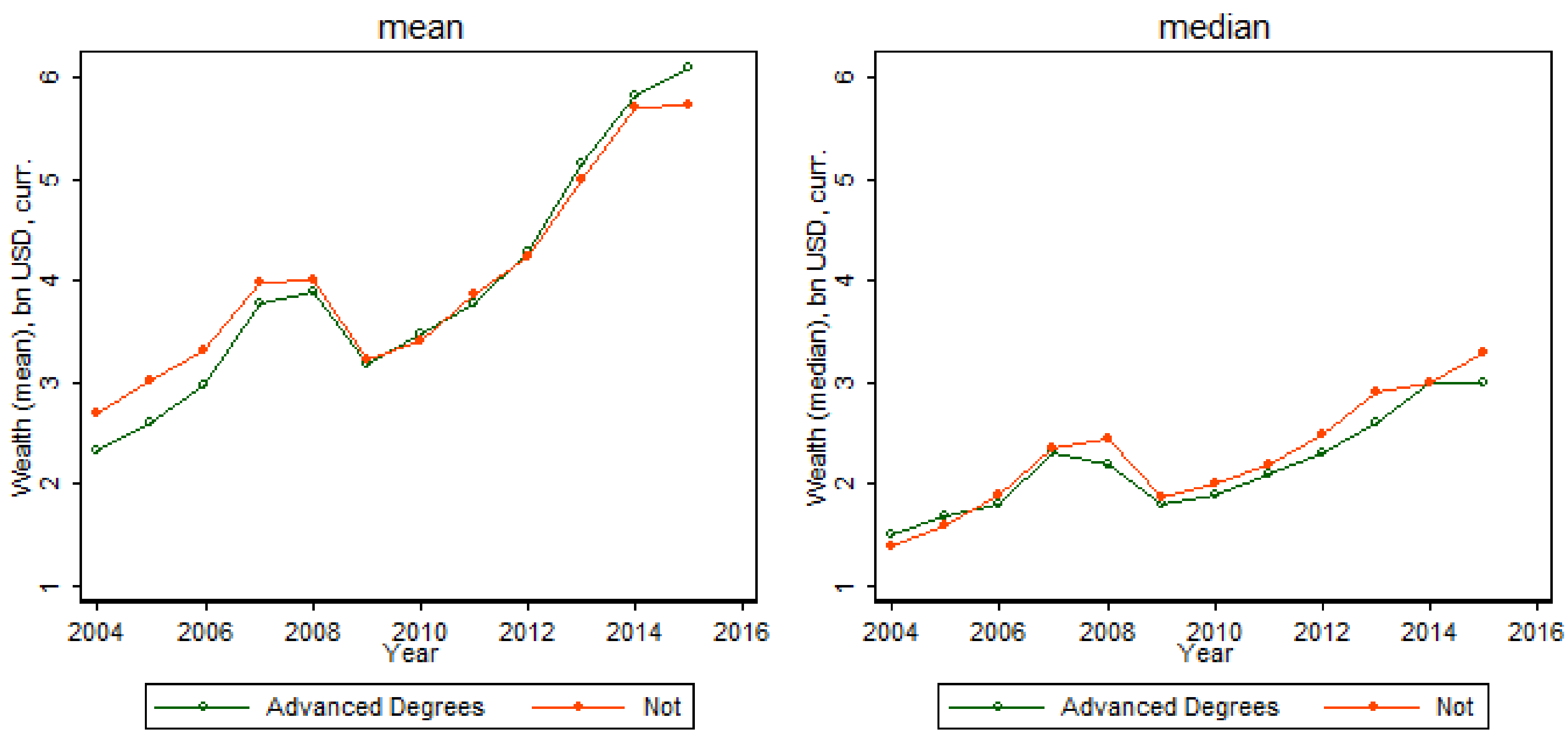
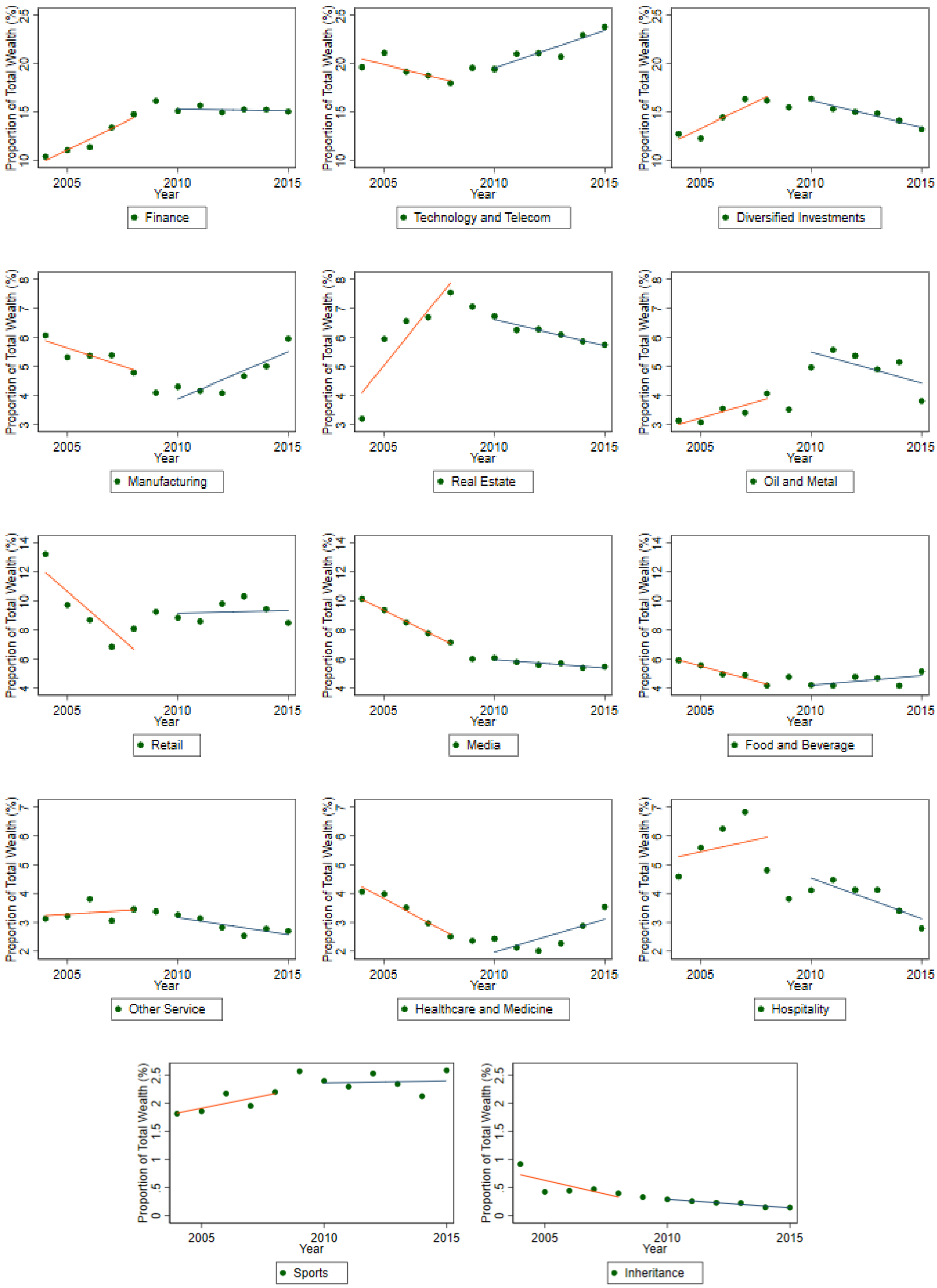


Table 2.2: By Sector: Unique Individuals and Education

		Adv. Deg. (%)		Self-Made (%)		
Source of wealth	No.	Yes	No	Yes	No	Total
Finance	109	49.5	50.5	88.1	11.9	100.0
Technology Telecom	107	49.5	50.5	89.7	10.3	100.0
Diversified Investments	70	67.1	32.9	72.9	27.1	100.0
Manufacturing	55	29.1	70.9	54.5	45.5	100.0
Real Estate and Construction	54	33.3	66.7	79.6	20.4	100.0
Oil and Metals	44	29.5	70.5	59.1	40.9	100.0
Retail	42	16.7	83.3	64.3	35.7	100.0
Media	41	26.8	73.2	61.0	39.0	100.0
Food and Beverage	36	13.9	86.1	55.6	44.4	100.0
Other Services	32	21.9	78.1	68.8	31.3	100.0
Healthcare and Medicine	30	53.3	46.7	86.7	13.3	100.0
Hospitality	27	25.9	74.1	37.0	63.0	100.0
Sports	25	36	64	72.0	28.0	100.0
Agriculture	16	18.8	81.3	43.8	56.3	100.0
Inheritance	8	37.5	62.5	0.0	100.0	100.0
Overall	696	38.6	61.4	71.4	28.6	100.0

Figure 2.6: Share of Sector* in the Total Wealth of the 400

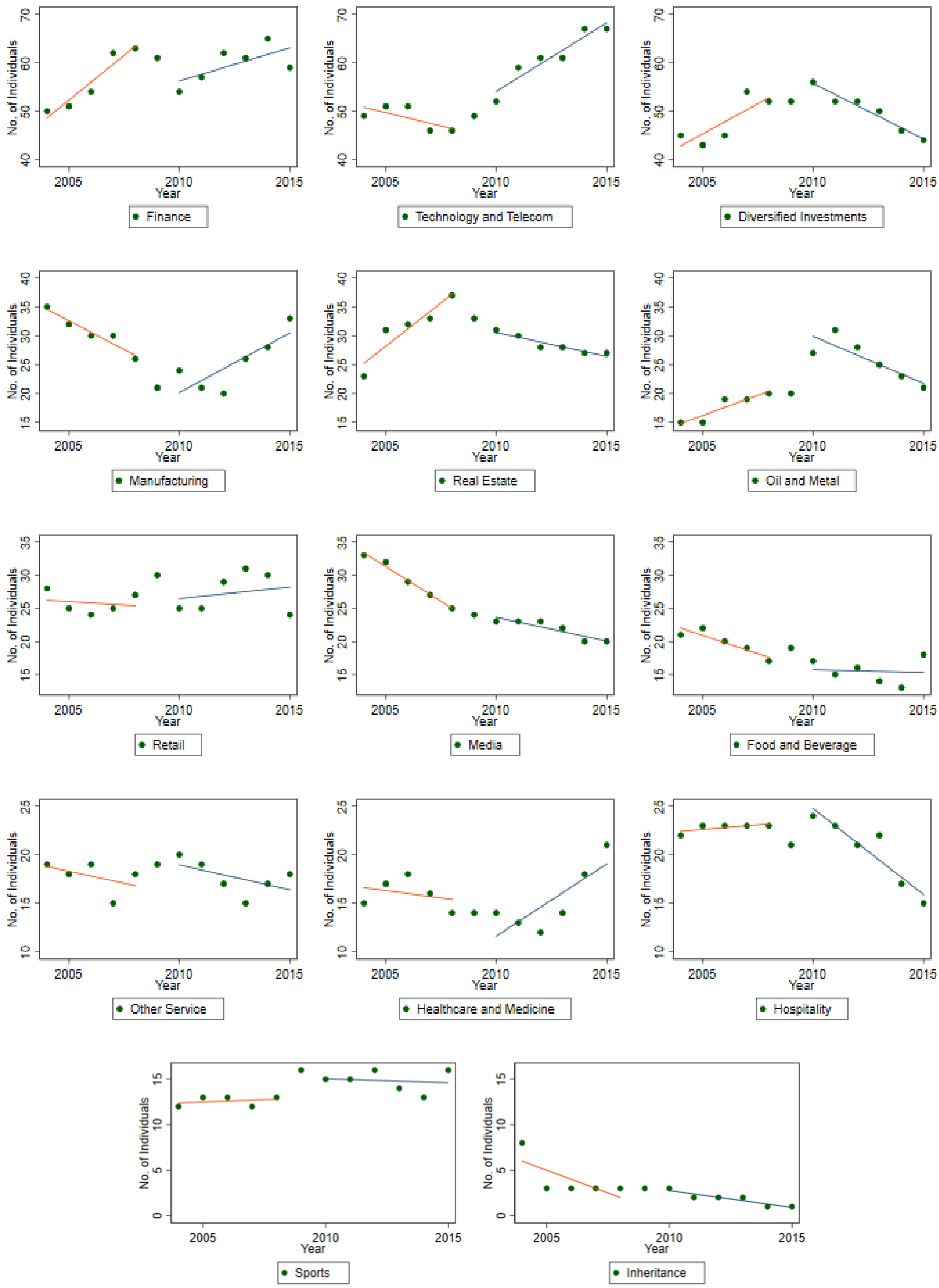
Linear Fit - Before 2009, After 2009



*Not displaying the Agriculture sector, since there is no one in this sector for certain years.

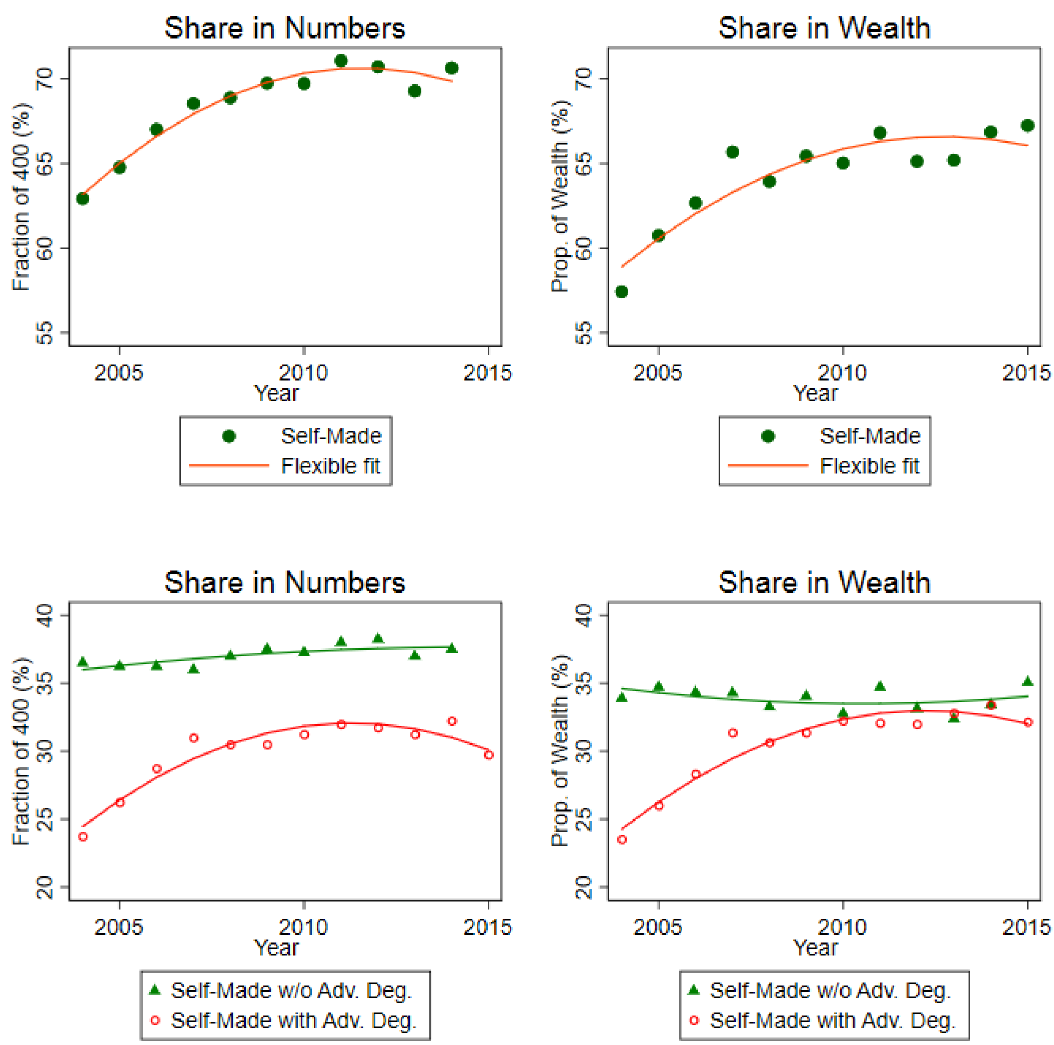
Figure 2.7: No. of Individuals by Sector*

Linear Fit - Before 2009, After 2009



*Not displaying the Agriculture sector, since there is no one in this sector for certain years.

Figure 2.8: "Self-Made" over the Years



Flexible fit - best-fitting fractional polynomial after estimating many functional forms of regress y $\sim$ g(x), where the power of g(x) is searched in the range (-2, -1, -.5, 0, .5, 1, 2, 3).

Figure 2.9: Year of Birth and Self-Made

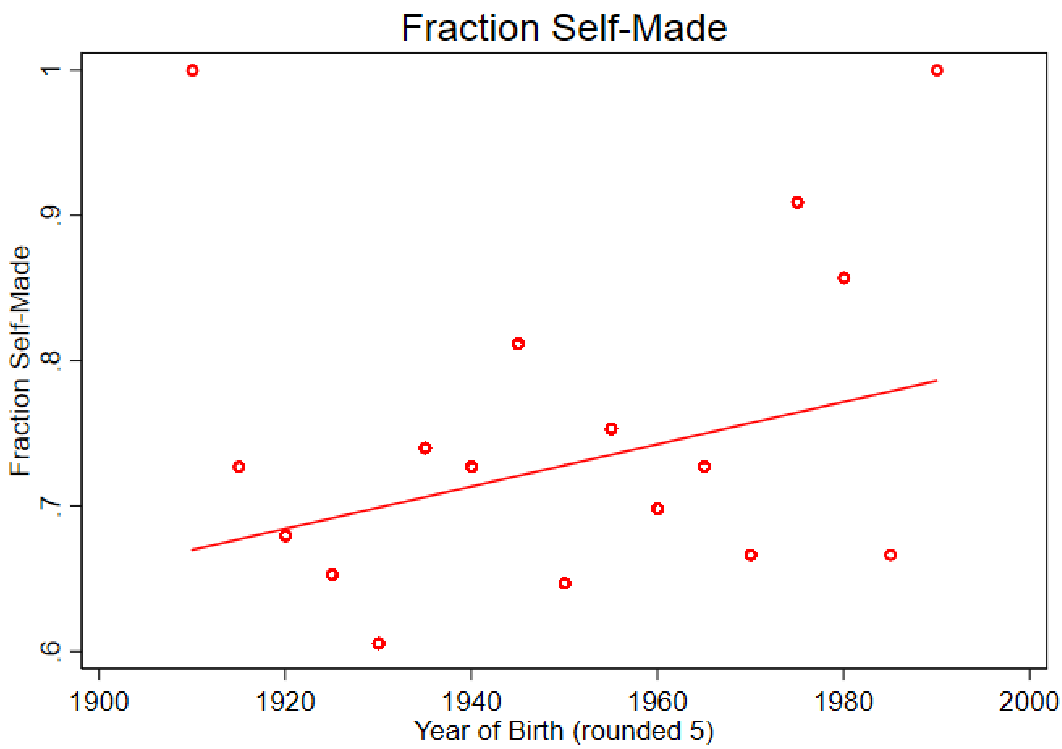
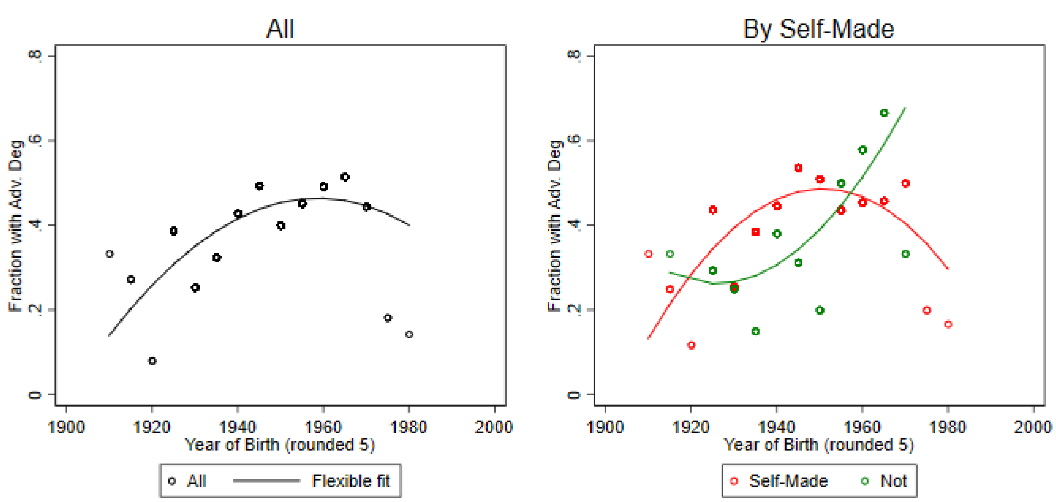


Figure 2.10: Year of Birth and Advanced Degrees



Flexible fit - best-fitting fractional polynomial after estimating many functional forms of regress y $\sim$ g(x), where the power of g(x) is searched in the range (-2, -1, -.5, 0, .5, 1, 2, 3).

Figure 2.11: Age

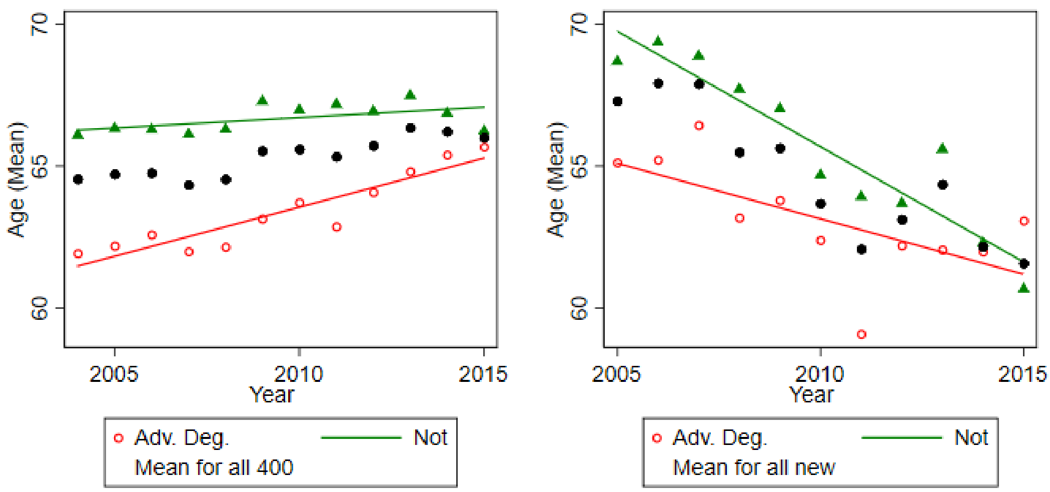


Figure 2.12: Age of Self-Made

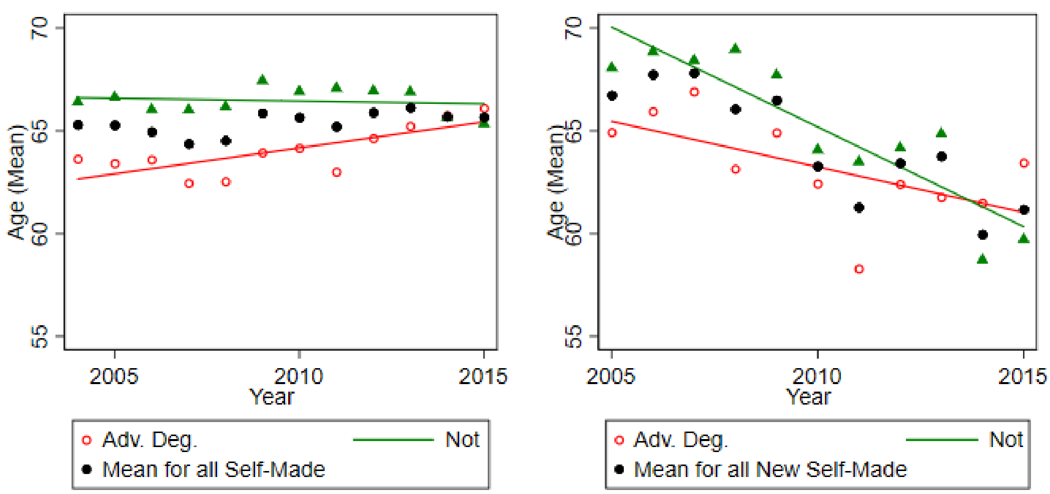


Figure 2.13: New Entrants over the Years

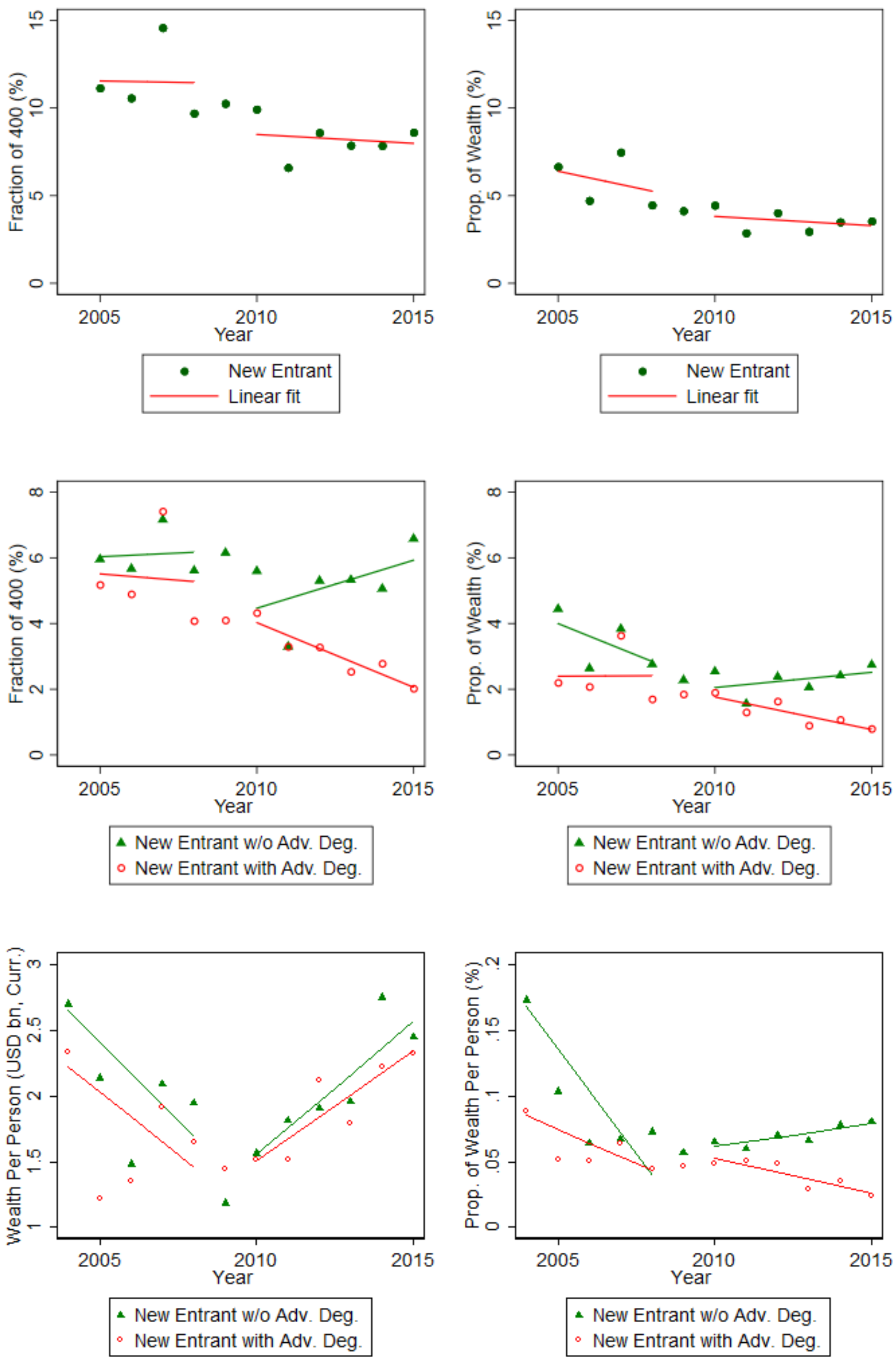


Table 2.3: New Entrants and Self-Made: Number of Self-Made and New Entrants

	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
New only	7	5	6	4	5	9	1	9	11	7	11
Self-Made only	214	224	217	236	237	244	255	255	253	255	253
Both	36	36	51	34	35	30	25	25	20	24	23
Neither	129	123	117	118	113	110	113	107	110	109	108
Total	386	388	391	392	390	393	394	396	394	395	395

Table 2.4: Transition Matrix, All Individuals

	Quartile in 2009					
Quartile in 2004	Not in the list	1	2	3	4	Total
Not in the list	0	17	27	43	35	122
1	16	67	14	2	2	101
2	14	17	27	29	10	97
3	35	2	16	29	26	108
4	50	4	8	8	7	77
Total	115	107	92	111	80	505
	Quartile in 2015					
Quartile in 2009	Not in the list	1	2	3	4	Total
Not in the list	0	12	31	35	46	124
1	14	73	11	9	0	107
2	14	13	27	27	11	92
3	38	6	20	24	23	111
4	53	1	6	7	13	80
Total	119	105	95	102	93	514

Between 2005 and 2009, 20 were dropped from the list after their death.
Between 2009 and 2015, 33 were dropped from the list after their death.

Table 2.5: Transition Matrix, Individuals with Advanced Degrees

		Quartile in 2009				
Quartile in 2004	Not in the list	1	2	3	4	Total
Not in the list	0	8	15	20	17	60
1	5	26	3	2	1	37
2	5	9	10	12	6	42
3	10	1	6	9	8	34
4	18	1	5	3	2	29
Total	38	45	39	46	34	202
		Quartile in 2015				
Quartile in 2009	Not in the list	1	2	3	4	Total
Not in the list	0	3	9	16	14	42
1	3	33	6	3	0	45
2	7	7	6	13	6	39
3	13	3	7	12	11	46
4	22	1	2	3	6	34
Total	45	47	30	47	37	206

Between 2005 and 2009, 3 were dropped from the list after their death.
Between 2009 and 2015, 6 were dropped from the list after their death.

Table 2.6: Transition Matrix, Individuals without Advanced Degrees

	Quartile in 2009					
Quartile in 2004	Not in the list	1	2	3	4	Total
Not in the list	0	9	12	23	18	62
1	11	41	11	0	1	64
2	9	8	17	17	4	55
3	25	1	10	20	18	74
4	32	3	3	5	5	48
Total	77	62	53	65	46	303
	Quartile in 2015					
Quartile in 2009	Not in the list	1	2	3	4	Total
Not in the list	0	9	22	19	32	82
1	11	40	5	6	0	62
2	7	6	21	14	5	53
3	25	3	13	12	12	65
4	31	0	4	4	7	46
Total	74	58	65	55	56	308

Between 2005 and 2009, 17 were dropped from the list after their death.
Between 2009 and 2015, 27 were dropped from the list after their death.

Table 2.7: Persistence in the List

	(1)	(2)	(3)	(4)	(5)	(6)
	No. Times in the List		Pr(Stay)		Pr(Rank Improves)	
Adv. Deg.	0.913**	0.846*	0.136	0.123	0.0745^{+}	0.0850*
	(0.323)	(0.334)	(0.0877)	(0.0901)	(0.0419)	(0.0422)
Self-Made	-1.012**	-0.965**	-0.404***	-0.393***	0.131**	0.141**
	(0.348)	(0.368)	(0.0958)	(0.101)	(0.0449)	(0.0465)
Deceased			-0.407*	-0.524**	-0.148^{+}	0.0121
			(0.160)	(0.168)	(0.0871)	(0.0884)
Year of Birth		Y		Y		Y
Sector-effect		Y		Y		Y
Year-effect				Y		Y
Observations	696	696	4716	4716	4716	4716

Standard errors in parentheses

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The results in column 1 - 2 are from OLS.

The dependent variable for regressions in column 1 and 2: No of times the person appears in the list in the period 2004-15.

The results in column 3 - 6, are from a random-effects panel probit regression.

Column 3 and 4: The dependent variable is likelihood of staying in the list after being on it last year.

Column 5 and 6: The dependent variable is likelihood of rising up the ranks after appearing in it last year.

Table 2.8: Regressions

	(1) Fixed Effects	(2) Random Effects	(3) Hybrid	(4) Sequential K-S Method
First-stage	Dependent variable is Log(Wealth)$_t$ - Log(Wealth)$_{t-1}$			
Method	GLS	GLS	GLS	GMM
Log(Wealth)$_{t-1}$	-0.389***	-0.036***	-0.280***	-0.023***
	(0.018)	(0.005)	(0.015)	(0.005)
Before 2008	0.214***	-0.023	-0.049***	-0.037***
	(0.020)	(0.014)	(0.015)	(0.013)
Before 2008 $\times$ Self-made	0.016	0.022	0.028	0.040***
	(0.020)	(0.016)	(0.018)	(0.014)
Before 2008 $\times$ Advanced	0.007	0.041**	0.016	0.041**
	(0.021)	(0.018)	(0.019)	(0.016)
GDP growth rate	0.123	3.603***	3.018***	3.688***
	(0.256)	(0.220)	(0.211)	(0.220)
Self-made	0.000	0.016*	0.060***	
	(.)	(0.009)	(0.014)	
Advanced	0.000	-0.002	0.010	
	(.)	(0.008)	(0.013)	
Age	0.047***	-0.005	-0.003	-0.004
	(0.008)	(0.004)	(0.003)	(0.004)
Age^2	-0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Mean of Log(Wealth)$_{t-1}$			0.299***	

			(0.016)	
Mean of Before 2008			-0.027	
			(0.040)	
Mean of Before 2008 $\times$ Self-made			-0.132***	
			(0.041)	
Mean of Before 2008 $\times$ Advanced			-0.007	
			(0.040)	
Mean of GDP growth rate			2.321**	
			(0.995)	
Constant	-2.502***	1.382***	0.806	0.128
	(0.293)	(0.482)	(0.506)	(0.123)
Second-stage	Dependent variable is residuals from the previous stage			
Method				GLS
Self-made				0.013**
				(0.006)
Advanced				-0.001
				(0.006)
Constant				0.011
				(0.012)
Sector-fixed effects	Yes	Yes	Yes	Yes
Observations	3900	3900	3900	3900

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2.9: Effect of Truncation

	(1)	(2)	(3)
	K-S Modified	K-S	K-S
Panel subset	All	Always in 400	Always in 300
First-stage	Dependent variable is Log(Wealth)$_t$ - Log(Wealth)$_{t-1}$		
Method		GMM	
Log(Wealth)$_{t-1}$	-0.025***	-0.012**	-0.015**
	(0.005)	(0.005)	(0.006)
Before 2008	-0.001	-0.026	-0.045**
	(0.031)	(0.017)	(0.021)
Before 2008 × Self-made	0.037***	0.064***	0.089***
	(0.014)	(0.017)	(0.020)
Before 2008 × Advanced	0.042***	0.065***	0.074***
	(0.016)	(0.017)	(0.020)
GDP growth rate	4.186***	3.480***	3.300***
	(0.729)	(0.269)	(0.316)
Age	-0.005		
	(0.004)		
Age^2	0.000		
	(0.000)		
Constant	0.128	-0.047***	-0.030**
	(0.134)	(0.012)	(0.015)
Inverse Mills Ratios	Yes		
Second-stage	Dependent variable is residuals from the previous stage		
Method		GLS	
Self-made	0.013**	0.006	-0.001
	(0.006)	(0.011)	(0.014)
Advanced	-0.002	-0.001	0.003
	(0.006)	(0.011)	(0.013)
Constant	0.012	0.000	0.000
	(0.011)	(.)	(.)
Sector-fixed effects	Yes	Yes	Yes
Observations	3900	1947	1408

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.10: Forbes 300 Demonstration

	(1)	(2)	(3)	(4)
	K-S	K-S Mod.	K-S	K-S Mod.
Panel subset	Completely Truncated 300		Partially Truncated 300	
First-stage	Dependent variable is Log(Wealth)$_t$ - Log(Wealth)$_{t-1}$			
Method	GMM			
Log(Wealth)$_{t-1}$	-0.025***	-0.028***	-0.025***	-0.026***
	(0.005)	(0.005)	(0.005)	(0.005)
Before 2008	-0.048***	0.026	-0.036***	-0.014
	(0.015)	(0.037)	(0.013)	(0.026)
Before 2008 $\times$ Self-made	0.046***	0.044***	0.041***	0.038***
	(0.016)	(0.015)	(0.015)	(0.015)
Before 2008 $\times$ Advanced	0.036**	0.038**	0.041**	0.042***
	(0.017)	(0.017)	(0.016)	(0.016)
GDP growth rate	3.786***	2.873***	3.702***	4.260***
	(0.259)	(0.877)	(0.226)	(0.607)
Age	-0.004	-0.003	-0.004	-0.003
	(0.004)	(0.004)	(0.004)	(0.004)
Age^2	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.111	0.131	0.132	0.068
	(0.136)	(0.140)	(0.127)	(0.138)
Inverse Mills Ratios		Yes		Yes
Second-stage	Dependent variable is residuals from the previous stage			
Method	GLS			
Self-made	0.014**	0.014**	0.014**	0.014**
	(0.007)	(0.007)	(0.006)	(0.006)
Advanced	0.002	0.002	-0.002	-0.002
	(0.006)	(0.006)	(0.006)	(0.006)
Constant	-0.002	-0.002	0.011	0.011
	(0.012)	(0.012)	(0.012)	(0.012)
Sector-fixed effects	Yes	Yes	Yes	Yes
Observations	2985	2985	3768	3768

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.11: Regressions For Largest Sectors

	(1)	(2)	(3)	(4)	(5)	(6)
	K-S	K-S Mod.	K-S	K-S Mod.	K-S	K-S Mod.
Sector	Finance		Tech. & Telecom		Div. Invest.	
First-stage	Dependent variable is Log(Wealth)$_t$ - Log(Wealth)$_{t-1}$					
Method	GMM					
Log(Wealth)$_{t-1}$	-0.008	-0.010	-0.015	-0.014	-0.013	-0.013
	(0.012)	(0.012)	(0.009)	(0.010)	(0.013)	(0.012)
Before 2008	0.019	-0.254	-0.076**	0.201*	-0.015	-0.163
	(0.058)	(0.179)	(0.033)	(0.108)	(0.039)	(0.100)
Before 2008 $\times$ Self-made	0.074	0.063	0.005	0.011	0.039	0.047
	(0.053)	(0.054)	(0.036)	(0.033)	(0.045)	(0.045)
Before 2008 $\times$ Advanced	-0.025	-0.024	0.072*	0.084**	0.126***	0.122***
	(0.035)	(0.032)	(0.041)	(0.042)	(0.044)	(0.043)
GDP growth rate	2.187***	6.296	4.546***	-2.590*	4.129***	7.305***
	(0.640)	(5.061)	(0.426)	(1.482)	(0.570)	(2.295)
Age	0.002	0.009*	-0.018**	-0.013	0.004	0.015**
	(0.005)	(0.006)	(0.009)	(0.009)	(0.006)	(0.006)
Age^2	-0.000	-0.000*	0.000**	0.000	-0.000	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.010	-0.362	0.513**	0.561**	-0.195	-0.675***
	(0.172)	(0.276)	(0.261)	(0.275)	(0.202)	(0.203)
Inverse Mills Ratios		Yes		Yes		Yes

Second-stage	Dependent variable is residuals from the previous stage

Method	GLS					
Self-made	0.036*	0.037*	0.025	0.024	0.001	-0.003
	(0.021)	(0.020)	(0.019)	(0.018)	(0.013)	(0.012)
Advanced	-0.013	-0.015	-0.023*	-0.018	0.008	0.007
	(0.017)	(0.016)	(0.013)	(0.013)	(0.010)	(0.010)
Constant	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)
Sector-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	569	569	537	537	510	510

Standard errors in parentheses

$^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$

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Chapter 3

Mental Health Policy in India: Seven Sets of Questions and Some Answers

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3.1 Abstract

Background: This paper frames the state of mental health policy in India in terms of seven sets of questions, and seeks to provide at least partial answers to these questions, based on a meta-analysis of existing research. The context of the analysis is the arguably poor state of mental health care in India, as well as an unprecedented level of policy attention to the issue.

Aims of the Study: In brief, the questions we pose pertain to (i) the provision of such care in hospitals, (ii) non-hospital provision, including by non-medical providers, (iii) issues of education and social acceptance, (iv) affordability, (v) within-country variation of care and possibilities for benchmarking, (vi) aggregate resource impacts of a concerted effort to change policies and improve care, and (vii) the shape of a more effective "continuum of care" for mental health issues.

Methods: Given the complexity of the subject, this paper is meant to serve as a framing of issues for further research, but in doing so, to clarify what issues are most pressing, those that are most difficult and perhaps those that can be tackled more readily, to create some momentum in changing the relatively poor state of mental healthcare in India.

Results: While new laws and policies being introduced in India propose ideas and changes that are groundbreaking for that country, leading to cautious optimism, there still are many gaps in the understanding of the challenges of the provision of increased access to, as well as better quality, mental health care in India. These challenges can be understood on two fronts: one is the psychiatric and medical aspect of the issues, and

the other is the management and administration of the system.

Discussion: Perhaps the highest priority in achieving the goals of greater access and better quality is to increase the number of trained personnel at all levels of specialization and skilling that are relevant. Further, while the new legal framework and policy identify the importance of information technology in rapid expansion of access to mental healthcare, more context-specific research and trials are needed. With respect to the administration and management needs of the public system, important challenges will be the need for significant organizational innovations in the education system, and cultural changes that allow specialized medical professionals to accept the use of software and less-qualified, more dispersed, frontline providers. A final area is the interface between the public and private sectors, including the role of non-profit organizations: challenges include information sharing, division of responsibilities, and resource allocation.

Implications for Health Care Provision and Use: Our analysis suggests that incorporating information technology, along with training professionals at a variety of skill levels in its use, may provide a resource-feasible approach to improving access to mental healthcare at reasonable cost and quality in the Indian context. Implications for Health Policies: Indias mental health policies are already undergoing major changes, and our analysis emphasizes the need for translating these generic policies into specific and implementable versions that can be tested at the local level across different regional and social contexts in India.

Implications for Further Research: The overall challenge is daunting, being the need to expand access and improve quality, while still managing costs, all within an overall healthcare system that is itself struggling to achieve these goals. Further research based on piloting and trials of assistive software and training programs will likely be useful.

3.2 Introduction

Mental health is a challenging subject for policy makers, even in advanced countries. For example, a 2006 Canadian report states, “In no other field, except perhaps leprosy, has there been as much confusion, misdirection and discrimination against the patient, as in mental illness ...” This is certainly true of India, where many laws date to the 19th century, and until as recently as 2017, which criminalized some forms of mental illness. However, as part of an overall focus on increased public funding of healthcare in India, mental health is also receiving more funds and attention. For example, in the sphere of legal frameworks, the national government in India has embarked on a major reform of mental health laws, aimed at changing policy so that people are treated in a humane manner and that the rights of persons suffering mental illness are preserved, just as for anyone with any other kind of illness.[1] The Mental Health Care Act, passed in 2017, is a laudable step in this direction, providing special place for the mentally disabled in the judicial system and decriminalizing suicide. Other initiatives, as part of a broader push to create an integrated national healthcare framework, include pilot mental health programs in rural areas, designed to reduce the inequalities that currently exist in

[1]Interview in New Delhi with senior Government of India policy maker, October 2013. All of our interviewees highlighted the problem of stigmatization of mental illness in India, and almost every discussion or study of mental health in India foregrounds this problem, which affects demand for treatment, but also the supply of caregivers.

mental healthcare (greater than in other forms of basic healthcare).[2] These efforts are in partnership with non-profits, and, according to senior policy makers, mental health policy reform in India represents the most ambitious effort by government to partner with grassroots organizations for effecting change. This heterogeneity of actors, along with the heterogeneity of conditions that can be grouped under "mental illness", constitute a challenge for policy formulation as well as details of effective implementation.[3]

Despite recent forward steps, mental health policy and mental healthcare delivery in India each still face multiple challenges. These include unequal distribution of public resources (more so than for other forms of primary healthcare), a heterogeneous array of caregivers (including various types of counselors as well as medically trained psychiatrists), severe shortages of trained personnel (again, much more than in other areas of healthcare), and, of course, continued social stigma and/or lack of understanding of mental illnesses such as depression. This paper seeks to provide a unified overview of the evolving situation with respect to mental health policy and care delivery in India, in the context of the countrys overall health policy.

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[2]For recent reports that illustrate changing policy, social norms and public discourses, see, for example Shankar and Shankar (2016), Govindarajan (2017b) and Evans (2017)

[3]Policy makers and professionals we spoke with noted the range of perspectives and approaches held by different non-profits and community organizations. Indias dismal history of treatment of those with mental illness has engendered considerable suspicion of the mental health specialists in the medical profession, and some activists have argued against any medical approaches to mental illness. Our impression is that the dialogue between a range of actors prior to the passage of the new mental health legislation led to some overcoming of distrust and finding of some areas of common ground.

This paper seeks to provide partial answers to seven sets of questions related to the multiple challenges of mental healthcare policy and service delivery in India. The next section lays out the questions, and provides some context and background for the various sets of issues. The following section offers some partial, tentative and incomplete answers for policy formulation and implementation issues. The final section serves as a summary conclusion, with suggestions for future research and policy attention.

3.3 Context and Questions

We first provide some basic statistics on mental health in India. The Census of India (2011) gathered data about disability[4] due to mental illness and "mental retardation" and reports that about 3 percent of the persons in the country suffered from these mental conditions. The latest data on incidence are reported by a National Mental Health Survey[5] (NMHS) conducted by National Institute of Mental Health and Neuro Sciences, NIMHANS, in 2015-16 (Gururaj et al. 2016). The same study also conducted a review of the state mental health care provision. The findings of the survey paint a rather dire picture of the incidence of mental health diseases, the gap between the demand and supply of health care, and the condition of health-care provision.

The NMH survey reports that common mental disorders[6] (including co-morbidities

[4]Data retrieved from the Census 2011 (Chandramauli 2013)

[5]The National Mental Health Survey was conducted during 2014-16 in 12 states of India. The sampling was representative, based on the Census of 2011, stratified by poverty rates, random, and proportional to all individuals aged eighteen years and above.

[6]In this paper, we will use the term mental disorders to include co-morbidities such as drugs, alcohol,

such as substance abuse) are a huge burden, affecting nearly 10 percent of the population.[7] Due to a lack of awareness, the stigma associated with mental disorders, difficulty in accessing care, the lack of resources needed for treatment, or some combination or subset of these factors, individuals and families ignore and neglect these disorders till they become severe. Nearly 1.9 percent of the population were affected with severe mental disorders in their lifetime and 0.8 percent were identified to be currently affected with a severe mental disorder. The prevalence is highest in the age group 30-49, and most of the persons who were identified as suffering such disorders experienced severe disability and were unable to work for long durations.

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tobacco, and other substance abuse, unless otherwise specified. It is important to note here the wide range of illnesses or disorders that come under the umbrella of mental health. Given the broad nature of our survey, we cannot adequately consider subcategories of illness and treatment in the detail that they deserve. Several of our interviewees noted imbalances in resource allocation across different categories of mental healthcare, as well as the widely differing sets of issues that could arise. For example, most obviously, milder forms of behavioral issues or common stress-related problems raise different challenges than severe clinical disorders that might require institutionalization. Another important area of differentiation is gender: see Malhotra and Shah (2015) for an overview on the topic of women and mental health in India. Sub-populations such as college students are also receiving more specific attention: see, for example Govindarajan (2017a).

[7]Other sources provide higher estimates of the prevalence of mental disorders in India. For example, the WHO put the percentage at double that reported in the NMH survey. See Roy (2016) for this figure and similar "headline" numbers from various sources. Of course, there can be variations in definitions and measurement techniques. Our purpose is to note the variation in estimates as well as the severity of the issues. Other examples include Banerjee (2016) and Habermann (2016). The latter piece describes a large-scale study assessing and comparing mental health issues in India and China.

Much more even than disability, the most severe outcome from mental health disorders is suicide, and India has one of the highest suicide rates in the world (Basu, Das and Misra 2016, Patel et al. 2012, Mayer 2003). In the more recent NMH survey (Gururaj et al. 2016), they also find that the incidence of suicidal ideation is very high, at nearly 1 percent of the population, even though it is not always correlated with other diagnosed metal illnesses. There is a general consensus, that while there are many structural and circumstantial issues that lead to suicides, timely and well targeted counseling and treatment can address the underlying stress and hopelessness. Inefficiencies in provision of public mental healthcare, thus, have welfare effects via the loss of work productivity, earning potential and the quality of life of these individuals and their families, and in the extreme cases loss of life.

To summarize, policy-makers and mental health experts in India have documented that mental illness is an important societal issue, with significant negative consequences for individual and social welfare. In this context, we aim to systematically assess various components of the challenges faced in treating mental illness in India. We do this by posing various sets of questions that serve to frame our assessment. The seven sets of questions that we tackle in this paper are as follows.

(i) What is the condition of Indias mental health hospitals, and can standards of quality and overall nature of care be improved in resource-efficient ways, through redesign of internal processes?

(ii) What is the condition of non-hospital provision of mental health care, through various levels of providers, from medically-trained psychiatrists to social workers and counselors? What are the deficits, on the demand side and the supply side, of provision of such services?

(iii) How can education about mental illness play a role in improving the scope and timing of care provisions? Can early recognition and addressing of symptoms through overcoming current stigmas associated with mental illness lead to better outcomes without increased calls on public or private resources? What is the condition of mainstreaming of recuperating patients with respect to social acceptance and services for aiding normalization?

(iv) What role is played by issues of affordability, particularly with respect to ongoing care through consultations and drugs? How can redesign of policies, including direct subsidies as well as health insurance coverage, overcome affordability issues?

(v) What are the differences in mental healthcare across different parts of India, especially rural-urban divides, and is there scope for identifying and benchmarking best practices in the Indian context?

(vi) What are the aggregate resource impacts of an integrated approach to mental healthcare that combines improvements in quality, access and awareness, and how will policy redesign fit into overall health policy goals and available resources?

(vii) What would a redesigned mental healthcare ecosystem look like, and to what extent can a "continuum of care" be developed, one which addresses impacts on family members of specific challenges of mental illness?

3.4 Some Partial Answers

Having laid out our questions, in this, the main section of our paper, we provide some partial answers to those questions, also highlighting where there are gaps in our knowledge.

3.4.1 Provision of Mental Healthcare - Infrastructure

In this section and in the next section on the state of human resources in the mental health sector, we develop somewhat interlinked answers to the first two sets of questions. To answer the questions regarding hospitals, we begin by describing the mental healthcare infrastructure more broadly, before making some specific observations on the organization and quality of mental healthcare facilities. To the extent that the answers also depend on human resources, the discussion in the next section will also be relevant for the answer to the first question. Some of the potential remedies explicitly or implicitly required in the first two sets of questions will also emerge in subsequent sub-sections.

We first summarize and discuss the overall mental healthcare infrastructure.[8] The infrastructure for general public healthcare in India is structured as outlined in figure 3.1. The first point of contact between a medical officer and a person are the Primary Health Centers, while the Community Health Centers are the first level for specialist care. The main towns at the district level[9] generally have a hospital with round-the-clock emergency care, many-bed hospitals for inpatients, and provision of advanced diagnostic and specialist services.

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[8]A useful history specifically of mental hospitals in India is provided in Krishnamurthy, Venugopal and Alimchandani (2000). That paper also provides some global historical context.

[9]Districts are the administrative units next below the state government level, and are often where day-to-day governance is managed, since many of Indias states are country-sized in population. There are about 600 districts in the country.

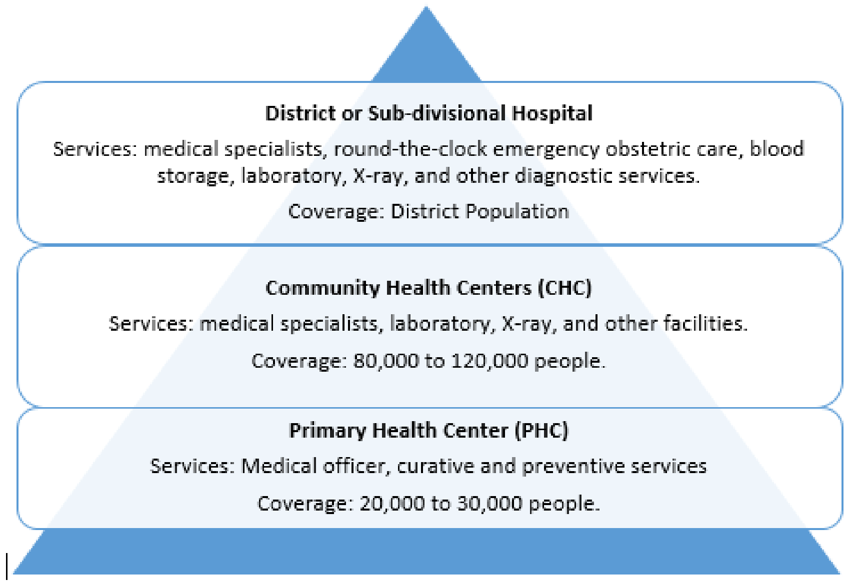

Figure 3.1: Organization of Public Healthcare in India

The provision of public mental healthcare in India is a joint responsibility of the central (i.e., national) and state governments.[10] At the center, the responsibility of mental health falls under the domain of the Ministry of Health and Family Welfare (MoHFW). There has been a National Mental Health Program (NMHP) since 1982, which was rechristened the District Mental Health Program, DMHP in 1996. The goals of the public mental health program are defined as provision of mental healthcare for all, particularly to the most vulnerable and most underprivileged sections of the population, but also to impart mental health knowledge in general health care and to promote community participation in mental health services development.

[10]India has a federal system with legislatures at the national and state levels, and divisions of powers and responsibilities are specified in the national constitution.

The organizational hierarchy of DMHP consists of the Central Mental Health Authority (CMHA) at the national level and the various State Mental Health Authorities (SMHA). Mental Health Authorities have been assigned the responsibility of development, regulation and coordination of mental health services in a State/Union Territory.

The infrastructure and associated human resources that DMHP can utilize are the 11 excellence centers for research that are within various psychiatry departments in state government-run hospitals and medical colleges; the psychiatry departments in district or sub-division hospitals, which are expected to have 30 beds for in-patients; medical officers/specialists at the PHC/CHC clinics which are at the sub-district level; and the Accredited Social Health Activists (ASHAs), who are the community health workers instituted by the MoHFW at the village level.

The NMH survey (Gururaj et al. 2016) reports that the treatment gap[11] for almost all mental diseases is very high: nearly 80 percent of persons suffering from mental disorders had not received any treatment despite the presence of illness for more than 12 months. The treatment gap was more than 60 percent for major mental disorders[12] and 85.2 percent for depressive disorders. Only a third of the dozen states surveyed by them had more than 50 percent of the population covered by the public supply of mental health. More than 60 percent of people who accessed this care did so directly at a district

[11]Treatment gap is defined as the proportion of people who suffer from illness but do not receive treatment. This can happen because the individuals do not seek treatment or because mental health resources are not available.

[12]Major mental disorders are the ones that can cause severe disability, for example schizophrenia, psychotic disorders, bipolar disorders, major depressive disorders, etc.

hospital rather than at a local primary health care clinic, and this provision was limited to psychiatric clinics (Patel et al. 2017). Up to 40 percent of the patients must travel more than 10 km to reach the first available services at the district headquarters. There have been efforts in some states to increases access to non-hospital mental health: many states have mobile mental units and de-addiction centers that provide mental health services, however the report emphasizes that even including these efforts, the existing facilities are "inadequate" and the holistic picture is of "limited care accessibility" (Gururaj et al. 2016). The NMH survey also reports that at the local Primary Healthcare Centers (PHCs) and Community Health Centers (CHCs) even the drugs listed as essential for mental health care are not availability continuously. While many of these issues are general issues of health care provision in India, such as continual absenteeism among doctors, interrupted supply of drugs, and abysmal standards of hygiene, mental health care suffers more severely. For example, the existing mental healthcare facilities have been described as "inhuman", where patients are kept in a "prison-like environment" (Dhawan 30 March 2016). As quoted in Sharma and Krishna (2013) According to the National Human Rights Commission (NHRC), there are only 43 government mental hospitals in India, of which hardly half a dozen are in a livable condition.[13]

3.4.2 Provision of Mental Healthcare Human Resources

In this sub-section, we consider the state of human resources in the mental health sector, going beyond hospital-based care providers. The basic answer to the second set

[13] A third example of a recent journalistic account of the state of mental hospitals is Barnagarwala (2014). The scholarly review in Krishnamurthy et al. (2000) while more muted in its language, suggests a similar conclusion. The more recent reporting indicates that improvement has been minimal in the new millennium.

of questions is that there are deficiencies in supply at every level of the system. The demand side is more difficult to assess, since it is related to problems of stigma and lack of awareness of mental health issues: these factors are considered in the next section on public education, early detection and rehabilitation.

Lack of qualified mental health care professionals is a challenge that mental healthcare programs face everywhere in the world, but in India and other low and middle-income countries, the lack of human resources is severe and likely to get worse unless there are effective interventions (Kakuma et al. 2011).

Table 3.1: Mental Health Professionals in India

	Need	Availability	Ratio: Availability/Need
Psychiatrists	11500	3800	33%
Clinical psychologists	17250	898	$\sim$ 5%
Psychiatric social workers	23000	850	$\sim$ 4%
Psychiatric nurses	3000	1500	50%

1. Originally appeared in Khurana and Sharma (2016).

2. Need was estimated using a norm of 1 psychiatrist per 100,000 populations, 1.5 clinical psychologists per 100,000 population, and two psychiatric social workers per 100,000 populations and one psychiatric nurse per 10 psychiatric beds.

Table 3.1 summarizes the availability of mental healthcare professionals per population of 100,000 people on average in the country based on the reporting in (Khurana and Sharma 2016). Note, in particular, the greater shortage at lower skill levels, a somewhat striking imbalance for a relatively poor country.[14] The number of medical officers at the district level trained to deliver mental health services (per 100,000 people) is very low and highly variable among Indias states, ranging from 0.1 to 10. This variation cannot be completely due to varying income levels of the states, since this range is much greater than the variation in income levels. It is likely due to differing priorities of mental health in different state budgets.

The scarcity of specialist mental healthcare in India has led to diverse community mental healthcare models that use lay health workers rather than doctors. In a recent paper, van Ginneken et al. (2013) study 72 such programs across twelve states, in which non-specialists provide care to patients of severe mental disorders. These non-specialist care managers often received support, often through multiple specialist and non-specialist organizations, including both voluntary, non-profits and public sector or government agencies. The study proposes a revised framework for different community outreach and collaborative care models, but leaves open questions of cost-effectiveness, scalability and the relative merits of different forms of organizing such care.[15]

Under the 11^{th} five-year plan in 2007,[16] the national government of India started two

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[14] Similar observations of relative shortages at different levels were made by several of the interviewees, including psychiatrists, educationists and officials. Arguably, the numbers are a symptom of a typical dual economy, but also may reflect imbalances in institutions that are specific to the Indian case.

[15] Experiments and innovations in this realm are multiplying in different Indian contexts. See, for example Chavan et al. (2012), Silberner (2016), Silberner (2017), and Shields-Zeeman et al. (2017).

[16] India used a form of indicative planning for allocating government resources from 1951 until 2017, when that approach was discontinued.

schemes for addressing the dearth of human resources in mental healthcare provision. Under scheme A, the goal was to establish a dozen centers of excellence in mental health by upgrading existing mental health institutions/ hospitals. A grant of about USD 50 million (INR 3380 million) was made available for undertaking the capital work, equipment acquisition, library creation, and faculty induction and retention. Scheme B was meant to support publicly funded medical college/hospitals in starting post-graduate courses or to increase their capacity for training in mental health. Each state identified a venue for departments of psychiatry, clinical psychology, psychiatric social work, and psychiatric nursing. The national government provided support of up to about USD 75,000 (INR 5 million) per department.

By 2015, academic sessions had started in 8 out of 11 centers proposed under the 11th five-year plan, and 27 postgraduate departments and 11 institutes had been established in various states.19 The NMH survey5 argues that the number of institutions providing a postgraduate course in psychiatry are still too few to meet the countrys requirements.[17] The yearly intake of the mental healthcare professionals across institutions is also very low, ranging from 0 to 52 per year. Some non-profit organizations offer education for practitioners, but these efforts are not sufficient to fill the gap. Research in mental health in India is limited to a few medical colleges and there is no appreciable research in any aspect of mental health other than psychiatry. The National Health

[17]This point was made to us by several of our interviewees, who also noted some barriers to expansion in the design of programs and organization of institutions. One psychiatric professional noted the separation of mental health training from general medical training, and made the case that all medical professionals should have some exposure to mental health issues and training in recognizing them for, at a minimum, referral to specialists

Policy 26 emphasizes increasing the training of specialists through public financing and giving preference to those persons willing to work in public systems after graduating.

3.4.3 Public Education, Early Detection and Rehabilitation

In this sub-section, we discuss the role of public education with respect to mental healthcare, and how it might affect the scope and timing of care. In particular, we consider the role of such education in overcoming the stigma associated with mental illness. Finally, we touch on issues of recuperation, at the opposite end of the care spectrum from initiation of treatment. Here, too, overcoming stigma is important. The focus of this sub-section is on answering the third set of questions, but the issues of deficits on the demand side framed in the second set of questions are also relevant here.

Stigma related to mental illness is a widespread problem in many countries (Clement et al. 2015). In India, the lack of awareness about mental disorders such as depression, anxiety, suicidal risk and emotional stress reinforces the stigma of getting mental health treatment, and are major impediments to demand for mental healthcare (Maulik et al. 2017, Shidhaye et al. 2017).[18] The responsibility of promotive and preventive activities lies with the District Mental Health Program (DMHP) and the program does provide sufficient funds for public education efforts (Khurana and Sharma 2016). The

[18]While various references in this paper highlight improvements in attitudes toward mental illness, the problem is still pervasive. For example, a popular Indian version of the reality TV show “Big Brother”, called Big Boss Tamil, tasked contestants with acting as if they were inmates in a mental health facility (BBC 2017). At least the episode was met with widespread condemnation, suggesting that there is greater awareness than in the past.

following programs are expected to be conducted regularly: life skill education and counseling in schools and colleges, work place stress management training, and suicide prevention counseling. Unfortunately, despite the available funding, the NMH survey (Gururaj et al. 2016) did not find any appreciable public education or communication efforts in any of the states.[19] Moreover, while the districts are required to make information publicly available regarding such education and communication activities and the associated funding for them, such information is not maintained in an easy-to-access format, making any review extremely difficult.

The large unaddressed need for mental health care education is highlighted in the work of Shidhaye et al. (2017). In their multi-media education project, they discovered that as the knowledge about mental disorders increased over the eighteen-month period, the demand for mental health care increased dramatically, from about 5 percent in the pre-period to about 27 percent in the post-period. Although their experiment does not have a control group, the large magnitude of increase is indicative of the order of the increase in the demand of the public services, especially among the households with the lowest incomes, that can be expected if the DMHP can perform the public education functions that are assigned to them.

Apart from the treatment and counseling services, there is a serious lack of resources for continued care and rehabilitation of persons suffering from mental disorders, in the form of facilities such as day care centers, half way homes, sheltered workshops, and

[19]There are examples of small-scale efforts by public institutions. For example, the Public Health Foundation of India held a local event in New Delhi, Indias capital, aimed at raising awareness of mental health issues among young people (Pal and Gonsalves 2016).

temporary stay facilities. The NMH survey reports that, although they are required to, most districts do not keep records of the data regarding public rehabilitation workers, special education teachers and paraprofessional counselors. The NMH surveys review of these facilities and the personnel also reveals that these facilities are very limited in number and were mainly concentrated in cities or district headquarters (Gururaj et al. 2016, pp 38). While there are many non-profit societies that attempt to fill this gap, there is a serious dearth of such support systems. In the NMH survey, across the 12 states, nearly 69 NGOs were reported to be functioning prominently in the sphere of mental healthcare (Gururaj et al. 2016, pp 39). IT-based innovations such as online video training modules in local languages (Mehta et al. 2018) may be able to reduce the cost of providing education to the care-givers and family members, and help in addressing this substantial mismatch.

3.4.4 Affordability, Subsidies and Insurance

In this section, we discuss the relative cost of mental diseases and their treatment, the condition of health insurance and the welfare transfers for disability brought on by mental diseases as partial answers to the issues framed in the fourth set of questions.

Disability brought on by any kind of illness presents challenges at multiple levels: the patients and their family members have to increase their spending towards the treatment of the illness, while the ill persons typically cannot contribute towards earning. Those who are nursing their disabled family members also lose productive time, which may further lead to reduced household income. Thus it is not surprising that, in the absence of monetary incentives (such as expected inheritance of property), the persons suffering mental illness may not be given the care they need (Patel and Prince 2001).

In principle, government health services are available to all citizens in India, but in practice, the low quality of the public care and poor availability of doctors compel households to seek expensive private care.34 In the absence of state or insurance coverage for most families, a large proportion of payments for treatment are out-of-pocket expenses and mental health care is no exception. The NMH survey (Gururaj et al. 2016) shows that median out-of-pocket expenditure per month on mental healthcare was approximately INR 1000 to 1500 (USD 17-25). The prevalence of mental disorders is decreasing in household income being highest in the lowest quintile, at 12 percent. These expenditures present a significant financial challenge to such households.* There is a direct impact of this cost on the demand for care among the lower income households, In their research Maulik et al. (2017) and Shidhaye et al. (2017) find that the prohibitive cost of treatment is one of the major reasons for low effective demand for mental healthcare among low income households.

There are a few public welfare programs in India that address the financial needs of persons suffering with mental illnesses. The Persons with Disabilities Act of 1995 allows for direct subsidies such as disability pensions, legal aid, and travel concessions for people with schizophrenia and intellectual disabilities, but the effective coverage of the welfare measures is not well studied or reported. Analyses based on small samples shows that about 70 percent of the persons suffering with chronic mental illnesses avail of this pension, but they do not have access to any other benefits described in the Act (Kashyap et al. 2012). Furthermore, the process of accessing these pensions and benefits is complicated. Arguably, it needs to be simplified and redesigned, keeping in mind the needs of the persons suffering from mental illnesses. For example, a single window clearance for all certification, pensions and other benefits has been suggested (Kashyap et al. 2012).

Mental healthcare could be affordable for persons from all economic classes if the known risks can be hedged during the times of ability to work by pooling these risks with health insurance (Raza et al. 2016). Currently, there are no specific public insurance programs for mental health care in India. The *Rashtriya Swasthya Bima Yojana* (RSBY) is a general health insurance program of the central government aimed at families living on incomes below the poverty line, and it also covers the medical needs of mental illnesses. The program began in 2008 under the national Ministry of Labour and Employment. Seven years after the start of the program, in 2015-2016 only 41.3 million families were enrolled, representing 57 percent of the target.[20] There are a few other general health insurance schemes that cover mental health specifically for the people employed by the various government departments: the central government has a health insurance scheme for its employees, railway and defense employees have their own schemes, state governments have schemes for their employees as well, and they also contribute towards the Employees State Insurance Scheme for factory workers. Despite these various schemes, only 15 percent of the population is covered by any form of health insurance (Raza et al. 2016). Hence, there likely is scope for designing insurance products that keep the needs of mental illness in mind, and that can be marketed to those already suffering, or who are at high risk of mental illnesses. For example, such insurance might cover costs of treatment as well as loss of income during times of disability.

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[20]See, for example, `http://www.rsby.gov.in/overview.aspx`. Some states such as Andhra Pradesh have introduced their own public schemes at the state government level, and allowing for this additional source of insurance will change the coverage figures.

3.4.5 The Mental Healthcare Divide

In the fifth set of questions, we raised concerns about the uneven distribution of access to mental healthcare. In this sub-section, we describe ways in which access to mental healthcare is not uniform across the country, and the situation is markedly worse in rural parts compared to urban areas. Of course, this divide is also broadly true of other forms of health care in India, but we do not have data that can identify the relative inequality for mental health care versus general health care, or other specific categories of health care.[21] One of our interviewees, a psychiatric professional, did provide one indicator of rural-urban differences in terms of time spent with patients. He estimated that a private practitioner specializing in psychiatric outpatient cases would, on average, see 15-20 cases a day at 15-30 minutes per patient in a metro area, while in a more remote rural area, the numbers would be 60-100 cases and 3-5 minutes per patient.[22]

While there are large variations from one state to the other, in general one can characterize three geographic categories that are relevant for comparisons: metro-cities and urban districts, smaller cities and towns, and rural districts/villages. There is a large difference in the density of population and thus the cost of living, living conditions, and the income opportunities in these three types of geographies. The NMH survey(Gururaj et al. 2016) reports a higher incidence rate of almost all mental illnesses and stress-related disorders in the metro regions compared to the non-metro regions, and in rural

[21] However, a useful recent study37 documents the poor quality of care in both urban and rural India, with urban care characterized as “somewhat better”.

[22] The interviewee also noted that rates charged would be different, with urban patients paying an average of 4-5 times what rural patients would pay per consultation.

regions compared to urban (non-metro) regions.[23] Access to care in general, and to mental health care specifically, is lower in rural areas as compared to urban and metro regions.[24] In their study of disability certificates and access to government disability pensions, Kashyap et al. (2012) find that while most of the mentally ill (in absolute numbers) live in the rural parts of the country almost none of them could avail of any benefits other than the disability pension; while about two thirds of the urban disabled were already residing in rehabilitation centers or custodial care centers.

The suicide rate in rural areas specifically among farmers is an issue that has been widely politicized and debated in the popular media.[25] However, Basu et al. (2016) study nineteen states over the period of 1995-2011, and find that, quite contrary to popular belief, suicide rates are lower among farmers compared to non-farmers. Also, in the years they studied, suicide rates were increasing among non-farmers while decreasing among farmers. Similarly, when Andrés et al. (2014) studied panel data for fifteen major Indian states over a period of eighteen years from 1992 to 2009, they found that

[23] This pattern, therefore, is not consistent with the possibility that variations are driven only by reporting or detection that is higher in more urban areas.

[24] One of our interviewees pointed out a further divide, which may widen in the short run. Specifically, multinational corporations import human resource practices that include behavioral health services for employees similar to what would be offered in advanced economies. Thus, even within an urban area, and aside from income and class differentials in affecting access, the type of employer may be emerging as important in shaping access to mental health services within the formal sector. Until such coverage becomes widespread among corporate employers, this will be a further source of unequal access.

[25] For example, see Umar (2015), Tiwary (2017) and Shiva (2017).

urbanization in general is correlated with an increase in suicide rates.

How can this divide between rural and urban mental healthcare be addressed? Our perspective is that there are two complementary avenues for possible intervention and improvement. The first is with respect to the management of the public health care system. The second is with respect to the sharing of resources between the different kinds of nonprofits that are working in various communities.

While the healthcare system is constrained by an alarming shortage of trained workers, this shortage is greatly exacerbated because of lack of proper incentives of the existing workers5. This is a general problem, not restricted to the case of mental healthcare provision.[26]

Turning to the second possible intervention, it is important to note that much of the countrys mental healthcare is de-facto provided by private non-profits. With their experience and goodwill in communities, some non-profits may be more effective in the public information and education campaigns (Gururaj et al. 2016, Shidhaye et al. 2017, van Ginneken et al. 2017). This situation raises an important and challenging question: how can existing or redesigned public programs facilitate sharing the work and results of various non-profits to learn and replicate the most effective methods for reducing the stigma against mental health, in rural as well as in urban areas?

[26]See, for example Chaudhury et al. (2006), Das and Hammer (2007), and Hammer, Aiyar and Samji (2007).

3.4.6 Integrated Care in the National Health Policy and Mental Health Care Bill

In this sub-section, we discuss some partial answers to the sixth and seventh sets of questions, regarding the place of integrated mental health care in the latest legislation and policy documents, namely the Mental Health Care Bill of 2016 and the National Health Policy of 2017 (Ministry of Health and Family Welfare, India 2017). The resource consequences of the policy proposals are touched on here, as well as in the next sub-section, along with potential implications for a revamped mental healthcare ecosystem.

The Mental Health Care Bill is a comprehensive document that was passed into law in August of 2016. The bill was under debate in parliament for several years: while the lower house of Indias parliament passed the bill in 2013, the upper house only passed it three years later, with many important amendments. The bill recognizes that all individuals in the country who are suffering from mental disorders have a right to get treatment, support, and lead a normal life free from discrimination and injustice. It also describes the responsibilities of various public agencies, such as the police, judicial system, and the public health care system, in protecting these rights; and sets goals of public mental health programs, and the role of DMHP.

To protect the rights of people who suffer mental illnesses and are caught in the judicial system, the bill describes the set-up of state level Mental Health Review Boards. These boards will be comprised of District Judges, persons from administrative services such as District Collectors,[27] along with psychiatrists and representatives of mental

[27] A District Collector or Deputy Commissioner is typically the most senior administrative official at

health nonprofits, as well as some persons with mental disorders, who can represent the interests of the affected population. The boards will have the power to decide whether a person suffers from mental illness, ascertain whether the rights of such persons are being harmed, overturn previous judicial directives, and adjudicate the complaints made by such persons under trial or serving a prison sentence.

The National Health Policy (Ministry of Health and Family Welfare, India 2017) identifies some specific problems in mental healthcare and makes some proposals targeted at these problems.

First, noting the dire lack of specialists in mental healthcare, the document emphasizes a need for increased training of specialists through public financing mechanisms that are specifically aimed towards those who are willing to work in public systems after graduation. Another measure of rapid expansion of human resources identified in the policy is training the accredited health workers, called ASHAs, to provide community or home-based care for prevention, cure, and rehabilitation from mental illnesses.[28]

Second, it proposes that a layer of non-specialist psychosocial support could be

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the district level in the system of Indias governance, preserving a structure mostly developed under British colonial rule.

[28]We have not been able to give much attention to discussing rehabilitation in this paper, but it remains a problematic issue. One professional we spoke with specializes in developing half-way houses for rehabilitation or longterm treatment that does not require traditional institutionalization. On the other hand, there is concern that the new legal framework has not really come to grips with the scale of the problem of rehabilitation and how to implement it (Bhattacharya 2017).

provided through networks of community members at primary level healthcare facilities. Third, the policy also recognizes that digital technology can be leveraged in contexts where access to qualified psychiatrists is difficult. Provision of internet- and mobile-based services have been suggested (and tested in other contexts) for the following purposes: multi-media based interactive online courses for training medical officers and ASHA workers in specialized skills required for provision of mental healthcare; multi-media and interactive apps for diagnosis of mental disorders and preliminary prescriptions to assist mental healthcare workers; and interactive therapies for common mental challenges such as stress and low intensity depression all in local languages which can be used flexibly.

There are also some proposals in the National Health Policy, in the context of overall public healthcare in India, which are aimed at bolstering healthcare more broadly, and which may further integrate mental healthcare with general healthcare.[29]

First, it is also proposed that government(s) partner with private agencies to operate health and wellness centers that will provide specialized preventative and care services, including mental healthcare, at a fee for households that can afford it and free for poor households.

Second, as a mechanism of rapid expansion of the public healthcare system, NMH proposes partnering with the private sector via a referrals system: charitable and non-

[29]Psychiatric professionals we interviewed noted the advantages of greater integration in training and treatment, to alleviate shortages of specialists, reduce stigmatization and improve care through diminishing silo effects. See also The MINDS Foundation (2017) as well as footnote 17.

profit hospitals may volunteer for accepting referrals from public health facilities. For-profit hospitals/clinics may also designate free/ subsidized services in their hospitals if proper incentives are provided.

Third, the policy also proposes creation of a unified emergency response system, linked to a dedicated universal access number (like 911), with a network of emergency care that has an assured provision of life support ambulances, trauma management centers (one per 3 million persons in urban and one per every 10 million in rural areas).

Fourth, recognizing the lack of good management systems, the National Health Policy envisions setting up of Health Information Exchanges and a National Health Information Network by 2025. As mentioned earlier, the present system was created with a focus on areas such as maternal services and does not serve the needs of mental healthcare well (Gururaj et al. 2016).The proposed integrated health information system is meant to track the complete health of all individuals in the country based on real-time records captured using phone and tablets, i.e., an Electronic Health Record (EHR), and will be linked to the unique identification numbers of individuals (known as *Aadhaar*). If the system is implemented effectively, this data could be very helpful in understanding the health systems and their limitations, and thus, serve to improve the efficiency and transparency of resource allocation.[30]

[30] Aside from issues of technical feasibility, there are also major potential concerns about privacy and security, as well as implications for the functioning of health insurance markets where private for-profit providers are part of the mix. The experience of advanced countries reminds us of the challenges of implementing this aspect of Indias National Health Policy, but further consideration of these issues is beyond the scope of the paper. It is worth remarking, however, that mental health records can be

While the National Mental Health Policy (Ministry of Health and Family Welfare, India October 2014) recognizes and addresses many issues about mental healthcare, there are many outstanding debates. One such debate is regarding the goal of the mental healthcare: whether the goal should be absence of extreme symptoms or that the person be able to perform as an independent agent.

This is not an easy question to answer since, as it is, treatment of mental illness presents a financial burden to the family that may be devastating (Gururaj et al. 2016). With limited resources available in the public health system, the amount of resources available per person is also constrained, and the question becomes one of trade-offs between the number of persons treated versus the extent of care they can get. What exactly should be the model of such recovery methods is still under debate, where advocates of cultural psychiatry such as Bayetti, Jadhav and Jain (2016) caution against taking western-culture-based recovery models (Jacob 2015, Davidson 2005) and applying them to the Indian context as a blanket policy goal of mental healthcare. Alternatively, rather than a top-down policy, the government could replicate, or facilitate and support the replication of, the community-based recovery models used by non-government organizations that have already been demonstrated to work well, as in Kumar et al. (2014) and Gautam, Bansal et al. (2014).

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particularly sensitive in the arena of privacy and security, for the kinds of reasons discussed in the introduction.

3.4.7 The Present Ecosystem, and Imagining a Redesigned System with a Continuum of Care

In this sub-section, we offer a critique of the current District Mental Health Program (DMHP) and the public healthcare system, and then outline a picture of the ecosystem for provision of continuum of healthcare that seems to emerge from the legislation, policy, and the DMH programs, as a partial answer to the seventh set of questions.

While the policy statements and laws are very comprehensive and thoughtfully crafted, the implementation of the mental healthcare policy is a very different story. The NMH Surveys Mental Health Systems Assessment reveals that very few of the states have well-defined mental health objectives and mechanisms. Mental health programs suffer from severe constraints in administrative and technical know-how, and in human and material resources. Mental health is still a low priority in the public health agenda and other than in a few states, the activities and programs are fragmented and disorganized.

As discussed earlier, the public mental healthcare system is working with an acute shortage of trained workers; moreover, the motivation of the existing mental healthcare workers is also low.5 The national health policy and mental health act both recognize the lack of good healthcare management systems, and propose systematic solutions that can rapidly improve the provision of healthcare. The motivation of healthcare workers, in general, can be improved by reinforcing the mission statements, incentive based remuneration, interactions with the community through in-person feedback and town-hall-style interactions, oversight of non-profit organizations, and promoting overall accountability with independent monitoring and evaluation activities. While the monitoring and evaluation activities are required by the DMHP, such activities are largely missing in all states (Gururaj et al. 2016). There also are some structural shortcomings that may specifically affect the motivation of workers in the DMHP, since, in its design the program does not have any element of comparison among different districts. An element of competition among the different districts based on outcomes and quality of services, along with a system of rewards for those that work well and penalties (even if symbolic) for the ones below par, may also help motivate the employees, and facilitate sharing of best practices benchmarked against each other. Again, this is such a pervasive problem that it may defy easy solutions: however, starting with very specific areas of healthcare such as certain kinds of mental health interventions may be more manageable than a systemwide solution.

The NIM Survey finds that the financing of mental healthcare is in a state of total disarray, and there is a lack of clarity in the sharing of responsibilities between central and state governments and the various state-level departments, which also leads to large under-spending of resources; for example, in 2012-13, only 42 percent of the total funds allocated for DMHP were spent (Patel et al. 2017). The NMH survey (Gururaj et al. 2016) reports that the budgeted funds for mental-health-related activities do not have clear specification, justification, and/or timely allocation, and are thus difficult to spend, and that most states were unable to utilize even clearly available funds due to lack of clear mechanisms, guidelines, and shortage of human resources.

The current working of mental healthcare provision is separate from general healthcare due to historical reasons: while it shares infrastructure with general healthcare, the management, oversight and financing of these systems are separate. As discussed earlier, the NMH study (Gururaj et al. 2016) found that the drugs identified as critical in the mental healthcare bill are not continuously available at most of the facilities they surveyed. There exist Urban/Rural Health Mission programs with established systems that DMHP can benefit from. For example, these health missions have a well-established drug logistics, procurement, and distribution system that ensures continuous and uninterrupted availability of the most important drugs. DMHP can benefit from using these existing drug logistics systems to ensure the availability of the most critical drugs.

The DMHP requires that the districts maintain reports on the functioning of the mental health program and information regarding monitoring and evaluation activities, such as measurable and defined indicators, methods of data collection, specified program officers for monitoring and review of program components, but there is no support system or records of monitoring and evaluation activities in any of the states.

There does exist a national Health Management Information System (HMIS), which is a portal of real time information about the status of healthcare. It has been established with a focus on maternal health, but the same system can possibly be used for monitoring and tracking mental healthcare. This could potentially help optimize the allocation of limited resources and identify the most important constraints to be overcome for improving the quality of care. As noted earlier, the health policy statement proposes setting up of Health Information Exchanges and National Health Information Network by 2025 (Ministry of Health and Family Welfare, India 2017) and given the urgent need for better mental healthcare, this might well be prioritized in these proposed information systems.

As discussed earlier in the section on public education, early detection and rehabilitation, major obstacles in the demand for mental healthcare are lack of knowledge and stigma around mental disorders. DMHP has assigned budgets for information and education programs which are not utilized (Gururaj et al. 2016). If the DMHP can perform the functions that are assigned to them, we might see an increase in the demand for public services in this area, especially among households with the lowest incomes (Maulik et al. 2017, Shidhaye et al. 2017).

As discussed in detail earlier in the section on affordability, subsidies and insurance another reason that demand for mental healthcare is low is the high cost of treatment. While pensions and subsidies are available for those experiencing severe disabilities, gaining access to these services is complicated and the process can be simplified and redesigned to keep in mind the disability of the target audience (Kashyap et al. 2012). For persons from all economic classes, mental healthcare will be much more affordable if the known risks can be hedged in times of ability to work by pooling these risks with general health insurance (Raza et al. 2016). There may also be scope for designing insurance products that will cover costs of treatment as well as lost income during times of disability.

The following picture of a system with a continuum of care emerges from the reading of the policy and the bill. The first contact between the urban population and the public care system would be counseling and community-based educational services provided via urban wellness centers, while in rural districts the ASHA would provide similar services. The planned synergy with non-profits would make this first contact more effective and expand the reach.

The second layer of care would be provided by primary and community health centers (PHC and CHC). There would need to be a rapid expansion in their capacity if referral services are made operational, and thus DMHP can involve local private clinics and hospitals to participate at low cost or for free.

The third layer is at district-level hospitals. These hospitals work around the clock, and can provide specialized diagnostic services and in-patient care. At this level also, their reach can be expanded through referral services. This level of care for the chronically disabled and those who need emergency care would also be expanded by a unified emergency response system, linked to a dedicated universal access number, and extra capacity in the form of trauma management centers, as described in the National Health Policy.

At all levels, there would need to be an increase in the number of mental healthcare workers, incentivized by the national and state governments investments in training for mental health education. An information architecture for data-based management could make resource allocation more transparent and objective, and patients would then be able to provide real time feedback that could inform the direction of future policy adjustments. Linking of health records to Aadhaar numbers might also make transfers of pensions and other welfare payments much easier to implement. The Mental Health Review Boards could protect the rights of the ill and the disabled in the judiciary system, whether under trial or serving prison terms.

3.5 Conclusions

The Mental Health Act (2017) and the National Health Policy (2016) propose groundbreaking ideas and changes for India. While there is cautious optimism with the new law and policies, there still are many gaps in the understanding of the challenges of the provision of increased access to, as well as better quality, mental health care in India.

These challenges can be understood on two fronts: one is the psychiatric and medical aspect of the issues, and the other is the management and administration of the system.

Perhaps the highest priority in achieving the goals of greater access and better quality is to increase the number of trained personnel. At the level of full medical practitioners, the cost of increasing the number of seats in medical colleges is not too great relative to the size of government budgets, since existing levels are so low. It is more difficult to determine the optimal trade-off between resources invested here and in other kinds of expansion of medical training, but our conversations with professionals and policy makers suggested that the current investment in training psychiatrists or similar medical professionals in the area of mental health is suboptimal. As noted earlier, there also seems to be a case for greater integration of training on mental health issues into general medical training. Increasing the number of qualified personnel at levels below that of full medical training, such as psychologists, counselors and social workers, will require greater resources, because, although the training required is less costly, the scaling up needed is much greater. It is here that technology might play a role, providing knowledge tools to less-qualified practitioners, including the ability to consult those more qualified at scale and across geographies.

In fact, the new legal framework and policy identifies the importance of information technology in rapid expansion of access to mental healthcare. There is some research that supports that the idea that ASHA workers can be trained to identify symptoms of common mental illnesses and be the front line for providing mental healthcare (van Ginneken et al. 2013, Nadkarni et al. 2017). Further research could provide models for internet- and mobile-based training for healthcare workers, for example an app-based or app-reinforced multi-media and interactive MOOC for training medical officers/ASHA workers in specialized skills required for provision of mental healthcare. Multi-media and interactive apps have also been used for diagnosis of mental disorders and preliminary prescriptions and for common mental challenges such as stress and low-intensity depression, in other contexts (Lee et al. 2016). However, further research is necessary for the context-specific challenges in India, such as translation in local languages, and the diverse education and abilities of the people who may be administering or using these apps, from highly trained psychiatrists/ medical officers to community activists (ASHAs).[31] Research is also needed to find context-specific models to support prevention mechanisms by identifying high risk individuals and providing them with care and training, e.g., the family members of people suffering high disability mental illnesses (Collishaw et al. 2016) and aging adults (Deb 2016).

With respect to the administration and management needs of the public system, one can highlight a few of the important issues that need attention. Some of these are implied by the need to expand the numbers and structure of the mental health profession. Increasing the number of mental health specialists and providing integrated training to generalists in the medical profession will require significant organizational innovations in the education system, not limited to medical colleges. This is likely to be a serious challenge. Furthermore, developing high-quality software and engaging with mental health specialists for this development, as well as encouraging their participation in a system where less-qualified professionals play a potentially greater role in diagnosis, and even treatment, will require changes in the culture of the system, including how the

[31] Some initial reports are encouraging: for example, Moses (2016), The George Institute of Global Health (2017), and D'Cunha (2017)

top of the skill pyramid see their personal and social roles.[32] These issues cut across the public and private sectors in the provision of healthcare in general, and mental health in particular.

Another set of issues pertain to the interface and potential coordination between the public system and private providers. One is the importance of identifying the most effective mechanisms for resource sharing between general healthcare and mental healthcare, including continuous and rigorous evaluation of welfare mechanisms, such as disability pensions, for persons suffering with mental health problems. While the new policy framework recognizes the potential positive role for public-private partnerships, there are a few outstanding questions in this regard, especially in determining the most effective mechanisms for resource and information sharing between the public organizational infrastructure and those private non-profits that are doing excellent work in the provision of mental healthcare. Clearly, there can be a potential for a great deal of diversity in the nature of the organizations and the types of care involved in such partnerships, complicating the crafting of agreements and sustainable relationships. On the information sharing aspect of partnerships, with their experience and goodwill in communities, some nonprofits may be more effective in public information and education campaigns: how can public programs facilitate sharing the work and results of various non-profits to learn from and replicate the most effective methods for reducing stigma against mental health? For example, the public education methods found effective in reducing stigma (Maulik et al. 2017, Shidhaye et al. 2017) could be scaled up by partnership between DMHP and nonprofits.

[32]Hence, there is the potential for new incentive problems on top of the existing ones alluded to earlier in the article.

Finally, it is also paramount to identify mechanisms for reducing the burden of cost of mental healthcare. One way could be public-private partnerships in the provision of insurance. Rigorous research is needed to understand how existing health insurance schemes provide for the specific needs of persons suffering with mental disabilities, and how to design and market an insurance product or scheme that may cover disability and treatment costs due to mentally related disabilities.[33] Greater access requires affordability as well as greater availability of care providers. The experience of healthcare in general in India and even in advanced economies has shown that all of these issues are major challenges. In the case of mental health in India, the only consolation is that the starting point is so dismal that the potential for improvement is enormous.

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[33]For an optimistic initial assessment of the impact of legislative changes on mental health insurance, see Kapoor (2017).

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