Supplemental Appendices to "Short Moves and Long Stays: Homeless Family Responses to Exogenous Shelter Assignments in New York City"

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This Appendix contains an expanded discussion of policy and data management, as well as a theory section and supplementary results. Portions are repeated for the main text for convenience.

A Data Appendix

Unless otherwise noted, data management activities are carried out using `Stata 16`. For certain tasks where `R` has a comparative advantage, I use it instead and make note.

A.1 Data Sources

My data consist of administrative records matched across several City agencies. The core data source is the Department of Homeless Services' (DHS) Client Assistance and Rehousing Enterprise System (CARES), which is the City's management information system of record for homeless families. CARES is designed to accommodate all aspects of homeless services provision and program management. At the front-end, CARES consists of a graphical user interface software application that allows both City staff and contracted service providers to enter, update, and view client information in accordance with role-based access privileges. Behind the scenes is an elaborate relational database where records are stored. While the primary purpose of CARES is prosaic—to permit efficient administration of homeless services—the system also includes fairly robust (if sometime convoluted) reporting capabilities to facilitate program evaluation and statistical reporting.

My sample consists of all eligible family shelter applications from January 1, 2010 to December 31, 2016[1]. I focus on these years because this is the period in which shelter capacity constraints have been the most binding, and thus where the case for random neighborhood assignment is the strongest. In addition, the CARES system came online during 2012; prior to that, DHS relied on less robust information technologies.

CARES is a comprehensive system, encompassing virtually all aspects of family homelessness, from application through case management[2]. Data in CARES is collected from two main sources. The first is the Temporary Housing Assistance (THA) application, which all families requesting shelter are required to fill out at intake[3]. The THA consists of information pertinent to the eligibility determination and placement decisions made by DHS staff. In addition to basic identifying information for all family members at the time of application (e.g., name, date of birth, Social Security Number) and their relationships, it also contains

[1]Specifically, it consists of all families who both began their application and their shelter stay between 1/1/10 and 12/31/16.

[2]CARES is similarly used to manage single adult homelessness, but as that is not the focus of this study, I do not discuss it here.

[3]While NYC has a right to shelter, families must be deemed eligible, in the sense that they are bona-fide homeless with no other place to go.

demographic attributes (e.g., sex, race, ethnicity, pregnancy status) as well as the family's address of origin and reason for applying for homeless assistance. As might be expected, CARES also records information relevant to the application process itself, including application type, eligibility determination outcome and official eligibility reason, diversion efforts, and dates of application and adjudication.

The second main CARES data domain relevant to this paper is known as the Lodge History (Lodge), which, as the name suggests, tracks families' experiences in shelter. Unlike the THA, it is not a form, but rather a query culling key stay-related data from multiple tables (and which are collected at various points during a family's time in shelter). It records the facility, building, and unit into which a family is placed, and for what dates they resided there[4]. It is not uncommon for families to change facilities or units during a shelter stay; correspondingly, the system tracks all of the ins and outs. When families leave shelter, the Lodge component of CARES records the date, as well as the type of exit and destination address (if known)[5].

The distinction between the THA and Lodge is somewhat artificial, as CARES is an integrated application used across multiple DHS administrative units (including eligibility and placement staff) and providers. Thus, families' information can continually be updated or augmented; indeed, the source of a particular data field is sometimes categorized by the main data tables upon which a particular query relies, rather than the point at which the data was collected. Another distinguishing feature is who does the data entry: THA information is entered by frontline DHS staff, while Lodge data may be entered by DHS staff or providers.

One example illustrative of the complexities of data collection in CARES is families' health status. Medical and mental health information relevant to shelter placements is collected via several standard assessments which may take place at various points during a family's shelter stay, beginning at intake. Consequently, DHS' health query comprises data from both the THA and the Lodge History.

To summarize, CARES client data may be categorized along several non-mutually exclusive dimensions: transactional source, point of collection, user role, topical content (as organized by relational database tables), or the query that extracts it. For purposes of this analysis, I typically classify CARES client data as coming from the THA or Lodge, depending on whether the data is primarily collected at intake (THA) or during a shelter stay (Lodge). Strictly speaking, this may be an oversimplification, but it is one that useful for organizing data concepts.

Though the focus of CARES, first and foremost, is on clients, DHS families need places

[4]Some facilities consist of multiple buildings. In the case of cluster units—apartments scattered across otherwise private residences—these buildings may not even be in the same borough. Thus, facility alone, which is more of a synonym for "provider contract," is not sufficient to identify shelter location.

[5]Families are not required to report their exit to DHS.

to go. Consequently, CARES also functions as an inventory management system, allowing staff to track the capacity and occupancy of all homeless shelter units within DHS' purview. These include, in addition to traditional Tier II shelters (these are apartment buildings officially designated as shelters), "cluster" units scattered among private apartments, contracted hotels, and commercial hotels. While the City owns and operates some shelters directly, the majority are under contract with non-profit service providers. This facility management aspect of CARES is critical to the ability of staff to place clients in suitable situations[6].

Correspondingly, the third CARES-based data source for this paper is DHS' facilities query. It includes daily capacity and occupancy for each facility and building within DHS' portfolio, along with addresses and unique identifiers.

Client data from CARES constitutes the core data for this paper. However, it is hardly the case that all information relevant to assessing homeless services is maintained by DHS alone. Indeed, the vast majority of the City's social services and poverty alleviation programs are the domain of the Human Resources Administration (HRA). Also known as the Department of Social Services (DSS), HRA is NYC's officially designated local social service agency. It bears responsibility for administering virtually all of the programs associated with the social safety net, notably: Temporary Assistance for Needy Families (TANF) and its NYS counterpart for single adults, Safety Net Assistance (SNA); the Supplemental Nutrition Assistance Program (SNAP, formerly know as Food Stamps); and Medicaid[7].

Data on public benefit use is maintained in HRA's Welfare Management System (WMS), which is the NYS information system of record for cash assistance (TANF/SNA) and SNAP. Reporting from WMS is conducted through an analytically-oriented front-end application, the Electronic Data Warehouse (EDW). For this study, HRA provided data for all individuals who interacted with CA from 2001–2016 and SNAP from 2004 to 2016, as well as the type of assistance received and the associated dates of receipt[8]. Linking information on patterns public benefit use to family shelter stays is critical for understanding how shelter services impact other economic outcomes.

Of course, the ultimate ambition of most government-administered human service programs, from homeless services to poverty assistance, is employment and earned income. Accordingly, a rigorous evaluation of family homelessness policy must include an accounting of labor market outcomes. To that end, the New York State Department of Labor (DOL) has

[6]As the facilities management component of CARES is not as well developed as the client management part, DHS also relies on several other information systems to manage facilities.

[7]In fact, the relationship between DHS and HRA is complicated and dynamic, largely for reasons having to do with the challenges of family homelessness. DHS was originally part of HRA, until it was spun off as an independent agency in 1993. However, in 2016, Mayor de Blasio again consolidated DHS under the HRA umbrella, managed by a single commissioner, Steve Banks. Nevertheless, it remains conventional to refer to the departments as distinct.

[8]Several demographic variables are present as well, including race and education. These fields can be used as a robustness check on CARES data (or as an IV for measurement error).

provided quarterly employment and earnings data for all DHS family shelter clients whose Social Security Numbers match DOL records. This labor data spans the first quarter of 2004 to the first quarter of 2017.

An earlier version of this paper, completed in November 2017, was based on DHS data through 2016. Subsequently, in early 2018, DHS data on stays of 2010–2016 family shelter entrants was provided and used to match the 2001–2016 CA and FS records. A second DHS data update, in May 2019, revised length of stay, exits, and returns data for the 2010–2016 DHS families cohort through May 2019. However, no additional match with CA, FS, or DOL records was made. Due to improved data quality, the May 2019 DHS data update also revised pre-2017 shelter exit dates for a small number of spells, with implications for pre-existing public benefit data matches. 79 spells previously marked as incomplete ended prior to 2017, and thus should have CA/FS data, while 7 spells erroneously marked as complete—and thus with CA/FS outcome data—are included in the sample. These observations have no meaningful impact on the results.

A.2 Querying

CARES is an ambitious and detailed information system, customized for DHS' unique needs with many features, user levels, and purposes. Although it was designed, in part, with reporting and analysis in mind, its underlying complexity—literally thousands of relational database tables—means that extracting information often requires a bit of programming gymnastics. In addition to user-entered data, CARES automatically generates several fields, including unique identifiers for individuals, families, and cases, as well as the dates on which transactions (e.g., application approval, moves, case closing) take place. Such automation simplifies data entry and facilitates reporting.

The majority of CARES statistical reporting is conducted by means of standard "stock" queries, including the THA and Lodge data discussed above. The underlying SQL code is written and maintained by staff in DHS' Management Information Systems (MIS) and Policy & Planning (PP) units, as well as by CIDI staff. A common extension is joining the results of several queries through unique identifiers. However, in the case of several fields crucial to this study—target schools, shelter building ID's and addresses, race, health status—DHS had to customize existing queries to include additional fields.

To be precise, the DHS data in this paper come from six separate CARES queries:

1. **Standard THA**: described above.

2. **Standard Lodge**: described above.

3. **THA supplemented with target school**: Given DHS' school-based placement policy, caseworkers collect information on youngest child's school. However, this field is

sparsely and irregularly populated.

4. **Lodge supplemented with race and shelter building ID**: Standard queries lack building identifiers and the race category variable.

5. **Facilities**: provides daily shelter capacity and occupancy at the facility-building level, along with addresses.

6. **Health**: contains information on family members' medical and mental health (including substance abuse), which may pertain to shelter placement decisions. Health assessments may occur both at intake and during shelter stay.

A.3 Structure of the Data

A.3.1 The Core DHS Data

As described above, the foundational data for this paper consist of a joined standard THA-Lodge query encompassing all eligible families with children who applied for shelter and began their stays between 1/1/2010 and 12/31/2016. The raw data are at the individual-bed stay level: that is, there is one record corresponding to each shelter unit assignment for each individual—437,337 observations in all.

Key variables in the foundational data include: unique family and individual identifiers (including system generated ID's as well as name, date of birth, and SSN); application attributes (e.g., type of application, client-provided homelessness reason, officially determined eligibility reason, address of origin, and key dates in the application process); basic personal characteristics (e.g., sex, household relationships, ethnicity, a pregnancy indicator); and shelter stay characteristics (facility, facility type, dates of stay). The majority of these variables are self-reported by the (prospective) clients; exceptions are staff-designated fields, such as official eligibility reason. However, all information is entered into CARES by caseworkers, providing a measure of validation and error-checking. Of note, this data entry process also provides rationale for asserting that, to the extent errors occur in the data, mismeasurement is of the classical variety.

To this foundational data is appended THA-based target school information and Lodge-based building ID and race category. None of these variables are present in the standard queries. Target school gives the name and code (or sometimes the address) of the youngest child's school, which provides the target shelter neighborhood. Unfortunately, this variable is populated irregularly. Race is self-reported based on standard categories (e.g., White, Black, Asian); note that Hispanic/Latino identity is recorded by the separate ethnicity variable. Building ID gives the precise building where a family is placed within a facility. In CARES nomenclature, "facility" is a loose term, referring more to a distinct provider contract than to a particular location. For example, buildings within cluster facilities may be spread widely across neighborhoods—in some cases, even across different boroughs.

Once a building ID for each family is established, records are linked to the facilities query in order to append data on shelter address (as well as such things as facility and building name).

As a final preliminary step, records are matched to the standalone health query. This provides information on all family members' physical and mental health, including such things a mobility limitations and medical device usage, which in part determine which shelters can suitably accommodate families with special needs.

These queries are linked together based on several identifier fields. Depending on the queries involved, uniquely identifying records may require using several ID fields simultaneously. Together, I refer to the aggregately joined DHS data as the "Core DHS" data.

A.3.2 HRA Data

On a parallel track, HRA benefits data are processed into a form suitable for linkage to the Core DHS data. Raw HRA data consists of individual-case status level records. There are separate files for each program (CA and SNAP) and each year (2001–2016 for CA and 2004–2016 for SNAP). That is, for each program and each year, a file consists of every case status (applying, active, single issue, sanctioned, closed, denied) each individual had during that year and the corresponding dates. These files also include personal identifiers (name, SSN, DOB, WMS ID, case number) as well as demographic information (e.g., sex, race, education level). Separate years are necessary as the files are very large, containing potentially millions of records.

Variable fields are first cleaned and standardized along the lines described for the DHS data below. Relevant analytical variables, such as length of benefit receipt and benefit indicators, are defined. At the same time, irrelevant variables are dropped, as are individuals too young to be heads of household.

The individual years of data are then appended together into a single file for each program (CA and SNAP) and collapsed to a single summary observation for each unique individual, as indicated by SSN[9]. This process reduces the resulting files—one for CA and one for SNAP—to manageable sizes for purposes of linking to the DHS Core data. As described below, the actual linkage of HRA and Core DHS data occurs only after the Core DHS data is cleaned and collapsed. This sequencing is practical: the linking process relies on probabilistic matching, which can only be accomplished in reasonable time if the number of records is modest.

[9]Neither WMS ID nor case number uniquely identify records; moreover, SSN provides a common link to DHS data.

A.3.3 DOL Data

DOL data consists of quarterly earnings and industry[10] for each individual in the DHS Core data with a matching Social Security Number. That is, in contrast to the DHS–HRA data match, the DHS–DOL match, discussed below, is entirely deterministic, requiring exact SSN matches. Observations are at the individual-quarter level.

Processing the DOL data consists of several steps. First, nominal dollars are converted to real fourth quarter (Q4) 2016 dollars, using the Consumer Price Index (CPI) for All Urban Consumers. In addition, industry codes are summarized in terms of NAICS sectors[11]. Then (and in reference to DHS family-episodes), data are aggregated over the appropriate analytical time periods—the year prior to shelter entry, the year following shelter entry, and the year post-shelter exit. For each of these periods, I define an indicator for employment, a count of quarters worked, and a sum of earnings. Finally, I calculate average quarterly earnings (always dividing by the minimum of four quarters or the number of quarters maximally observed in the given period, regardless of whether an individual was employed). For analytical purposes I add one to this total and take the natural logarithm, thus arriving at measures of log average quarterly earnings for the three periods of interest, and without excluding individuals with zero earnings.

A.4 Geocoding and Linking

A.4.1 Preprocessing

Having constructed the DHS portion of the Analytical dataset, two major data management steps remain: linking records across agencies and geocoding. Each is described in its own section below.

To carry out either task with maximal effectiveness, however, first requires cleaning and standardizing the variables implicated. This turns out to be a not inconsiderable challenge.

Geocoding software generally requires addresses to be inputed in standardized format—with, for example, street address, city, and zip codes in stored in separate fields—and largely error free (some software is better than others at discerning near matches). In other words, address data requires some of the highest accuracy of any field to be useful; if it contains errors, the software is unable to code addresses correctly. Ironically, addresses tend to be one of the most error-prone fields in DHS data. Common mistakes include misspelled street names, erroneous zip codes, addresses out of the valid range for a street, and boroughs inconsistent with street names. Particularly problematic are hyphenated addresses and prefixed street names (e.g., East or West). In addition, some entries erroneously merge separate fields

[10]Industry is described by standard North American Industry Classification System (NAICS) codes.

[11]However, I exclude sector covariates from earnings analysis due to the possible simultaneous determination of industry and wages.

(e.g., a street address containing an apartment number).

To address these address issues, I wrote a simple `R` script that corrects the most glaring mistakes. The program takes as its input the list of addresses from my Analytical Stata dataset. It parses addresses into conceptually distinct elements (address number, street, borough, city, state, and zip code). Then, using regular expressions and other string functions, it corrects the most common spelling, punctuation, grammatical, and notational mistakes, resulting in a list of mostly standardized addresses. Finally, using string distance algorithms, it compares street names to an official registry, replacing likely mistakes with their closest valid substitutes. These cleaned and standardized addresses are then inputed to geocoding software, with better success than the raw data.

The second place cleaning and standardization arises is with linking administrative records across agencies. The City does not, in general, have unique cross-agency identifiers for clients who interact with multiple departments. What's more, the standard individual identifier—Social Security Number—is error prone and often missing, either because clients' forget them or never had them. Thus, to achieve the highest possible matching rate between DHS and HRA data—the absence of evidence is not evidence of absence, after all—requires use of probabilistic linkage techniques.

Because probabilistic linkage typically relies on string comparison metrics, the success of the process will only be as good as the quality of the underlying data. Thus, I make simple alterations to improve the data quality of matching fields—first name, last name, date of birth, and SSN. Adjustments include: adding leading zeros to erroneously front-truncated SSN's, ensuring all names are fully uppercase, and arranging dates in standard formats.

A.4.2 Geocoding

Broadly, geocoding is the process of assigning standardized geographical coordinates or categories to addresses, areas, or other spatial positions—in essence, a systematic way of locating places on a map. In the case of administrative records, it entails iterating multiple rounds with specialized software packages.

The first step, as described in the previous section, is to clean and standardize the raw address data queried from CARES. This consists of parsing the data into its topically distinct subcomponents—address number, street name, city (borough), state, and zip—and making several simple cosmetic adjustments, such as removing extraneous punctuation and spaces and enforcing uniform capitalization. This is necessary because geocoding software can be quite literal its interpretation, demanding punctilious formatting and offering scant ability to make approximate matches.

The client address of origin variables from the Stata dataset are then exported to a Microsoft Excel file, which serves as the input to my geocoding software of choice, Geosupport Desktop Edition, version 17.1, which is a highly customized geocoding application for addresses in New York City published by the NYC Department of City Planning (DCP). Usually referred to by its acronym, GBAT, Geosupport Desktop Edition is a publicly available graphical front-end to the comprehensive Geosupport System mainframe application designed and maintained by DCP.

Taking as inputs address number, street name, and borough (or zip), GBAT can return a wide array of geographical classifiers. For purposes of this study, I emphasize several important neighborhood classifications: borough (boro), school district (SD), community district (CD), Census tract (CT), and neighborhood tabulation area (NTA).

I also output spatial X-Y coordinates for each address. GBAT uses the State Plane Coordinate (SPC) system, which approximates the Earth's surface as being flat within relatively confined geographic areas. According SPC, NYC falls in the New York-Long Island zone (NAD 83). With the origin of this zone set to the extreme Southwest, all NYC locations receive positive Cartesian coordinates, with X indicating East and Y indicating North. Units are in feet. Thus, SPC makes it simple to calculate the Cartesian distance between two addresses (NYC Department of City Planning, 2017).

GBAT returns an updated Excel file appended with the geocoded fields, which is straightforward to merge back into the original Stata dataset using unique record identifiers. (Recall there is one record per family-episode.)

Approximately 20 percent of addresses fail to geocode in the first round. For about half of these, this is appropriate: the addresses are outside NYC, as a nontrivial share of the family shelter population arrives from other cities and states (though some of these families may have prior ties to NYC).

The other half of geocoding failures are attributable to frequent errors in the raw DHS data. To remedy such mismeasurement, I import the list of failed addresses into `R` and implement the address cleaning program discussed in the previous section. This code corrects common data entry errors, such as misspellings and inconsistent use of directional prefixes. I then export the results to a second Excel file and repeat the GBAT geocoding process. This improves the success rate somewhat.

Overall, 57,500 of 70,000 client address observations code successfully. Of the remainder, 7,300 are out-of-towners. 5,200 fail to geocode. Future work will entail investigating the reasons for these failures and writing code to improve the success rate. In other words, the iterative data cleaning-geocoding process will repeat several more cycles.

Of course, addresses of origin are only half the story, and I repeat the geocoding process for shelter building addresses. As these addresses are maintained by DHS staff, the success rate is quite high.

Finally, with all geocoding data merged back into the Analytical dataset, I use the geocoded neighborhoods to classify families assigned to shelters in their neighborhoods of origin and those placed in distant neighborhoods. Given the fluid definition of neighborhood, I use the full set of potential categories: borough, SD, CD, CT, NTA, and zip. Spatial coordinates also permit a continuous proximity metric.

Future work may also involve geocoding exit addresses in those cases where these addresses are known.

A.4.3 Record Linkage

In the presence of common individual identifiers, linking records from disparate databases is simple and fast. Unfortunately, DHS family and individual ID's are not the same as those used by HRA in the administration of CA and SNAP, complicating the task of discerning patterns of public benefit use among homeless families.

In principle, Social Security numbers should serve as a cross-agency link, but in practice SSNs are frequently entered erroneously or missing. Thus, it is necessary to rely of probabilistic, or stochastic, linking methods. Also know as "fuzzy matching," there are several probabilistic linkage techniques common in the computer science and statistics literatures, most of which entail the use of string comparison metrics and are based on the pioneering work of Fellegi and Sunter (1969).

Though the mathematics can get complicated, the basic idea is to compare all possible pairs of records in each data set and assess their similarity—for instance, by counting the number of changes (insertions, deletions, and substitutions) to one string necessary to arrive at the other (the Levenshtein distance), or by considering the number of shared character sequences of a given length (q-grams). Patterns of matches among the compared fields are fed into an maximum likelihood type algorithm in order to categorize probable matches and non-matches, with probability thresholds set to distinguish true matches. Though sophisticated, these techniques also review considerable clerical review and judgment calls.

In this study, I primarily rely upon the user-written `reclink2` Stata command, which utilizes a bigram (two-character) string comparator and achieves success rates on the order of 97 percent(Wasi, Flaaen et al., 2015). In some cases, I also rely upon the `R` packages `RecordLinkage` and `stringdist` (Sariyar and Borg, 2010; Borg and Sariyar, 2016; van der Loo, 2014)[12]. I match on four variables: SSN, first name, last name, and date of birth (as a six-digit string with two-digit day, month, and year).

Besides distinguishing between true matches on the one hand and false positives and false negatives on the other, the other major challenge of probabilistic record linkage is computational efficiency. Comparing datasets of size m and n requires $m \times n$ computations, which become unmanageably slow on computers with conventional memory capabilities, given the millions of records involved.

I employ several strategies to improve the speed of computation. First, I reduce the

[12] The help files and associated journal articles documenting these commands have also been invaluable resources in learning about the techniques, as described above.

linking datasets to the minimal useful record sets. In the case of the core Analytical dataset, this means running the match after collapsing the data to one observation per family-episode (so that the match occurs based on household head only). For the HRA data, this entails dropping all observations with a date of birth such that they would not be 16 years of age by the end of the sample period (New York requires individuals to be 16 in order to be a CA or SNAP head of household), as well as collapsing to a unique observation for each SSN.

However, there are still in excess of 2 million CA observations and 3 million SNAP observations that must be matched with the 68,079 DHS family observations. Exact matches—where all four fields perfectly correspond—reduce the workload greatly. About 57,000 DHS observations are perfect matches, removing these from subsequent computation. In addition, as is conventional, I employ a "blocking" strategy on all four linking variables, which means than only pairs with an exact match on at least one of these fields is considered, significantly reducing the number of comparisons. Finally, I match on CA first and then take only the remaining non-matches to the larger SNAP data; this is possible because HRA maintains common identifiers across the programs it administers.

Erring modestly on the side of false positives, I successfully match about 67,600 of the 70,000 DHS families to HRA—in line with what would be expected about homeless family participation of public benefit programs.

Currently, I am able to identify whether a family received CA or SNAP, during which years, and their lifetime lengths of benefit receipt. The next steps in this process are to use the unique identifiers—which obviate the need for future fuzzy matching—to link DHS data to the uncollapsed HRA data sets, in order to distinguish between benefit receipt occurring before, during, and after shelter episodes. This is a data-intensive task, since it entails unique start and end dates for each family (rather than simple year indicators). However, since my DHS and HRA data are now deterministically linked, it should be computationally feasible.

The linking process for the DOL data is simplified by an administrative constraint: because DOL conducts strictly deterministic SSN matches with DHS data, my DOL data sample consists only of successfully matched SSN's present in the DHS Core data.

A.5 Defining Analytical Variables

Having pre-processed each data set—DHS, HRA, and DOL—and defined data linkage rules, what remains is to use the raw data to construct variables that are most appropriate for analytical purposes. These variables include both covariates to be used as controls (e.g., earnings and benefit use pre-shelter) as well as outcomes (e.g., earnings and benefit use post-shelter). Creating these variables is not a simple task, either conceptually or logistically.

The complexity arises from the flow nature of the data sample: I do not observe all families for the same length of time. This is true not only of the core DHS data in isolation—

obviously families who enter shelter in 2016 have less potential observation time than those entering in 2010—but, in fact, it is doubly true of the matched HRA and DOL data: families who enter shelter earlier in my sample have less potential observation time pre-shelter and more potential observation time post-shelter. As a result, raw comparisons of earnings, employment, or benefit use can be misleading—biased as an artifact of the sampling scheme.

To best put families on an equal footing for purposes of benefit and employment analysis, I take the approach of focusing three one-year windows: the year (or, as necessary, four quarters) prior to shelter entry, the year following shelter entry, and the year following shelter exit. (When quarters are the unit of time, all such periods are defined as excluding the quarter of transition and inclusive of the following four quarters. When days are the time unit, periods begin on the day of transition and extend for the the next 365 days, inclusive.)

Because observations can still be censored within these year intervals, my second normalization is use indicator or rate variables. Specifically, for benefit use and employment, I prioritize binary indicators (e.g., a dummy for employment or CA receipt) or fractional responses, with denominators set to the minimum of a year or the length of observation before censoring (e.g., percent of quarters employed or percent of days active on CA). For earnings, I focus on average real quarterly earnings, where the denominator is the minimum of four quarters or the number of quarters before censoring. In addition, I count all quarters, whether or not employed, so this measure is not conditional upon working.

A second complexity is that some families are observed for more than one episode during the sample period, necessitating separate computation of these analytical variables for each episode, which, for technical reasons, requires considerable care, as well as iterating the variable definition code for each episode instance. For purposes of variable definition, my general approach is to treat each episode as independent. This means that certain components of the raw data can overlap episodes. For example, if a family reenters shelter within six months of exiting, the subsequent six months of earnings will count as post-exit earnings for the first episode and post-entry earnings for the second episode.

A.5.1 DHS Analytical Data: Reshaping and Conceptualizing

Returning to the Core DHS data, the centerpiece of the analysis, the first step in creating the final "Analytical" dataset is to organize and restructure the raw data. The raw individual-bed date file structure is too detailed to be analytically tractable, so the basic idea is to collapse records into a single observation for each family and shelter episode. As described below, this data management process consists of four key activities: reshaping, deduplicating, defining, and recoding.

To do so is not necessarily straightforward, as it requires defining the key concept of shelter "episode." Conceptually, an *episode* is a discrete stay in shelter. However, it is common in the family shelter system that families enter and exit multiple times in close proximity—a few days in and a few days out—as they shuttle between shelter apartments, family, and friends. Brief hiatuses are not true exits. Conventionally, DHS defines the true end of a shelter episode as one in which a family does not return for at least 30 days; thus, any return within 30 days is considered to be part of the same episode.

I adopt the same 30-day standard for defining episodes in this paper. However, this notion does not have an analogue in CARES; case numbers, which are probably the closest proxy, are not defined by gaps in stays but by applications and case composition.

Thus, it is necessary to define an episode "by hand." To do so, I order observations by family ID (which uniquely identify families)[13]. A further complexity in this regard is that, in the raw data, there are potentially multiple observations for each individual in each family and, moreover, family composition can change during the course of a stay as members enter and leave[14]. This creates complex patterns of overlapping and interweaving shelter unit stays for families; recall that each move within the shelter system—it is common for families to move to different units within a building or to different facilities altogether—triggers a new observation in the raw data. What's more, data for certain fields are occasionally missing, which complicates accurate ordering of the data.

To deal with these complications, I take the following approach in defining episodes. First, I drop any observations with irredeemably missing data (e.g., lack all key identifiers), about 10,000 observations in all (a trivial fraction of the data). I then define the start date of an observation as the "bed start" date for that record (in DHS terminology, "bed start" means beginning of stay in a particular unit), or, if this is missing, as the application date. The corresponding observation end date is the "bed end" date for the record, or, if it is missing, the exit date. I then order the observations by date within each unique family ID. Note that in this setup, observations for each individual in the family are not sequential; the continuity of a family-episode is defined by the continued (without > 30-day gaps) presence of *any* family member, not dependent upon particular family members. I then calculate the gap between the beginning of one observation and the end of its predecessor. Any gap greater than 30 days defines a new episode for that family. Episode start date is defined as the minimum (first) observed date for the family, while episode end date is defined as the maximum (most recent) observation date.

Corresponding to the concept of episode are measures of length of stay (LOS), the proximate outcome of utmost importance to City policymakers. While there is not official LOS metric (and specifically none recorded in the data), DHS maintains two standard concepts.

The most straightforward is *system* length of stay, which is simply defined as the difference, in days, between the family's episode end date and start date. It does not exclude any

[13]Note that an individual may be part of more than one family, e.g., in the case of child that has her own child and subsequently becomes a head of household.

[14]It is not uncommon, for instance, for older children to come and go during a parents' stay in shelter, spending the interludes with relatives.

gaps in stay that might occur if a family leaves temporarily and returns within 30 days. A somewhat more refined concept is *shelter* length of stay, which does deduct shelter occupancy gaps from the total. In practice, the both concepts yield similar results, so for simplicity I favor the system LOS measure. Note that many episodes are censored in the sense of stays not completed during the sample period. Such observations are tracked with a censoring indicator and assigned a LOS based on the latest observed bed end date of 1/1/2017.

Having defined a coherent concept of episode, I collapse observations into the desired single observation per family-episode structure. From a data management perspective, this is classified as deduplication: creating unique records at the desired unit of analysis.

Other data management tasks are of the more routine variety, and include the following:

- **Converting variables to formats suitable for analysis**: Many variables are initially stored as strings and must be converted to factors or continuous variables. In addition, dates (also strings) must be converted to analytical date formats.

- **Recoding overly-detailed categorical variables**: Some fields, such as eligibility reason and exit reason, contain a multitude of nuanced codes that can more helpfully be classified in fewer broader categories.

- **Defining derivative variables**: Some variables must be transformed for purposes of analysis. For example, age is more useful than date of birth. Other examples include indicators for year of entry, quarter of entry, incomplete episodes, originating from outside NYC, and having a school age child.

When all is said and done, there is one unique record for each family-shelter episode (some families enter and leave shelter multiple times). The raw data consists of 70,632 family-episodes. 2,553 were dropped due to decisively missing data (e.g., family ID, entry dates, no children present), leaving 68,079 observations in my complete Analytical dataset. However, for two reasons my effective Analytical sample is smaller. 7,099 families originate from outside NYC, leaving 60,980 family-episodes relevant for assessing neighborhood effects (non-NYC families cannot be placed in their home neighborhood). However, 8,008 NYC family-episodes were unable to be geocoded, due to missing or erroneous origin or shelter address. Thus, what I refer to as my "full sample" consists of 52,972 family-episodes, which both originate in NYC and are not missing any defining data.

In addition to a family identifiers, key variables of DHS origin include household demographics (age, sex, race); household composition (household size, number of children, number of adults, ages, and relationship descriptors); address of origin; and homelessness episode attributes (reason found eligible (e.g., eviction, overcrowding, domestic violence), shelter ID, shelter address, shelter type (Tier II, cluster, contracted hotel, commercial hotel), shelter entry date, shelter exit date, exit type (subsidized, unsubsidized, type of subsidy), exit destination type and address).

A.5.2 HRA and DOL Analytical Data: Reshaping and Conceptualizing

For both the HRA and DOL data, I only retain analytical information only for family heads for computational simplicity. In practice, this is not likely to significantly impact the results, as most families are headed by a single adult, upon who the family depends for both employment and benefits access. Moreover, of necessity, many family covariates, such as race and age, are defined in terms of the household head, so this is consistent with my general approach to defining family attributes.

From a technical standpoint, constructing analytical variables from the HRA and DOL data require four steps. First, using only key individual identifiers (like SSN and name), I create the DHS-HRA and DHS-DOL linkage keys (as described above). Second, I use these keys to respectively merge DHS family-episodes and associate key attributes (like start and end dates) into each of the HRA and DOL datasets. Third, I create the pre/during/post-shelter analytical variables of interest in each dataset. If necessary, I collapse the data so as to maintain a unique observation for each family-episode. Finally, I merge the results back to the DHS Core data, such that my main dataset is neatly appended with the necessary HRA and DOL analytical variables.

In the following section, I outline the basic principles and assumptions used in constructing the key analytical variables. I then describe these variables, organized by source, beginning with those derived from DHS data, followed by HRA and DOL.

A.6 Basic Principles for Analytical Variables

From an econometric standpoint, my population of interest is the universe of potential entrants to NYC family shelter. Viewed from this perspective, my (raw) sample consists of all families who applied for and were found eligible for NYC family shelter from 2010 to 2016.

In the ideal world, I would fully observe all families in my sample, with complete, accurate data on all characteristics of interest, including uncensored lengths of stay and post-shelter outcomes.

In practice, of course, this is impossible. The recency of the data combined with flow sampling guarantees right-censoring; moreover, the censoring point will be variable, with families who entered shelter more recently more likely to be censored.

While I could focus on earlier entrants, there are several strong reasons for not doing so. DHS' information systems underwent a major overhaul in 2011–2012, and the more recent data is higher quality. What's more, shelter capacity has gotten tighter over time, which makes the natural experiment assumption more viable in recent years. Finally, recency means relevance, and all else equal it is of greatest policy interest to characterize the situation today.

But the data is imperfect in other ways, too. While administrative data carries with it the legitimacy of official records, errors remain. In particular, key variables, such as client addresses, can be missing or mistaken. Identifiers can be miscoded or absent as well, and match rates are not 100 percent.

Dealing with these inevitable imperfections means making assumptions. Most important are the following four.

First, I assume censoring is noninformative. That is, conditional on what I can observe, length of stay is independent of censoring time. This is plausible since censoring is an artifact of my flow sampling scheme. Of course, for any given shelter entry date, families that stay longer are more likely to be censored; for purposes of estimating the causal effect of local placement, independent censoring means I must be able to assume uncensored observations are representative of censored ones. In other words, there is no unobservable that is systematically related to both treatment status and censoring.

In some cases, I also make the related assumption that, "selected" observations—families for whom post-shelter outcomes are fully observed because their shelter stays ended early enough relative to the censoring date in my sample—are are representative of those for whom outcomes are unavailable. But I also pursue estimations strategies that allow me to weaken this assumption.

Second, I assume missing data is noninformative. Since missing data can arise in my sample either because a field is missing or because of a non-match, this assumption actually nested two subparts. On one hand, I assume that when fields are missing or miscoded, such errors happen at random—or at least for reasons unrelated to treatment status. On the other, I assume that a non-linkage between DHS and HRA/DOL data consists a true non-match: these families are truly not receiving benefits or not working. Or, at the least, if a false negative occurs (due to, for instance, erroneous SSN), it is at random conditional on observables and not systematically related to treatment status. This assumption is strengthened by the fact that the data is entered by case workers, who both serve as a quality control and a potential source of errors; in either case, the point is that the flawed data is not systematically attributable to family unobservables.

Third, and along related lines, to avoid incidentally truncating the analytical sample, where defensible I code potentially missing data as zero for binary indicators and continuous variables, and as an "unknown" category for categorical variables. This arises in two types of cases. In the first type of case, as with the indicator for health issues, missing values are interpreted as indicative of true absences. Health is an important criterion in shelter placement decisions, and thus families not receiving such a screening are assumed not to have significant limitations. Similarly, a non-link to CA data is interpreted as truly not being on CA. While these assumptions are surely violated in some cases, it is reasonable that they hold on average—and average marginal effects is typically what I am interested in measuring.

The second type of case arises when I introduce covariates to control for potentially confounding influences—but not with the goal of interpreting these covariate coefficients causally. Prominent cases are race and education. Some families do not report their race or have missing education data. I wish to control for race and education when estimating treatment effects, but I do not want to exclude the (small) subsets of families from whom such information is unavailable. Group such families into an "unknown" category is a compromise. While this complicates interpretation of race and education coefficients due to the potential heterogeneity within these groups, these are not the coefficients I care about. What's more, if such data is missing at random, then these categories approximate a group with average characteristics (which is somewhat interpretable). At the other extreme, if data is not unknown at random, unknowingness can itself be informative. As a matter of practice, my results do not much change whether I omit missing data or code it as unknown.

My fourth and final data assumption is to treat family-episodes as independent events, with the exception of clustering standard errors at the family group level. While the data are clearly not completely independent and identically distributed (iid), as an approximation it is not so bad, and it simplifies the analysis. For one thing, over two-thirds of families in the data are present for only one episode. For another, prior research (O'Flaherty, 2010) has demonstrated family homelessness is largely a matter of bad luck—and so the event of becoming homeless, even among those with a history of homelessness, is driven in part by factors beyond a family's control. This, combined with adjusting standard errors appropriately, accounts for arbitrary within family-group correlation of unobservables.

I do, however, explore the robustness of this assumption using several strategies. First, I re-estimate important results keeping only the first episode for each family-group, which leaves the results unchanged. (On the other hand, doing this is undesirable as a control for prior shelter experience, as some families may have had shelter episodes before my sample period began.) Second, at the other extreme, I estimate a family fixed effects specification (which includes families with two or more episodes), and also find my main results to be unchanged.

Having made the necessary assumptions about the data generating process, I adhere to two general rules when defining analytical variables. Note that I use the term "analytical variable" to distinguish variables I create for purposes of analysis from "raw" variables present in the original administrative data. Unless otherwise noted, "variable" used without a qualifier refers to analytical variables, since almost all fields requiring some degree of editing to be suitable for econometric analysis.

The first rule is to define variables at the time of shelter entry. This is sensible because, at least for the DHS data, this is the point at which the data is actually collected. Further, it puts all families on equal footing in terms of their shelter experiences. Finally, for factors where endogeneity might be a concern, it is the point at which conditions are most plausibly exogenous. (For example, initial shelter placement is likely to be more exogenous than subsequent moves to other facilities.) Implicit in this setup is the assumption that variables are time-invariant. As a first approximation, this is probably sufficient. Although family circumstances change (e.g., the birth of a child), most shelter stays are less than two years long, a relatively brief window for evolution. As with most rules, there are a few exceptions to this edict, which I discuss below.

The second rule consists of a two-level hierarchy for assigning characteristics to families. For "compilable" characteristics which are shared by all family members, like shelter assignment or eligibility reason, I do the obvious thing and assign that value upon shelter entry to the family. For compilable characteristics which can be sensibly aggregated across family members (e.g., family size or number of children), I violate the "at-entry" rule and assign the family its maximum (or total, as the case may be) for the episode. For example, family size is defined as the total unique number of family members present during a shelter episode, whether or not initially present. It is relatively common for both children and adults to come and go during the course of a shelter stay (spending interims with relatives or friends). Thus, fully accounting for all family members, rather than just those present on day one, seems more sensible. Econometric considerations guide these choices. For example, *maximum* household size likely best reflects a family's true resource constraints and opportunities, while *initial* shelter assignment is more plausibly exogenous than subsequent moves, which a family may have a stronger role in directing

The second level of family characteristics consists of what I refer to as "uncompilable" characteristics. These are attributes that have no simple aggregate (at least insofar as econometric meaningfulness is concerned), such as age, sex, and race. Rather than try to create summary measures of questionable import (e.g., average age), I instead define these characteristics in terms of the (initial) head of family, on the basis the family head exerts the greater influence on outcomes—especially given that the typical homeless family is consists of a single mother with young children.

With these guiding principles in mind, I now turn to definitions of key concepts and variables. I highlight only the most important variables used in the analysis. For a complete listing of variables and descriptive statistics, refer to the tables at the end of the document. The following sections categorize variables based on their role in the analysis: outcomes, treatments, or explanatory covariates. In the presentation, I emphasize key assumptions, missing data issues, and resolving potential ambiguities.

A.6.1 Covariates

Most of my explanatory variables consist of family characteristics. Female is a dummy that is equal to one for female head of family and zero otherwise. Age is a continuous measure of the duration between the head's date of birth and shelter entry date. Race consists of six mutually exclusive categories: White, Black, Hispanic, Asian, Other, and Unknown (if race is refused or missing). Partner present is a dummy equal to one if the head's significant other is present in shelter, whether or not such a partner is a married spouse. Family size is a count of unique individuals present at any time during a shelter stay. Children (under 21 year of age) and dependents (which may include adults) are similarly defined. Pregnancy is a dummy equal to one if the family indicates a pregnant member at shelter entry, and zero otherwise. School age is a dummy equal to one if there is a family member present between the ages of five and 21 (inclusive) prior to 2014, and between four and 21 from 2014 on (the year universal pre-k (UPK) began in the City). Health issue is a dummy based on screenings performed by DHS and providers both at intake and during shelter stays. It equals one if any family member has a medical, mental health, or substance abuse issue (each consisting of multiple subcategories). Education consists of four mutually exclusive categories: no degree (less than high school), high school graduate, some college or more, and unknown. On Cash Assistance and On Food Stamps are dummies equal to one if a family has an active benefit case in the respective program at the time of shelter entry. Log average quarterly earnings in the year prior to shelter entry is exactly what it sounds like; it factors in all quarters, whether or not a family is working (and I add one to each family's earnings before taking the log, to avoid omitting these families).

The next important category of controls are shelter covariates: variables related to a family's shelter episode. These include categorical variables for primary (official) shelter eligibility reason (8 categories: eviction, overcrowding, conditions, domestic violence, child welfare, existing case, discharge, and other) and facility type (4 categories: Tier II shelter, commercial hotel, cluster unit, or other). I also include a dummy for whether a family receives diversion services designed to prevent homelessness.

All main regression specifications also include fixed effects (dummies) for year of shelter entry, quarter of shelter entry, borough of origin, and shelter borough. Some specifications also include borough-year fixed effects, which are interaction dummies for year and origin borough and year and shelter borough. To control for unobservable facility and provider quality, some specifications additionally feature facility fixed effects (264 dummies). In all cases with dummies, categorical variables, and fixed effects, a base category is dropped in estimation to avoid multicollinearity in the presence of a constant term.

A.6.2 Treatments

I use several definitions of treatment. Key to treatment definitions are the address data maintained by DHS. To be part of the analytical sample, families must have valid, non-missing, geocodable addresses, both of origin and of shelter. Origin address is defined as the family's "last known address" reported to DHS. Note that a small share of families (less than 4%) report other shelters as their prior address. In light of this, and given that unstably housed family may move frequently, it is best to interpret origin addresses as a place where families have some preexisting community ties.

In my main analysis, treatment is defined as a family being placed in its borough of origin. New York City consists of five boroughs, or counties, Manhattan, the Bronx, Brooklyn, Queens, and Staten Island, ranging in size from about half a million persons in Staten Island to 2.5 million in Brooklyn. Clearly, referring to geographies of such breadth does not quite comport with the conventional definition of a neighborhood. Nevertheless, as geographically contiguous entities with legally designated boundaries, distinct identities, and palpable intra-borough affinities, NYC's five counties do embody many of the characteristics associated with small communities. Boroughs are also appealing as a neighborhood definition from the standpoint of treatment balance: about half of homeless families in my sample are placed in shelters in their home boroughs and half in other boroughs.

Alternatively, I also define neighborhoods in terms of the City's 32 school districts, which are administrative boundaries for the public school system. These are the next largest geographies for which data is readily available; about 9% of my sample is placed in their school districts of origin. Smaller units of geography, such as Community Districts or Census Tracts, do not have sufficient local placements to permit precise analysis.

Finally, I consider a continuous measure of treatment that measures the distance, in miles, between a family's last known address and its shelter address. This is based on Cartesian geospatial coordinates produced by GBAT. It is straightforward to calculate the Euclidean straight line distance between pairs of addresses and convert the units to miles.

A.6.3 Outcomes

I consider a range of outcomes. The most salient one, and the one I feature most prominently, is length of stay (LOS). This is a measure, in days, of the elapsed time between a family's entry into shelter and its exit. In particular, I prioritize a "system" LOS concept, which counts gaps in stay towards the total, so long as these gaps are 30 days or fewer; it is not uncommon for families to leave shelter for a few days, then return. Out-of-shelter gaps longer than 30 days are considered true exits; subsequent returns are consider new episodes. Incidentally, this is how another outcome I consider, returns to shelter within a year of exit, is computed. Subsidized exits from shelter are those in which the family receives any form of rental assistance. This encompasses a variety of programs, which typically offer time-limited benefits that partially offset housing costs so long as the family meets eligibility criteria. An alternative duration measure, "shelter" LOS, excludes the interludes from the count. In practice, both measures produce similar results, so I use the shelter concept, because it is simpler.

I also consider two other primary categories of outcomes: public benefit use and labor market results. My public benefit use data comes from HRA and consists of indicators and durations of families' receipt of Cash Assistance and Food Stamps. I focus on two period: the year post-shelter entry and the year post-shelter exit. While I have durations of active receipt, for simplicity I prioritize dummies indicating active program status at any time during these periods.

My labor market data derives from DOL. Again focusing the year post-entry and year post-exit, I construct indicators for positive earnings during any quarter in those years as my measure of employment. Correspondingly, my measure of earnings is log average quarterly earnings. Average quarterly earnings themselves are in real 2016 dollars, are inclusive of all quarters, whether working or not, and have one dollar added to them for each family, so as not to incidentally drop observations when taking logs.

B Policy Background: Family Homelessness in NYC

Neither homelessness nor poverty are foreign to municipalities anywhere in the United States, but nowhere is the intersection of these issues thrown into starker resolution than it is in New York City. Complicating understanding of homelessness—and perhaps, in part, explaining its absence from economists' agenda—is a fundamental misconception about *who* the homeless really are. While disheveled shopping carts, cardboard tatters, and infelicitous hygiene pervade the popular consciousness, it is actually the case that some 200,000 of the 550,000 Americans who are homeless each day are *families with children* (National Alliance to End Homelessness, 2016; Khadduri and Culhane, 2016).

Unlike their single adult counterparts, this misbranded cohort—by and large, single, African-American and Hispanic mothers and young children—suffers not, primarily, from substance abuse and mental illness, but from poverty. Aside from bad luck—often in form of unexpected income loss, health crisis, or domestic strife—these families are otherwise mostly indistinguishable from the marginally housed poor at large, not in the least in that the "shelters" in which they are placed frequently resemble the momentarily unaffordable apartments from whence they came (O'Flaherty, 2010; Culhane et al., 2007; Shinn et al., 1998; Curtis et al., 2013).

For them, homelessness is a temporary condition, not an immutable characteristic—a particularly acute form of poverty manifested in the deprivation of a fundamental element of the consumption bundle (Mullainathan and Shafir, 2013; Desmond, 2016). Getting these families back on their feet fast—or preventing their displacement in the first place—is thus an important policy goal.

The task in an exceedingly difficult one. Since 1994, New York's homeless census has nearly tripled, from 24,000 to 60,000 in 2017. More than two-thirds of these are people in families; fully 23,000 are children (NYC Department of Homeless Services, 2019*b*). Indeed, NYC accounts for about a fifth of all homeless families in the U.S (NYC Department of

Homeless Services, 2019*e*; National Alliance to End Homelessness, 2016).

Family homelessness is particularly pronounced in New York City for two reasons. First, unique among municipalities in the U.S., NYC has a legal right to shelter, the consequence of a series of consent decrees in the 1980s (NYC Independent Budget Office, 2014). The City is legally obligated to provide emergency accommodations to any family able to demonstrate it has no suitable alternative.

This legal mandate has evolved over time as settlements worked their ways through the courts; the right originated from a class action, *McCain v. Koch*, brought by the Legal Aid Society in 1983, in which New York State Court held the City and State were required to provide homeless families with emergency housing under the State Constitution and Social Services Law (NYC Independent Budget Office, 2014; University of Michigan Law School, 2017; Kaufman and Chen, 2008) [15].

Derivative cases during the ensuing decades established standards for temporary shelter, as homeless services where governed by a mix of executive policymaking and judicial edict. A formal settlement was not reached until 2008, in the form of *Boston v. City of New York*, whereupon the Bloomberg administration, Legal Aid, and the courts came to agreement on appropriate eligibility determination and shelter management standards (NYC Independent Budget Office, 2014; University of Michigan Law School, 2017; Kaufman and Chen, 2008). These mandates mean that NYC faces a steady inflow of homeless families in ways that other cities do not; indeed, a tenth of family shelter entrants report most recent prior addresses that are outside of the City.

Further complicating matters is NYC's notoriously competitive real estate market. New York is a city of renters, with over two-thirds of households renting their residences, nearly double the national average. In the decade ending in 2015, median rent in NYC grew three times the pace of median incomes (18.3% versus 6.6%). Vacancy rates are consistently below 4% (NYU Furman Center, 2016). According the City, demand for affordable apartments exceeds supply by a factor of two; approximately half of renters in the City as rent-burdened, defined as allocating more than 30% of household income to rent (NYC Mayor's Office, 2017). The situation is especially severe for the lowest income families most at-risk for homelessness. Nine in ten households with income below 30% of the area median spent upwards of 30% of their income on rent (NYU Furman Center, 2016).

Expensive housing, paired with poverty's relentless vicissitudes and a legal escape valve, make NYC's steady rise in homelessness none too surprising. The City has had to expand shelter apace. In 2016, shelter vacancy rates were easily below 1%, even as commercial hotels were brought into the mix to fill gaps (NYC Mayor's Office, 2017). Yet adding capacity is a Sisyphean struggle of its own, with proposals for new shelters frequently greeted by virulent

[15] A 1981 predecessor case, also brought by Legal Aid, *Callahan v. Cary*, introduced the right to shelter for single adults. (NYC Independent Budget Office, 2014)

community opposition (Stewart, 2017). Homeless service provision is thus forced to strike a delicate compromise between policy ideals and political realities, an important constraint on optimal implementation.

Responsibility for managing shelters and supports for homeless families and individuals falls primarily to the Department of Homeless Services (DHS), a Mayoral agency under the purview of the larger City's Department of Social Services (DSS), which is the City's officially designated local social service agency. Families apply for shelter at at a central intake center in the Bronx, known as PATH (Prevention Assistance and Temporary Housing). There, they are screened by HRA caseworkers for prevention services, including eligibility for temporary rental assistance and anti-eviction legal services, as well as for domestic violence. If alternative housing remedies are unavailable, families apply for shelter apartments, which requires, among other things proper, identification and detailed housing histories. Families are given temporary (generally about 10-day) accommodations while DHS investigative staff assesses eligibility. Families deemed eligible are then given formal shelter assignments by dedicated placement staff, who consider such criteria as family size, health issues, safety, and proximity to children's schools. Often the preliminary and formal shelter assignments are the same[16]. It is this group of families (those deemed eligible) and this placement step (initial formal shelter assignment) that constitute my sample and treatment.

NYC's family shelter system is vast and complex. As of November 2016, the City's shelter portfolio consisted of 169 traditional Tier II shelters (housing 8,617 families and 26,225 individuals), 276 cluster apartments scattered in otherwise private buildings (3,045 familes ; 11,067 individuals), and 68 commercial hotels (2,057 families; 5,798 individuals) (NYC Mayor's Office, 2017).

It is also expensive. In 2017, the average cost of sheltering one family for one night (inclusive of rent and services) was $171. Overall, DHS' budget, inclusive of management operations, is $1.8 billion—and this does not include welfare benefits administered by other agencies (NYC Mayor's Office of Operations, 2017).

Also of note is how services are carried out. While DHS does operate some shelters directly, most homeless services provision is carried out through contracts with community-based non-profit organizations who operate shelters. A case in point: 82% of DHS' budget consists of such contracts. This service arrangement is not unique to homeless services; most social service programs in the City are administered this way (NYC Mayor's Office of Operations, 2017).

Given homelessness' stubborn rise, my sample period, 2010–2016 has been a time of flux for homeless policy in New York City. The sample begins in the aftermath of the Great Recession and concludes at a time when the economy had regained nearly full strength.

[16]Details are based on NYC Department of Homeless Services (2019*c*); NYC Independent Budget Office (2014) as well as author's conversations with City officials.

Michael Bloomberg's mayoralty spanned the first four years, while Bill de Blasio's tenure began in 2014. Developments at the State and Federal levels—both critical funding sources—has also played a leading role.

Throughout this period, a pillar of the City's homelessness strategy has been community continuity. To the extent capacity allows, the City endeavors to place families in their neighborhoods of origin. Predicated on the goal of keeping children in their home schools', the policy reflects a more general premise—that families are better positioned to expeditiously return to permanent housing when they remain connected to their support networks, including relatives, friends, and places of work and worship (NYC Mayor's Office, 2017). Since at least 1997, the city has monitored the share of families placed in shelters according to their youngest child's school as a DHS performance indicator. By this measure, 84 percent of families where successfully placed in their home neighborhoods as of 2010. However, capacity constraints have become increasingly binding as the shelter population has grown. By 2017, this share of families placed in proximity to their children's schools had dropped to 50 percent (NYC Mayor's Office of Operations, 2002, 2012, 2017).

While a full accounting homeless policy developments is beyond the scope of this paper, a brief discussion of its contours provide context. Core elements of the City's strategy to reduce homelessness include prevention, affordable housing, and rental assistance[17].

Homebase, the City's signature homeless prevention program, offers families at risk for homelessness a panoply of supports, ranging from case management and counseling to benefits assistance and referrals. Instituted in 2004, as of 2016 it serves 25,000 families a year. Academic research finds it to be effective in forestalling shelter entries. Further, as of 2017, the City spends upward of $62 million a year on anti-eviction legal services, which helped to avoid about 20,000 evictions per year. Similarly, emergency rental assistance, typically for families in arrears, stop temporary difficulties from ballooning. From 2014–2016, the City allocated $551 million to assisting 161,000 such households. In terms of affordable housing, the de Blasio administration has pledged to create of preserve 200,000 units, of which 62,000 were financed as of 2016. Strategies include zoning regulations, tax credits, and capital funding.

For families in shelter, rental assistance is frequently a catalyst for returns to permanent housing. Advantage, the most prominent Bloomberg-era program, provided some 25,000 formerly homeless families with two years of subsidized housing. At its peak it cost $207 million, but ended in controversial fashion in 2011 when the State withdrew funding. In its place has come Living in Communities (LINC), launched by the de Blasio administration in 2014. LINC, a collection of six programs targeting families meeting various criteria—

[17]The following discussion of prevention, affordable housing, and rental assistance is primarily based NYC Mayor's Office (2017) and discussions with City officials. Additional details are provided by: NYC Department of Homeless Services (2019*d*); NYC Independent Budget Office (2011, 2014)

involving such things as employment, age, or domestic violence status—offers time-limited (usually 2–5 years) rental assistance to families meeting income standards (usually below 200% of the federal poverty level) and minimum shelter stays (usually 90 days). Along related lines, CityFEPS provides families who have been evicted or are at-risk for losing their homeless with an "eviction prevention supplement." Both programs require families to contribute 30% of their income towards rent; the subsidy covers the remainder, up to a maximum of $1,515 for a family of three. From 2014 to 2016, the programs combined to serve more than 26,000 people. Subsequent to my study period, LINC and CityFEPS have been replaced by CityFHEPS (NYC Human Resources Administration, 2019*a*). Traditional federal programs, including Section 8 Housing Choice Vouchers and public housing also play a role, though both have been limited by funding constraints and long waiting lists in recent years. There are also some smaller programs.

Of course, homeless services is but one—albeit highly visible—component of NYC's safety net for low-income families. The City's Human Resources Administration (HRA)—which along with DHS comprises the the Department of Social Services (DSS)—oversees the nation's largest apparatus for administering poverty alleviation programs[18]. Notable in HRA's portfolio are the "big three" social benefit programs: Cash Assistance (CA), the Supplemental Nutrition Assistance Program (SNAP, formerly know as Food Stamps), and Medicaid. Because Cash Assistance and Food Stamps figure prominently in the analysis—and also because they help to characterize the poverty that homeless families face—a bit of background is helpful.

Cash Assistance (CA) consists of Temporary Assistance for Needy Families (TANF; which, in New York, is referred to as FA, or Family Assistance) and its State counterpart for single adults and time-limited families, Safety Net Assistance (SNA). Sometimes described as "public assistance" or "welfare," CA provides unrestricted monetary transfers to poor individuals and families. As such, CA can be thought of as the present-day version of the classic poverty alleviation program. Since welfare reform of the 1990s, work requirements have been the centerpiece of CA. In order to maintain eligibility, able recipients must be engaged in 30 hours of employment activities per week, which can include such things as training, education, and job search. (In practice, exemptions are common and sanctions may be unevenly enforced.) Eligibility for CA is limited to the very poorest. In New York, maximum monthly income at initial eligibility is $879 per month for a family of three. Benefits are similarly tight, topping out at $789 a month for a three-person family. Together, these strict requirements, and well as the need for periodic recertification, means benefits can frequently

[18] In fact, the relationship between DHS and HRA is complicated and dynamic, largely for reasons having to do with the challenges of family homelessness. DHS was originally part of HRA, until it was spun off as an independent agency in 1993. However, in 2016, Mayor de Blasio again consolidated DHS and HRA under the DSS umbrella, managed by a single commissioner, Steve Banks. Nevertheless, it remains conventional to refer to the departments as distinct. See NYC Department of Homeless Services (2019*a*) for more detail.

lapse as families are sanctioned. 358,000 New York City residents were actively receiving CA as of August 2017 (Cohen and Giannarelli, 2016; New York State Office of Temporary and Disability Assistance, 2016, 2015, 2017; NYC Human Resources Administration, 2019*b*).

Food Stamps (FS), officially known as SNAP, provides low-income families with categorical dollars each month that must be spent on food. Its eligibility standards are less strict than CA; correspondingly, its caseloads are much larger. Income is the primary criterion; as of 2017, a family of three with earned income could quality so long as household income was $30,636 or less ($2,500/month). (For such families without earnings, the eligibility standard was $26,556.) While some able-bodied adults without dependents may be required to work, such requirements are typically mild and unevenly enforced. Benefits, like eligibility, is based on a formula determined by family size. In 2017, a family of three receives $504 monthly. 1.7 million NYC residents received SNAP as of August 2017 (New York State Office of Temporary and Disability Assistance, 2019; NYC Human Resources Administration, 2019*b*).

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C Supplementary Tables

Table A.1: Summary of Key Variables by Shelter Entry Year

	Year of Shelter Entry							
	2010	2011	2012	2013	2014	2015	2016	Total
A. Shelter Entry Characteristics								
Families Entering	9,911	7,475	7,937	7,642	8,752	8,161	9,375	59,253
Individuals Entering	31,789	25,219	27,873	26,619	29,610	27,264	30,370	198,744
Borough Placement	0.66	0.59	0.51	0.51	0.44	0.46	0.38	0.51
Placement Distance (miles)	4.68	5.21	5.88	5.80	6.43	6.37	6.91	5.89
Ineligibility Rate	0.25	0.23	0.24	0.21	0.17	0.28	0.26	0.23
Aversion Ratio	1.53	1.17	1.09	1.05	0.75	1.58	1.32	1.22
Occupancy Rate	0.89	0.90	0.95	0.96	0.96	0.97	0.96	0.94
B. Stays and Returns								
Length of Stay	365.1	441.2	451.9	436.2	436.3	438.1	417.3	424.3
Subsidized Exit	0.34	0.14	0.26	0.39	0.50	0.56	0.53	0.39
Returned to Shelter	0.12	0.15	0.17	0.16	0.13	0.15	0.20	0.15
C. Year Post-Shelter Entry								
Cash Assistance	0.77	0.80	0.81	0.79	0.79	0.81	0.72	0.78
Food Stamps	0.91	0.90	0.91	0.91	0.91	0.89	0.85	0.90
Employed	0.47	0.44	0.44	0.46	0.52	0.53	0.48	0.48
Avg. Quarterly Earnings	1094.6	1015.1	958.1	1045.2	1232.8	1416.2	1500.6	1188.9
D. Year Post-Shelter Exit								
Cash Assistance	0.72	0.72	0.74	0.74	0.77	0.77	0.68	0.74
Food Stamps	0.89	0.88	0.89	0.89	0.89	0.88	0.85	0.88
Employed	0.44	0.43	0.44	0.47	0.49	0.49	0.40	0.45
Avg. Quarterly Earnings	1219.9	1169.8	1175.5	1322.3	1476.9	1550.0	1342.3	1306.2
E. Censoring								
Family Spell	0.00	0.00	0.00	0.01	0.02	0.04	0.07	0.02
Full Year Post-Spell	0.00	0.00	0.01	0.02	0.04	0.08	0.21	0.05
CA/FS Year Post-Entry	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.16
CA/FS Year Post-Exit	0.01	0.03	0.07	0.13	0.31	0.72	1.00	0.34
Labor Year Post-Exit	0.01	0.02	0.06	0.11	0.24	0.61	0.98	0.30

Includes only family shelter entrants originating from NYC. Unit of observation is family-spell. Families and individual entering are counts; all other statistics are family-spell means.

Table A.2: Families by Number of Spells

Homeless Spells	# of Families	Percent
1	37,587	78.3
2	8,015	16.7
3	1,831	3.8
4+	544	1.1
Total	47,977	100.0

Includes only family shelter entrants originating from NYC.

Table A.3: Descriptives and Random Assignment

	Overall			Randomization Check		
Variable	N	Mean	SD	Out-of-Boro	In-Boro	Diff.
Year Entered Shelter	59,253	2013.01	2.07	2013.38	2012.65	-0.72**
Month Entered Shelter	59,253	6.52	3.40	6.78	6.28	-0.50**
Q1 Entry	59,253	0.25	0.43	0.22	0.27	0.05**
Q2 Entry	59,253	0.23	0.42	0.22	0.25	0.03**
Q3 Entry	59,253	0.28	0.45	0.31	0.26	-0.05**
Q4 Entry	59,253	0.24	0.42	0.25	0.22	-0.03**
Manhattan Origin	59,253	0.12	0.33	0.16	0.09	-0.07**
Bronx Origin	59,253	0.41	0.49	0.33	0.49	0.16**
Brooklyn Origin	59,253	0.32	0.47	0.31	0.32	0.01**
Queens Origin	59,253	0.12	0.33	0.15	0.10	-0.06**
Staten Island Origin	59,253	0.03	0.16	0.05	0.01	-0.04**
Family Size	59,253	3.35	1.39	3.34	3.36	0.02*
Family Members Under 18	59,253	1.97	1.19	1.95	1.99	0.04**
Oldest Child's Grade	59,253	2.57	5.32	1.95	3.18	1.23**
Health Issue Present	59,253	0.30	0.46	0.32	0.28	-0.04**
Eligibility: Eviction	59,253	0.33	0.47	0.28	0.39	0.10**
Eligibility: Overcrowding	59,253	0.18	0.38	0.17	0.19	0.02**
Eligibility: Conditions	59,253	0.08	0.28	0.08	0.09	0.01**
Eligibility: Domestic Violence	59,253	0.30	0.46	0.37	0.22	-0.15**
Eligibility: Other	59,253	0.11	0.31	0.10	0.11	0.01**
Eligibility: Unknown	59,253	0.00	0.01	0.00	0.00	0.00
Female	59,253	0.92	0.28	0.92	0.91	-0.01**
Age	59,253	31.54	8.86	30.94	32.13	1.20**
Partner/Spouse Present	59,253	0.26	0.44	0.27	0.24	-0.03**
Pregnant	59,253	0.07	0.25	0.07	0.06	-0.01**

Treatment defined as placed in-borough. Group contrasts obtained from separate bivariate OLS regressions of each characteristic on treatment indicator. Differences between in-borough and out-of-borough means are coefficients on treatment indicator. Standard errors clustered at the family group level. Unit of observation is family-spell. Full sample. * $p < 0.10$, ** $p < 0.05$

Table 3 (Cont.): Descriptives and Random Assignment

	Overall			Randomization Check		
Variable	N	Mean	SD	Out-of-Boro	In-Boro	Diff.
Black	59,253	0.56	0.50	0.57	0.55	-0.02**
White	59,253	0.03	0.16	0.03	0.02	-0.01**
Hispanic	59,253	0.38	0.48	0.36	0.39	0.03**
Asian	59,253	0.00	0.07	0.00	0.00	-0.00
Other Race	59,253	0.00	0.06	0.00	0.00	-0.00
Unknown Race	59,253	0.03	0.17	0.03	0.03	-0.00*
No Degree	59,253	0.57	0.50	0.56	0.58	0.01**
High School Grad	59,253	0.32	0.47	0.32	0.32	-0.01*
Some College or More	59,253	0.05	0.22	0.05	0.05	-0.00
Unknown Education	59,253	0.06	0.24	0.06	0.06	-0.00
On Cash Assistance	59,253	0.35	0.48	0.36	0.35	-0.01**
On Food Stamps	59,253	0.73	0.44	0.73	0.73	0.00
Employed Year Pre	59,253	0.43	0.50	0.44	0.43	-0.01**
Log AQ Earnings Year Pre	59,253	3.01	3.58	3.02	2.99	-0.03
Tier II Shelter	59,253	0.55	0.50	0.55	0.55	0.01**
Commercial Hotel	59,253	0.28	0.45	0.30	0.25	-0.05**
Family Cluster Unit	59,253	0.16	0.37	0.14	0.19	0.05**
Other Facility	59,253	0.01	0.10	0.01	0.01	-0.01**
Manhattan Shelter	59,253	0.18	0.39	0.27	0.09	-0.18**
Bronx Shelter	59,253	0.39	0.49	0.29	0.49	0.20**
Brooklyn Shelter	59,253	0.27	0.44	0.22	0.32	0.11**
Queens Shelter	59,253	0.15	0.36	0.21	0.10	-0.11**
Staten Island Shelter	59,253	0.01	0.09	0.01	0.01	-0.01**
School District Placement	54,306	0.10	0.30	0.00	0.19	0.19**
Placement Distance (miles)	54,306	5.89	4.65	9.27	2.66	-6.61**
Borough Placement	59,253	0.51	0.50	0.00	1.00	1.00

Treatment defined as placed in-borough. Group contrasts obtained from separate bivariate OLS regressions of each characteristic on treatment indicator. Differences between in-borough and out-of-borough means are coefficients on treatment indicator. Standard errors clustered at the family group level. Unit of observation is family-spell. Full sample. * $p < 0.10$, ** $p < 0.05$

Table A.4: Descriptives and Random Assignment

Variable	Overall N	Overall Mean	Overall SD	Randomization Check Out-of-Boro	Randomization Check In-Boro	Randomization Check Diff.
Jan Entry	59,253	0.09	0.29	0.08	0.10	0.01**
Feb Entry	59,253	0.08	0.26	0.07	0.08	0.02**
Mar Entry	59,253	0.08	0.27	0.07	0.09	0.02**
Apr Entry	59,253	0.08	0.27	0.07	0.08	0.02**
May Entry	59,253	0.08	0.27	0.07	0.08	0.01**
Jun Entry	59,253	0.08	0.27	0.08	0.08	0.01**
Jul Entry	59,253	0.09	0.28	0.10	0.08	-0.02**
Aug Entry	59,253	0.10	0.30	0.11	0.09	-0.02**
Sep Entry	59,253	0.10	0.30	0.10	0.09	-0.02**
Oct Entry	59,253	0.09	0.28	0.09	0.08	-0.01**
Nov Entry	59,253	0.08	0.27	0.08	0.07	-0.01**
Dec Entry	59,253	0.07	0.26	0.08	0.07	-0.01**
2010 Entry	59,253	0.17	0.37	0.12	0.22	0.10**
2011 Entry	59,253	0.13	0.33	0.10	0.15	0.04**
2012 Entry	59,253	0.13	0.34	0.13	0.14	0.00

Treatment defined as placed in-borough. Group contrasts obtained from separate bivariate OLS regressions of each characteristic on treatment indicator. Differences between in-borough and out-of-borough means are coefficients on treatment indicator. Standard errors clustered at the family group level. Unit of observation is family-spell. Sample is all NYC family shelter entrants from 2010–2016 with non-missing origin and shelter boroughs. * $p < 0.10$, ** $p < 0.05$

Table A.5: Descriptives and Random Assignment

Variable	Overall N	Overall Mean	Overall SD	Randomization Check Out-of-Boro	Randomization Check In-Boro	Randomization Check Diff.
Log Length of Stay	59,253	5.50	1.24	5.43	5.57	0.14**
Log Shelter LOS (Excl. Gaps)	59,253	5.50	1.24	5.42	5.57	0.14**
Length of Stay (Days)	59,253	424.33	406.67	410.96	437.35	26.40**
Log LOS (2017)	59,253	5.48	1.21	5.40	5.55	0.15**
Subsidized Exit	57,962	0.39	0.49	0.39	0.40	0.01*
Unsubsidized Exit	57,962	0.60	0.49	0.60	0.60	-0.00
Returned to Shelter (One Year)	52,274	0.15	0.36	0.16	0.14	-0.03**
Cash Assistance Post Entry	59,253	0.78	0.41	0.77	0.79	0.02**
CA Post Entry Percent	59,253	0.62	0.41	0.61	0.64	0.02**
Food Stamps Post Entry	59,253	0.90	0.31	0.89	0.90	0.01**
FS Post Entry Percent	59,253	0.82	0.34	0.80	0.83	0.03**
Employed Post Entry	59,253	0.48	0.50	0.48	0.48	0.01
Empl. Post Entry Percent	59,253	0.34	0.41	0.33	0.34	0.01**
Log AQ Earnings Post Entry	59,253	3.38	3.68	3.33	3.42	0.09**
AQ Earnings Post Entry	59,253	1188.87	2274.61	1153.03	1223.76	70.73**
Cash Assistance Post Exit	48,082	0.74	0.44	0.73	0.74	0.01**
CA Post Exit Percent	59,253	0.41	0.44	0.39	0.42	0.03**
Food Stamps Post Exit	48,082	0.88	0.32	0.88	0.89	0.01**
FS Post Exit Percent	59,253	0.60	0.45	0.57	0.62	0.05**
Employed Post Exit	48,082	0.45	0.50	0.45	0.46	0.01
Empl. Post Exit Percent	59,253	0.27	0.40	0.26	0.29	0.03**
Log AQ Earnings Post Exit	48,082	3.27	3.73	3.22	3.31	0.09**
AQ Earnings Post Exit	48,082	1306.24	2515.85	1247.82	1358.75	110.93**

Treatment defined as placed in-borough. Group contrasts obtained from separate bivariate OLS regressions of each characteristic on treatment indicator. Differences between in-borough and out-of-borough means are coefficients on treatment indicator. Standard errors clustered at the family group level. Unit of observation is family-spell. Sample is all NYC family shelter entrants from 2010–2016 with non-missing origin and shelter boroughs. * $p < 0.10$, ** $p < 0.05$

Table A.6: OLS Outcome Robustness

	Full Sample					Non-DV	Pre-2015
Outcome	Outcome Mean (1)	Raw (2)	Placement (3)	Main (4)	Shelter (5)	Main (6)	Main (7)
A. Stays and Returns							
Log LOS (excl. gaps)	5.496**	0.141**	0.108**	0.120**	0.115**	0.086**	0.126**
	(1.243)	(0.010)	(0.010)	(0.011)	(0.011)	(0.012)	(0.013)
	{59,253}	{59,253}	{59,253}	{59,253}	{59,247}	{41,744}	{41,717}
Length of Stay (days)	424.333**	26.397**	17.587**	23.090**	22.341**	19.767**	24.741**
	(406.668)	(3.334)	(3.417)	(3.544)	(3.541)	(4.430)	(4.446)
	{59,253}	{59,253}	{59,253}	{59,253}	{59,247}	{41,744}	{41,717}
Log LOS (as of 2017)	5.476**	0.146**	0.105**	0.117**	0.113**	0.083**	0.125**
	(1.215)	(0.010)	(0.010)	(0.011)	(0.011)	(0.011)	(0.013)
	{59,253}	{59,253}	{59,253}	{59,253}	{59,247}	{41,744}	{41,717}
Unsubsidized Exit	0.600**	-0.004	-0.020**	-0.017**	-0.016**	-0.016**	-0.015**
	(0.490)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)
	{57,962}	{57,962}	{57,962}	{57,962}	{57,954}	{40,766}	{41,420}
B. Year Post-Shelter Entry							
CA Percent of Year	0.624**	0.024**	0.009**	0.004	0.004	0.006	0.006
	(0.410)	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)
	{59,253}	{59,253}	{59,253}	{59,253}	{59,247}	{41,744}	{41,717}
FS Percent of Year	0.815**	0.032**	0.004	-0.001	-0.000	-0.006**	0.004
	(0.342)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)
	{59,253}	{59,253}	{59,253}	{59,253}	{59,247}	{41,744}	{41,717}
Employed: Quarterly Proportion	0.337**	0.010**	0.014**	0.012**	0.011**	0.011**	0.011**
	(0.406)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
	{59,253}	{59,253}	{59,253}	{59,253}	{59,247}	{41,744}	{41,717}
Avg. Quarterly Earnings	1188.870**	70.734**	36.204*	27.902	23.739	29.523	22.168
	(2274.606)	(18.974)	(19.470)	(17.893)	(18.000)	(22.207)	(20.448)
	{59,253}	{59,253}	{59,253}	{59,253}	{59,247}	{41,744}	{41,717}
C. Year Post-Shelter Exit							
CA Percent of Year	0.407**	0.027**	-0.002	-0.006*	-0.005	-0.002	-0.001
	(0.435)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
	{59,253}	{59,253}	{59,253}	{59,253}	{59,247}	{41,744}	{41,717}
FS Percent of Year	0.596**	0.053**	-0.004	-0.010**	-0.008**	-0.013**	-0.003
	(0.451)	(0.004)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
	{59,253}	{59,253}	{59,253}	{59,253}	{59,247}	{41,744}	{41,717}
Employed: Quarterly Proportion	0.270**	0.031**	0.007**	0.004	0.004	0.006	0.005
	(0.397)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
	{59,253}	{59,253}	{59,253}	{59,253}	{59,247}	{41,744}	{41,717}
Avg. Quarterly Earnings	1306.237**	110.929**	48.035**	33.994	28.066	38.382	24.918
	(2515.846)	(23.163)	(24.293)	(23.227)	(23.470)	(29.069)	(25.269)
	{48,082}	{48,082}	{48,082}	{48,082}	{48,076}	{33,761}	{39,974}
Time Control		None	Year^3	Year^3	Year^3	Year^3	Year^3
Placement Controls		No	Yes	Yes	Yes	Yes	Yes
Family & Shelter Controls		No	No	Yes	Yes	Yes	Yes
Shelter FE		No	No	No	Yes	No	No

Each cell reports the coefficient on in-borough shelter placement from a separate OLS regression of the row-delineated outcome on the treatment indicator, controlling for the column-enumerated covariates. Supercolumns give samples. Standard errors clustered at family group level in parentheses. Number of observations given in braces. * $p < 0.10$, ** $p < 0.05$

Table A.7: Compliance Type Shares: Ineligibility Rate Instrument

	1%	1.5%	2%
Compliers	0.08	0.08	0.07
Always-Takers	0.64	0.64	0.64
Never-Takers	0.28	0.28	0.28

Main sample. Results from linear first-stage, controlling for year and month of shelter entry. Percentages in second row refer to percentiles used as thresholds to define low and high instrument values. See Cassidy (2019) for estimation method details.

Table A.8: Compliance Type Shares: Aversion Ratio

	1%	1.5%	2%
Compliers	0.10	0.10	0.09
Always-Takers	0.62	0.62	0.62
Never-Takers	0.28	0.28	0.28

Main sample. Results from linear first-stage, controlling for year and month of shelter entry. Percentages in second row refer to percentiles used as thresholds to define low and high instrument values. See Cassidy (2019) for estimation method details.

Table A.9: Complier Characteristics: Ineligibility Rate Instrument

	Compliers	Non-Compliers	Diff.
Manhattan Origin	0.00	0.14	-0.13
	(0.003)	(0.000)	[-2.56]
Bronx Origin	0.57	0.39	0.18
	(0.006)	(0.000)	[2.28]
Brooklyn Origin	0.25	0.32	-0.07
	(0.005)	(0.000)	[-0.99]
Queens Origin	0.10	0.13	-0.02
	(0.003)	(0.000)	[-0.45]
Staten Island Origin	0.02	0.03	-0.00
	(0.000)	(0.000)	[-0.33]
Health Issue Present	0.33	0.30	0.04
	(0.004)	(0.000)	[0.61]
Eligibility: Eviction	0.29	0.34	-0.05
	(0.005)	(0.000)	[-0.67]
Eligibility: Overcrowding	0.16	0.18	-0.02
	(0.003)	(0.000)	[-0.34]
Eligibility: Conditions	0.11	0.08	0.03
	(0.002)	(0.000)	[0.67]
Eligibility: Domestic Violence	0.30	0.30	0.00
	(0.004)	(0.000)	[0.01]
Eligibility: Other	0.08	0.11	-0.03
	(0.003)	(0.000)	[-0.67]
Female	0.97	0.91	0.06
	(0.002)	(0.000)	[1.26]
Partner/Spouse Present	0.31	0.25	0.06
	(0.004)	(0.000)	[0.99]
Pregnant	0.04	0.07	-0.03
	(0.001)	(0.000)	[-0.86]
Black	0.43	0.57	-0.14
	(0.006)	(0.000)	[-1.79]
Hispanic	0.46	0.37	0.09
	(0.006)	(0.000)	[1.18]
White	0.06	0.02	0.04
	(0.001)	(0.000)	[1.57]
No Degree	0.61	0.57	0.05
	(0.005)	(0.000)	[0.67]
High School Grad	0.30	0.32	-0.02
	(0.005)	(0.000)	[-0.29]
Some College or More	0.06	0.05	0.01
	(0.001)	(0.000)	[0.21]
Unknown Education	0.02	0.07	-0.05
	(0.001)	(0.000)	[-1.27]
On Cash Assistance	0.30	0.36	-0.06
	(0.005)	(0.000)	[-0.78]
On Food Stamps	0.75	0.73	0.02
	(0.006)	(0.000)	[0.29]
Employed Year Pre	0.39	0.44	-0.05
	(0.005)	(0.000)	[-0.67]
Tier II Shelter	0.63	0.54	0.08
	(0.004)	(0.000)	[1.27]
Commercial Hotel	0.08	0.29	-0.21
	(0.005)	(0.000)	[-3.08]
Family Cluster Unit	0.19	0.16	0.02
	(0.003)	(0.000)	[0.46]
Family Size 1–3	0.54	0.64	-0.11
	(0.006)	(0.000)	[-1.43]
Family Size 4–5	0.39	0.28	0.11
	(0.004)	(0.000)	[1.68]
Family Size 6+	0.07	0.08	-0.01
	(0.002)	(0.000)	[-0.27]
Age	31.69	31.53	0.16
	(1.350)	(0.013)	[0.14]
Log AQ Earnings Year Pre	2.73	3.03	-0.30
	(0.259)	(0.002)	[-0.60]

Main sample. Treatment is in-borough placement. Instrument is 15-day moving average of the initial ineligibility rate for 30-day application period. Compliers are families placed in-borough when the ineligibility rate is high, but not otherwise. Non-compliers consist of always-takers and never-takers. Compiler and non-complier characteristics, adjusted for year and month of shelter entry, are estimated from the algorithm described in the Cassidy (2019). Standard errors (in parentheses) and differences in means (with t-stats in brackets) are calculated from 200 bootstrap replications, clustering by family.

Table A.10: Complier Characteristics: Aversion Ratio Instrument

	Compliers	Non-Compliers	Diff.
Manhattan Origin	0.09	0.13	-0.04
	(0.001)	(0.000)	[-1.18]
Bronx Origin	0.55	0.39	0.16
	(0.004)	(0.000)	[2.67]
Brooklyn Origin	0.20	0.33	-0.13
	(0.003)	(0.000)	[-2.29]
Queens Origin	0.12	0.13	-0.01
	(0.002)	(0.000)	[-0.17]
Staten Island Origin	0.03	0.03	0.01
	(0.000)	(0.000)	[0.51]
Health Issue Present	0.35	0.29	0.06
	(0.002)	(0.000)	[1.27]
Eligibility: Eviction	0.33	0.34	-0.01
	(0.003)	(0.000)	[-0.13]
Eligibility: Overcrowding	0.15	0.18	-0.03
	(0.002)	(0.000)	[-0.61]
Eligibility: Conditions	0.11	0.08	0.02
	(0.001)	(0.000)	[0.73]
Eligibility: Domestic Violence	0.27	0.30	-0.03
	(0.002)	(0.000)	[-0.59]
Eligibility: Other	0.10	0.11	-0.01
	(0.001)	(0.000)	[-0.28]
Female	0.94	0.91	0.03
	(0.001)	(0.000)	[0.82]
Partner/Spouse Present	0.28	0.25	0.03
	(0.002)	(0.000)	[0.61]
Pregnant	0.05	0.07	-0.02
	(0.001)	(0.000)	[-0.66]
Black	0.47	0.57	-0.09
	(0.004)	(0.000)	[-1.51]
Hispanic	0.43	0.37	0.06
	(0.003)	(0.000)	[0.98]
White	0.05	0.02	0.03
	(0.000)	(0.000)	[1.46]
No Degree	0.59	0.57	0.02
	(0.003)	(0.000)	[0.41]
High School Grad	0.31	0.32	-0.01
	(0.002)	(0.000)	[-0.21]
Some College or More	0.07	0.05	0.02
	(0.001)	(0.000)	[0.76]
Unknown Education	0.02	0.07	-0.04
	(0.001)	(0.000)	[-1.47]
On Cash Assistance	0.23	0.37	-0.14
	(0.003)	(0.000)	[-2.43]
On Food Stamps	0.70	0.74	-0.04
	(0.003)	(0.000)	[-0.63]
Employed Year Pre	0.39	0.44	-0.05
	(0.003)	(0.000)	[-0.91]
Tier II Shelter	0.59	0.55	0.04
	(0.003)	(0.000)	[0.82]
Commercial Hotel	0.14	0.29	-0.16
	(0.003)	(0.000)	[-2.83]
Family Cluster Unit	0.19	0.16	0.02
	(0.001)	(0.000)	[0.63]
Family Size 1–3	0.60	0.64	-0.04
	(0.003)	(0.000)	[-0.76]
Family Size 4–5	0.35	0.28	0.06
	(0.003)	(0.000)	[1.26]
Family Size 6+	0.05	0.08	-0.02
	(0.001)	(0.000)	[-0.82]
Age	32.20	31.47	0.73
	(0.949)	(0.014)	[0.74]
Log AQ Earnings Year Pre	2.76	3.03	-0.27
	(0.147)	(0.002)	[-0.71]

Main sample. Treatment is in-borough placement. Instrument is 15-day moving average of the aversion ratio. Compliers are families placed in-borough when the aversion ratio is high, but not otherwise. Non-compliers consist of always-takers and never-takers. Compiler and non-complier characteristics, adjusted for year and month of shelter entry, are estimated from the algorithm described in the Cassidy (2019). Standard errors (in parentheses) and differences in means (with t-stats in brackets) are calculated from 200 bootstrap replications, clustering by family.

Table A.11: IV Robustness: Ineligibility Rate

	Borough			School District			Distance		
	Full	Non-DV	Pre-2015	Full	Non-DV	Pre-2015	Full	Non-DV	Pre-2015
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
A. Stays and Returns									
Log Length of Stay	1.367**	0.971*	5.083*	4.650**	2.205*	7.198**	-0.203**	-0.166*	-0.497**
	(0.527)	(0.573)	(2.820)	(2.084)	(1.201)	(3.135)	(0.078)	(0.097)	(0.213)
	[28.8]	[18.3]	[4.0]	[8.7]	[11.7]	[6.9]	[17.1]	[8.6]	[7.2]
Subsidized Exit	-0.789**	-1.145**	-2.513*	-2.070**	-1.998**	-2.244**	0.094**	0.161**	0.173**
	(0.257)	(0.380)	(1.489)	(0.885)	(0.721)	(1.017)	(0.037)	(0.071)	(0.084)
	[26.2]	[16.8]	[3.3]	[9.2]	[12.7]	[7.2]	[15.6]	[7.7]	[6.0]
Returned to Shelter	0.287*	0.362*	-0.301	1.287	1.039	-0.201	-0.039	-0.066	0.017
	(0.166)	(0.210)	(0.405)	(0.879)	(0.676)	(0.397)	(0.025)	(0.047)	(0.032)
	[25.2]	[15.3]	[4.3]	[4.3]	[5.3]	[9.2]	[13.4]	[4.7]	[7.8]
B. Year Post-Shelter Entry									
Cash Assistance	0.651**	0.699**	0.356	1.498**	1.051**	0.688	-0.085**	-0.107**	-0.048
	(0.183)	(0.238)	(0.415)	(0.654)	(0.457)	(0.519)	(0.027)	(0.045)	(0.036)
	[28.8]	[18.3]	[4.0]	[8.7]	[11.7]	[6.9]	[17.1]	[8.6]	[7.2]
Food Stamps	-0.142	-0.199*	-0.107	-0.546*	-0.456*	-0.065	0.017	0.029	0.005
	(0.093)	(0.120)	(0.247)	(0.323)	(0.251)	(0.279)	(0.013)	(0.020)	(0.020)
	[28.8]	[18.3]	[4.0]	[8.7]	[11.7]	[6.9]	[17.1]	[8.6]	[7.2]
Employed	-0.020	0.012	0.037	-0.161	-0.050	0.226	0.001	-0.001	-0.015
	(0.171)	(0.213)	(0.474)	(0.511)	(0.410)	(0.560)	(0.023)	(0.032)	(0.040)
	[28.8]	[18.3]	[4.0]	[8.7]	[11.7]	[6.9]	[17.1]	[8.6]	[7.2]
Log Avg. Quarterly Earnings	1.245	1.020	0.606	2.445	1.437	1.817	-0.155	-0.149	-0.118
	(1.243)	(1.553)	(3.354)	(3.747)	(2.997)	(3.973)	(0.169)	(0.240)	(0.280)
	[28.8]	[18.3]	[4.0]	[8.7]	[11.7]	[6.9]	[17.1]	[8.6]	[7.2]
C. Year Post-Shelter Exit									
Cash Assistance	0.428**	0.227	0.283	1.289*	0.487	0.598	-0.059**	-0.048	-0.045
	(0.210)	(0.236)	(0.405)	(0.763)	(0.529)	(0.482)	(0.030)	(0.047)	(0.036)
	[20.3]	[14.1]	[5.2]	[6.2]	[7.1]	[9.3]	[12.5]	[4.5]	[8.9]
Food Stamps	-0.064	-0.187	-0.197	-0.102	-0.416	-0.122	0.001	0.031	0.008
	(0.130)	(0.165)	(0.271)	(0.381)	(0.372)	(0.293)	(0.017)	(0.032)	(0.022)
	[20.3]	[14.1]	[5.2]	[6.2]	[7.1]	[9.3]	[12.5]	[4.5]	[8.9]
Employed	0.397*	0.405	0.448	1.422*	1.002	0.632	-0.066*	-0.091	-0.047
	(0.232)	(0.279)	(0.479)	(0.862)	(0.675)	(0.537)	(0.034)	(0.064)	(0.040)
	[20.3]	[14.1]	[5.2]	[6.2]	[7.1]	[9.3]	[12.5]	[4.5]	[8.9]
Log Avg. Quarterly Earnings	2.508	2.133	1.998	9.156	5.547	2.754	-0.419*	-0.509	-0.206
	(1.673)	(1.988)	(3.298)	(5.991)	(4.640)	(3.726)	(0.240)	(0.427)	(0.277)
	[20.3]	[14.1]	[5.2]	[6.2]	[7.1]	[9.3]	[12.5]	[4.5]	[8.9]
Time Control	$Year^3$	$Year^3$	$Year^3$	$Year^3$	$Year^3$	$Year^3$	$Year^3$	$Year^3$	$Year^3$
Placement Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Family & Shelter Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Shelter FE	No	No	No	No	No	No	No	No	No

Each cell reports the coefficient on local shelter placement from a separate 2SLS regression of the row-delineated outcome on the treatment using the ineligibility rate as the instrument and controlling for Main covariates. Columns give samples; supercolumns give treatment definitions. Standard errors clustered at family group level in parentheses. First-stage F-stats in brackets. * $p < 0.10$, ** $p < 0.05$

Table A.12: IV Robustness: Aversion Ratio

	Borough			School District			Distance		
	Full	Non-DV	Pre-2015	Full	Non-DV	Pre-2015	Full	Non-DV	Pre-2015
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
A. Stays and Returns									
Log Length of Stay	0.946**	0.531	2.110**	2.930**	1.275	4.479**	-0.120**	-0.071	-0.205**
	(0.342)	(0.357)	(0.634)	(1.109)	(0.806)	(1.547)	(0.043)	(0.048)	(0.058)
	[60.8]	[42.9]	[27.5]	[20.3]	[21.4]	[14.6]	[45.2]	[26.7]	[38.1]
Subsidized Exit	-0.331**	-0.527**	-0.483**	-0.874**	-1.078**	-0.836*	0.034*	0.061**	0.035*
	(0.147)	(0.190)	(0.219)	(0.427)	(0.416)	(0.445)	(0.018)	(0.026)	(0.020)
	[55.8]	[38.8]	[26.3]	[20.3]	[22.1]	[14.7]	[41.8]	[23.8]	[36.4]
Returned to Shelter	0.088	0.098	-0.337**	0.276	0.240	-0.702**	-0.006	-0.009	0.038**
	(0.104)	(0.122)	(0.162)	(0.372)	(0.345)	(0.330)	(0.013)	(0.019)	(0.016)
	[55.7]	[37.7]	[27.1]	[12.2]	[11.7]	[16.2]	[37.2]	[17.4]	[37.8]
B. Year Post-Shelter Entry									
Cash Assistance	0.338**	0.318**	0.015	0.600**	0.384	0.123	-0.041**	-0.042**	-0.006
	(0.105)	(0.125)	(0.149)	(0.304)	(0.268)	(0.304)	(0.013)	(0.017)	(0.014)
	[60.8]	[42.9]	[27.5]	[20.3]	[21.4]	[14.6]	[45.2]	[26.7]	[38.1]
Food Stamps	-0.100	-0.133*	-0.028	-0.374*	-0.336*	0.071	0.009	0.015	-0.003
	(0.064)	(0.076)	(0.095)	(0.195)	(0.176)	(0.189)	(0.008)	(0.010)	(0.009)
	[60.8]	[42.9]	[27.5]	[20.3]	[21.4]	[14.6]	[45.2]	[26.7]	[38.1]
Employed	0.116	0.164	0.284	0.190	0.279	0.576	-0.013	-0.021	-0.027
	(0.118)	(0.141)	(0.190)	(0.334)	(0.308)	(0.396)	(0.014)	(0.019)	(0.018)
	[60.8]	[42.9]	[27.5]	[20.3]	[21.4]	[14.6]	[45.2]	[26.7]	[38.1]
Log Avg. Quarterly Earnings	1.085	1.258	1.101	2.085	2.354	2.541	-0.126	-0.172	-0.121
	(0.851)	(1.019)	(1.310)	(2.424)	(2.245)	(2.686)	(0.104)	(0.138)	(0.126)
	[60.8]	[42.9]	[27.5]	[20.3]	[21.4]	[14.6]	[45.2]	[26.7]	[38.1]
C. Year Post-Shelter Exit									
Cash Assistance	0.265**	0.087	0.102	0.789*	0.192	0.285	-0.033**	-0.018	-0.015
	(0.129)	(0.148)	(0.171)	(0.447)	(0.392)	(0.331)	(0.016)	(0.024)	(0.017)
	[46.4]	[34.2]	[27.2]	[12.5]	[11.4]	[16.2]	[33.5]	[15.1]	[37.1]
Food Stamps	0.023	-0.075	0.003	0.089	-0.214	0.018	-0.007	0.009	-0.004
	(0.086)	(0.103)	(0.114)	(0.267)	(0.275)	(0.214)	(0.011)	(0.016)	(0.011)
	[46.4]	[34.2]	[27.2]	[12.5]	[11.4]	[16.2]	[33.5]	[15.1]	[37.1]
Employed	0.338**	0.352**	0.268	1.138**	0.930*	0.585	-0.047**	-0.060**	-0.028
	(0.149)	(0.174)	(0.197)	(0.545)	(0.509)	(0.387)	(0.019)	(0.030)	(0.019)
	[46.4]	[34.2]	[27.2]	[12.5]	[11.4]	[16.2]	[33.5]	[15.1]	[37.1]
Log Avg. Quarterly Earnings	2.035*	1.975	1.221	7.314*	5.541	3.126	-0.295**	-0.358*	-0.143
	(1.078)	(1.261)	(1.406)	(3.850)	(3.590)	(2.739)	(0.138)	(0.215)	(0.137)
	[46.4]	[34.2]	[27.2]	[12.5]	[11.4]	[16.2]	[33.5]	[15.1]	[37.1]
Time Control	Year^3	Year^3	Year^3	Year^3	Year^3	Year^3	Year^3	Year^3	Year^3
Placement Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Family & Shelter Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Shelter FE	No	No	No	No	No	No	No	No	No

Each cell reports the coefficient on local shelter placement from a separate 2SLS regression of the row-delineated outcome on the treatment using the aversion ratio as the instrument and controlling for Main covariates. Columns give samples; supercolumns give treatment definitions. Standard errors clustered at family group level in parentheses. First-stage F-stats in brackets. * $p < 0.10$, ** $p < 0.05$

Table A.13: Time Trend Robustness

	OLS				Ineligibility Rate IV				Aversion Ratio IV			
Outcome	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
A. Stays and Returns												
Log Length of Stay	0.121**	0.119**	0.120**	0.118**	1.704**	3.941**	1.943**	0.093	1.298**	1.787**	1.284**	0.108
	(0.011)	(0.011)	(0.011)	(0.011)	(0.438)	(1.815)	(0.652)	(0.352)	(0.275)	(0.542)	(0.318)	(0.274)
	{59,253}	{59,253}	{59,253}	{59,253}	[47.0]	[6.5]	[23.2]	[52.8]	[106.2]	[32.3]	[76.8]	[85.8]
Subsidized Exit	0.024**	0.019**	0.021**	0.021**	0.110	-1.301*	-2.675**	0.338**	1.446**	-0.207	0.057	0.227*
	(0.004)	(0.004)	(0.004)	(0.004)	(0.159)	(0.712)	(0.635)	(0.154)	(0.176)	(0.196)	(0.127)	(0.118)
	{57,962}	{57,962}	{57,962}	{57,962}	[44.7]	[5.5]	[20.8]	[48.9]	[101.7]	[28.3]	[70.5]	[79.3]
Returned to Shelter	-0.006*	-0.005	-0.006*	-0.005	0.347**	-0.047	0.772**	0.208*	-0.147*	-0.234	-0.064	0.156*
	(0.003)	(0.003)	(0.003)	(0.003)	(0.141)	(0.294)	(0.258)	(0.120)	(0.083)	(0.143)	(0.093)	(0.091)
	{52,274}	{52,274}	{52,274}	{52,274}	[36.9]	[7.2]	[18.2]	[46.7]	[91.2]	[33.1]	[69.2]	[79.2]
B. Year Post-Shelter Entry												
Cash Assistance	0.011**	0.011**	0.012**	0.012**	-0.361**	-1.348**	0.954**	-0.387**	-0.346**	-0.572**	0.642**	-0.380**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.124)	(0.618)	(0.250)	(0.117)	(0.083)	(0.174)	(0.112)	(0.091)
	{59,253}	{59,253}	{59,253}	{59,253}	[47.0]	[6.5]	[23.2]	[52.8]	[106.2]	[32.3]	[76.8]	[85.8]
Food Stamps	0.003*	0.003	0.004*	0.004*	-0.257**	-1.015**	-0.048	-0.473**	-0.120**	-0.372**	0.101*	-0.352**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.080)	(0.452)	(0.099)	(0.095)	(0.048)	(0.115)	(0.056)	(0.066)
	{59,253}	{59,253}	{59,253}	{59,253}	[47.0]	[6.5]	[23.2]	[52.8]	[106.2]	[32.3]	[76.8]	[85.8]
Employed	0.010**	0.010**	0.011**	0.011**	-0.877**	-0.441	-0.087	-0.276**	-0.384**	0.168	0.439**	-0.207**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.187)	(0.407)	(0.193)	(0.132)	(0.099)	(0.167)	(0.115)	(0.101)
	{59,253}	{59,253}	{59,253}	{59,253}	[47.0]	[6.5]	[23.2]	[52.8]	[106.2]	[32.3]	[76.8]	[85.8]
Log Avg. Quarterly Earnings	0.095**	0.093**	0.100**	0.097**	-3.259**	-1.624	0.975	-1.473	-1.096*	0.343	3.084**	-1.412*
	(0.028)	(0.028)	(0.028)	(0.028)	(1.081)	(2.702)	(1.383)	(0.929)	(0.658)	(1.186)	(0.825)	(0.725)
	{59,253}	{59,253}	{59,253}	{59,253}	[47.0]	[6.5]	[23.2]	[52.8]	[106.2]	[32.3]	[76.8]	[85.8]
C. Year Post-Shelter Exit												
Cash Assistance	0.017**	0.017**	0.017**	0.017**	-0.441**	0.240	-0.098	-0.062	-0.193*	0.271	0.159	-0.075
	(0.004)	(0.004)	(0.004)	(0.004)	(0.200)	(0.406)	(0.235)	(0.160)	(0.109)	(0.182)	(0.111)	(0.117)
	{48,082}	{48,082}	{48,082}	{48,082}	[23.1]	[4.9]	[13.3]	[28.8]	[66.4]	[25.3]	[60.0]	[53.1]
Food Stamps	0.009**	0.009**	0.009**	0.009**	-0.131	-0.090	-0.188	-0.256**	0.021	0.139	0.035	-0.112
	(0.003)	(0.003)	(0.003)	(0.003)	(0.124)	(0.271)	(0.166)	(0.121)	(0.071)	(0.122)	(0.075)	(0.084)
	{48,082}	{48,082}	{48,082}	{48,082}	[23.1]	[4.9]	[13.3]	[28.8]	[66.4]	[25.3]	[60.0]	[53.1]
Employed	0.003	0.003	0.004	0.003	-1.171**	0.477	-0.018	0.322*	-0.716**	0.375*	0.326**	0.171
	(0.004)	(0.004)	(0.004)	(0.004)	(0.314)	(0.493)	(0.266)	(0.189)	(0.148)	(0.209)	(0.130)	(0.132)
	{48,082}	{48,082}	{48,082}	{48,082}	[23.1]	[4.9]	[13.3]	[28.8]	[66.4]	[25.3]	[60.0]	[53.1]
Log Avg. Quarterly Earnings	0.042	0.042	0.047	0.040	-7.755**	2.137	-0.792	2.054	-4.504**	1.855	1.978**	1.029
	(0.033)	(0.033)	(0.033)	(0.033)	(2.186)	(3.385)	(1.970)	(1.371)	(1.039)	(1.477)	(0.945)	(0.973)
	{48,082}	{48,082}	{48,082}	{48,082}	[23.1]	[4.9]	[13.3]	[28.8]	[66.4]	[25.3]	[60.0]	[53.1]
Time Control	Year Linear	Year Dummies	3-Knot Month^2 Spline	7-Knot Month^3 Spline	Year Linear	Year Dummies	3-Knot Month^2 Spline	7-Knot Month^3 Spline	Year Linear	Year Dummies	3-Knot Month^2 Spline	7-Knot Month^3 Spline
Main Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Each cell reports the coefficient on in-borough shelter placement from a separate regressions of the row-delineated outcome on the treatment indicator using the supercolumn-enumerated method, controlling for Main covariates. Columns give alternative time trend controls. Standard errors clustered at family group level in parentheses. Number of observations given in braces. First-stage F-stats in brackets. * $p < 0.10$, ** $p < 0.05$

Table A.14: Regression Discontinuity Main Results: Wald Estimates

	No Controls				Controls			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A. Stays and Returns								
Log Length of Stay	1.986**	1.619**	1.557**	1.612**	1.205**	0.732**	0.705*	0.467
	(0.705)	(0.311)	(0.442)	(0.271)	(0.569)	(0.299)	(0.388)	(0.284)
	{7,679}	{15,436}	{7,430}	{14,925}	{7,679}	{15,436}	{7,430}	{14,925}
Subsidized Exit	0.353*	0.473**	0.406**	0.661**	0.128	0.231**	0.170	0.363**
	(0.211)	(0.109)	(0.152)	(0.106)	(0.184)	(0.108)	(0.141)	(0.111)
	{7,548}	{15,156}	{7,299}	{14,642}	{7,548}	{15,156}	{7,299}	{14,642}
Returned to Shelter	-0.067	-0.199**	-0.167	-0.247**	-0.060	-0.167*	-0.172	-0.220**
	(0.153)	(0.083)	(0.117)	(0.075)	(0.152)	(0.095)	(0.122)	(0.094)
	{6,798}	{13,725}	{6,590}	{13,268}	{6,798}	{13,725}	{6,590}	{13,268}
B. Year Post-Shelter Entry								
Cash Assistance	0.223	0.126	0.172	0.025	0.131	0.146*	0.248**	0.162**
	(0.188)	(0.087)	(0.126)	(0.076)	(0.151)	(0.085)	(0.112)	(0.082)
	{7,679}	{15,436}	{7,430}	{14,925}	{7,679}	{15,436}	{7,430}	{14,925}
Food Stamps	0.070	-0.049	-0.034	-0.137**	0.012	-0.002	0.052	0.018
	(0.130)	(0.062)	(0.089)	(0.056)	(0.089)	(0.050)	(0.065)	(0.049)
	{7,679}	{15,436}	{7,430}	{14,925}	{7,679}	{15,436}	{7,430}	{14,925}
Employed	0.001	-0.094	-0.275*	-0.268**	0.000	-0.027	-0.108	-0.083
	(0.223)	(0.108)	(0.159)	(0.098)	(0.189)	(0.106)	(0.138)	(0.102)
	{7,679}	{15,436}	{7,430}	{14,925}	{7,679}	{15,436}	{7,430}	{14,925}
Log Avg. Quarterly Earnings	0.881	0.059	-1.491	-1.131	0.567	0.306	-0.560	-0.100
	(1.623)	(0.776)	(1.130)	(0.690)	(1.333)	(0.745)	(0.970)	(0.718)
	{7,679}	{15,436}	{7,430}	{14,925}	{7,679}	{15,436}	{7,430}	{14,925}
C. Year Post-Shelter Exit								
Cash Assistance	0.403**	0.250**	0.354**	0.138*	0.303*	0.255**	0.373**	0.231**
	(0.191)	(0.096)	(0.140)	(0.084)	(0.172)	(0.103)	(0.135)	(0.099)
	{6,295}	{12,675}	{6,092}	{12,246}	{6,295}	{12,675}	{6,092}	{12,246}
Food Stamps	0.212	-0.031	0.107	-0.107*	0.130	0.008	0.157*	0.021
	(0.130)	(0.065)	(0.094)	(0.059)	(0.106)	(0.062)	(0.082)	(0.061)
	{6,295}	{12,675}	{6,092}	{12,246}	{6,295}	{12,675}	{6,092}	{12,246}
Employed	-0.147	-0.189*	-0.189	-0.287**	-0.170	-0.088	-0.009	-0.092
	(0.203)	(0.109)	(0.153)	(0.099)	(0.190)	(0.114)	(0.143)	(0.110)
	{6,295}	{12,675}	{6,092}	{12,246}	{6,295}	{12,675}	{6,092}	{12,246}
Log Avg. Quarterly Earnings	-0.901	-1.063	-1.404	-1.533**	-1.241	-0.603	-0.305	-0.458
	(1.485)	(0.793)	(1.126)	(0.714)	(1.372)	(0.826)	(1.039)	(0.798)
	{6,295}	{12,675}	{6,092}	{12,246}	{6,295}	{12,675}	{6,092}	{12,246}
First Stage	0.051**	0.076**	0.077**	0.089**	0.053**	0.068**	0.075**	0.073**
	(0.011)	(0.008)	(0.012)	(0.008)	(0.010)	(0.007)	(0.011)	(0.008)
	[20.4]	[90.3]	[44.1]	[117.8]	[25.9]	[83.8]	[50.0]	[89.8]
Bandwidth	{-1,0}	[-2,1]	{-1,1}	{-2,-1,1,2}	{-1,0}	[-2,1]	{-1,1}	{-2,-1,1,2}
Covariates	No	No	No	No	Yes	Yes	Yes	Yes

This table presents a more comprehensive set of Wald fuzzy regression discontinuity estimates. Each cell reports the coefficient on in-borough shelter placement from a separate 2SLS regression of the row-delineated outcome on the treatment indicator, using as the instrument an indicator for whether a family's oldest child's grade year (end-of-school-year age year minus five) is zero or greater. Wald estimates pool the running variable (grade year) for the given bandwidth; coefficients are thus instrumented mean comparisons between families without and with school-aged children. The first four columns have no covariates. The last four control for RD Main covariates. Standard errors clustered at family group level in parentheses. Number of observations given in braces. First-stage given for in-borough placement indicator. First-stage F-stat, in brackets, given for log length of stay regressions. * $p < 0.10$, ** $p < 0.05$

Table A.15: Regression Discontinuity Main Results: Linear Estimates

	No Controls					Controls				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
A. Stays and Returns										
Log Length of Stay	1.611	0.910	2.075	1.357**	1.281**	1.505*	0.917	1.885*	1.065**	0.918**
	(0.993)	(0.959)	(1.340)	(0.436)	(0.354)	(0.827)	(0.855)	(1.042)	(0.331)	(0.285)
	{26,046}	{22,316}	{19,641}	{50,480}	{55,118}	{26,046}	{22,316}	{19,641}	{50,480}	{55,118}
Subsidized Exit	0.247	0.121	0.261	0.622**	0.479**	0.160	0.092	0.159	0.370**	0.256**
	(0.299)	(0.333)	(0.365)	(0.171)	(0.131)	(0.255)	(0.302)	(0.297)	(0.126)	(0.104)
	{25,543}	{21,886}	{19,284}	{49,334}	{53,907}	{25,543}	{21,886}	{19,284}	{49,334}	{53,907}
Returned to Shelter	0.226	0.204	0.212	0.013	-0.084	0.187	0.131	0.193	-0.042	-0.107
	(0.230)	(0.265)	(0.277)	(0.120)	(0.097)	(0.212)	(0.252)	(0.246)	(0.101)	(0.089)
	{23,141}	{19,860}	{17,508}	{44,574}	{48,712}	{23,141}	{19,860}	{17,508}	{44,574}	{48,712}
B. Year Post-Shelter Entry										
Cash Assistance	0.361	0.363	0.400	0.170	0.059	0.242	0.333	0.215	0.183**	0.104
	(0.301)	(0.318)	(0.381)	(0.128)	(0.107)	(0.216)	(0.253)	(0.254)	(0.092)	(0.079)
	{26,046}	{22,316}	{19,641}	{50,480}	{55,118}	{26,046}	{22,316}	{19,641}	{50,480}	{55,118}
Food Stamps	0.157	0.086	0.228	-0.037	-0.095	0.033	0.061	0.029	0.009	-0.018
	(0.203)	(0.214)	(0.261)	(0.090)	(0.077)	(0.125)	(0.143)	(0.146)	(0.055)	(0.048)
	{26,046}	{22,316}	{19,641}	{50,480}	{55,118}	{26,046}	{22,316}	{19,641}	{50,480}	{55,118}
Employed	0.090	-0.293	0.403	-0.123	-0.145	-0.019	-0.341	0.238	-0.081	-0.070
	(0.340)	(0.380)	(0.455)	(0.156)	(0.131)	(0.265)	(0.312)	(0.319)	(0.114)	(0.101)
	{26,046}	{22,316}	{19,641}	{50,480}	{55,118}	{26,046}	{22,316}	{19,641}	{50,480}	{55,118}
Log Avg. Quarterly Earnings	1.169	-2.488	4.022	-0.568	-0.747	0.374	-2.688	2.673	-0.277	-0.213
	(2.476)	(2.784)	(3.483)	(1.124)	(0.940)	(1.868)	(2.244)	(2.335)	(0.815)	(0.723)
	{26,046}	{22,316}	{19,641}	{50,480}	{55,118}	{26,046}	{22,316}	{19,641}	{50,480}	{55,118}
C. Year Post-Shelter Exit										
Cash Assistance	0.650**	0.672*	0.670*	0.398**	0.173	0.557**	0.666**	0.505*	0.347**	0.206**
	(0.301)	(0.349)	(0.378)	(0.152)	(0.119)	(0.253)	(0.312)	(0.294)	(0.120)	(0.099)
	{21,348}	{18,327}	{16,182}	{41,110}	{44,941}	{21,348}	{18,327}	{16,182}	{41,110}	{44,941}
Food Stamps	0.322*	0.299	0.346	0.091	-0.016	0.183	0.264	0.130	0.071	0.029
	(0.193)	(0.218)	(0.242)	(0.100)	(0.081)	(0.144)	(0.177)	(0.166)	(0.073)	(0.062)
	{21,348}	{18,327}	{16,182}	{41,110}	{44,941}	{21,348}	{18,327}	{16,182}	{41,110}	{44,941}
Employed	-0.132	-0.222	-0.017	-0.219	-0.268**	-0.178	-0.236	-0.056	-0.135	-0.134
	(0.283)	(0.322)	(0.349)	(0.162)	(0.135)	(0.255)	(0.292)	(0.298)	(0.128)	(0.113)
	{21,348}	{18,327}	{16,182}	{41,110}	{44,941}	{21,348}	{18,327}	{16,182}	{41,110}	{44,941}
Log Avg. Quarterly Earnings	-1.315	-2.477	-0.269	-1.606	-1.898*	-1.561	-2.406	-0.547	-0.909	-0.866
	(2.095)	(2.444)	(2.566)	(1.192)	(0.992)	(1.873)	(2.171)	(2.162)	(0.935)	(0.826)
	{21,348}	{18,327}	{16,182}	{41,110}	{44,941}	{21,348}	{18,327}	{16,182}	{41,110}	{44,941}
First Stage	0.033**	0.045**	0.032**	0.051**	0.057**	0.039**	0.050**	0.040**	0.058**	0.063**
	(0.014)	(0.018)	(0.014)	(0.013)	(0.011)	(0.013)	(0.016)	(0.013)	(0.012)	(0.010)
	[7.4]	[4.9]	[4.3]	[89.6]	[109.1]	[8.6]	[5.6]	[6.8]	[104.1]	[120.7]
Bandwidth	[-3,3]	[-3,3]	[-3,2]	[-3,12]	[-4,12]	[-3,3]	[-3,3]	[-3,2]	[-3,12]	[-4,12]
Includes Threshold	Yes	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes
Covariates	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes

This table presents a more comprehensive set of linear fuzzy regression discontinuity estimates. Each cell reports the coefficient on in-borough shelter placement from a separate 2SLS regression of the row-delineated outcome on the running variable (oldest child's grade year; i.e., end-of-school-year age year minus five), the treatment indicator, and treatment interacted with the running variable, so as to allow for different slopes on either side of the threshold (school starting; i.e., grade year zero). The instrument an indicator for whether a family's oldest child's grade year is zero or greater; the interaction term is also instrumented. Reported cofficients are thus the difference in intercepts at the threshold. The first four columns have no covariates. The last four control for RD Main covariates. Standard errors clustered at family group level in parentheses. Number of observations given in braces. First-stage given for in-borough placement indicator. First-stage F-stat, in brackets, given for log length of stay regressions. * $p < 0.10$, ** $p < 0.05$

Table A.16: Regression Discontinuity Robustness: Alternative Samples for Borough Treatment

	Non-DV Sample				Pre-2015 Sample				One School Age Sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
A. Stays and Returns												
Log Length of Stay	1.070*	0.968**	0.107	0.590**	1.788**	1.426**	0.197	0.675**	1.588**	1.331**	0.645**	1.172**
	(0.632)	(0.265)	(0.267)	(0.192)	(0.771)	(0.284)	(0.322)	(0.319)	(0.620)	(0.264)	(0.277)	(0.395)
	{4,986}	{9,718}	{9,718}	{36,023}	{5,435}	{10,541}	{10,541}	{35,758}	{7,441}	{13,212}	{13,212}	{32,006}
Subsidized Exit	0.203	0.561**	0.263**	0.252**	0.236	0.513**	0.310**	0.255**	0.255	0.471**	0.290**	0.451**
	(0.246)	(0.123)	(0.119)	(0.085)	(0.229)	(0.103)	(0.121)	(0.115)	(0.196)	(0.097)	(0.104)	(0.148)
	{4,889}	{9,508}	{9,508}	{35,155}	{5,411}	{10,479}	{10,479}	{35,498}	{7,321}	{12,969}	{12,969}	{31,310}
Returned to Shelter	0.027	-0.150*	-0.118	-0.059	-0.124	-0.165**	-0.174*	-0.037	-0.070	-0.239**	-0.177**	0.024
	(0.173)	(0.081)	(0.092)	(0.070)	(0.182)	(0.077)	(0.101)	(0.097)	(0.148)	(0.073)	(0.088)	(0.124)
	{4,419}	{8,595}	{8,595}	{31,764}	{5,305}	{10,260}	{10,260}	{34,744}	{6,607}	{11,787}	{11,787}	{28,404}
B. Year Post-Shelter Entry												
Cash Assistance	0.437*	0.031	0.114	0.178**	0.230	0.055	0.145	0.102	0.213	0.071	0.155**	0.259**
	(0.234)	(0.089)	(0.086)	(0.062)	(0.208)	(0.080)	(0.092)	(0.088)	(0.177)	(0.077)	(0.079)	(0.110)
	{4,986}	{9,718}	{9,718}	{36,023}	{5,435}	{10,541}	{10,541}	{35,758}	{7,441}	{13,212}	{13,212}	{32,006}
Food Stamps	0.119	-0.152**	-0.033	-0.019	0.110	-0.100*	-0.026	-0.041	0.069	-0.064	0.053	0.038
	(0.143)	(0.064)	(0.051)	(0.037)	(0.141)	(0.056)	(0.054)	(0.053)	(0.122)	(0.055)	(0.048)	(0.064)
	{4,986}	{9,718}	{9,718}	{36,023}	{5,435}	{10,541}	{10,541}	{35,758}	{7,441}	{13,212}	{13,212}	{32,006}
Employed	0.127	-0.221*	-0.026	-0.090	-0.150	-0.342**	-0.118	-0.149	0.051	-0.008	-0.007	0.083
	(0.262)	(0.113)	(0.107)	(0.077)	(0.252)	(0.105)	(0.116)	(0.113)	(0.210)	(0.095)	(0.098)	(0.133)
	{4,986}	{9,718}	{9,718}	{36,023}	{5,435}	{10,541}	{10,541}	{35,758}	{7,441}	{13,212}	{13,212}	{32,006}
Log Avg. Quarterly Earnings	1.806	-1.032	0.081	-0.619	-0.116	-2.008**	-0.616	-0.745	1.257	0.697	0.265	0.858
	(1.957)	(0.811)	(0.760)	(0.555)	(1.774)	(0.735)	(0.808)	(0.802)	(1.539)	(0.693)	(0.694)	(0.949)
	{4,986}	{9,718}	{9,718}	{36,023}	{5,435}	{10,541}	{10,541}	{35,758}	{7,441}	{13,212}	{13,212}	{32,006}
C. Year Post-Shelter Exit												
Cash Assistance	0.561**	0.141	0.179*	0.260**	0.364*	0.093	0.157	0.226**	0.385**	0.173**	0.210**	0.478**
	(0.230)	(0.096)	(0.102)	(0.077)	(0.218)	(0.087)	(0.105)	(0.105)	(0.185)	(0.084)	(0.096)	(0.154)
	{4,091}	{7,912}	{7,912}	{29,238}	{5,234}	{10,112}	{10,112}	{34,229}	{6,144}	{10,882}	{10,882}	{26,170}
Food Stamps	0.225	-0.088	0.016	0.021	0.115	-0.130**	-0.058	-0.029	0.209*	-0.030	0.066	0.126
	(0.145)	(0.065)	(0.063)	(0.047)	(0.146)	(0.062)	(0.065)	(0.065)	(0.127)	(0.058)	(0.059)	(0.090)
	{4,091}	{7,912}	{7,912}	{29,238}	{5,234}	{10,112}	{10,112}	{34,229}	{6,144}	{10,882}	{10,882}	{26,170}
Employed	-0.020	-0.287**	-0.075	-0.168**	-0.275	-0.281**	-0.074	-0.172	-0.097	-0.095	-0.048	0.028
	(0.230)	(0.113)	(0.113)	(0.083)	(0.243)	(0.104)	(0.118)	(0.117)	(0.197)	(0.095)	(0.107)	(0.156)
	{4,091}	{7,912}	{7,912}	{29,238}	{5,234}	{10,112}	{10,112}	{34,229}	{6,144}	{10,882}	{10,882}	{26,170}
Log Avg. Quarterly Earnings	0.159	-1.582*	-0.271	-1.215**	-1.450	-1.694**	-0.518	-1.211	-0.616	-0.309	-0.345	0.056
	(1.698)	(0.825)	(0.824)	(0.607)	(1.744)	(0.747)	(0.852)	(0.858)	(1.444)	(0.699)	(0.777)	(1.140)
	{4,091}	{7,912}	{7,912}	{29,238}	{5,234}	{10,112}	{10,112}	{34,229}	{6,144}	{10,882}	{10,882}	{26,170}
First Stage	0.054**	0.093**	0.084**	0.064**	0.055**	0.101**	0.078**	0.069**	0.055**	0.096**	0.081**	0.061**
	(0.014)	(0.010)	(0.009)	(0.015)	(0.013)	(0.010)	(0.009)	(0.014)	(0.012)	(0.009)	(0.008)	(0.012)
	[15.3]	[85.4]	[79.8]	[94.6]	[16.6]	[106.1]	[73.4]	[86.1]	[23.0]	[115.9]	[97.7]	[76.3]
Order	Wald	Wald	Wald	Linear	Wald	Wald	Wald	Linear	Wald	Wald	Wald	Linear
Bandwidth	{-1,0}	{-2,-1,1,2}	{-2,-1,1,2}	[-3,12]	{-1,0}	{-2,-1,1,2}	{-2,-1,1,2}	[-3,12]	{-1,0}	{-2,-1,1,2}	{-2,-1,1,2}	[-3,12]
Threshold	Yes	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes
Covariates	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes

This table extends the fuzzy regression discontinuity analysis for three alternative samples, given in supercolumns. The Non-DV sample consists of families eligible for shelter for reasons other than domestic violence. The Pre-2015 sample consists of families entering shelter before 2014. The One School Age Sample consists of families with a single school-aged child. Each cell reports the coefficient on in-borough shelter placement from a separate 2SLS regression of the row-delineated outcome on the treatment indicator, using as the instrument an indicator for whether a family's oldest child's grade year (end-of-school-year age year minus five) is zero (i.e., in-school) or greater. The first three columns for each sample present Wald estimates for varying bandwidths, while the fourth fits a linear regression on the running variable for the given bandwidths, allowing for different slopes on either side of the threshold. The first two columns for each sample have no covariates; the last two control for Main RD covariates. Standard errors clustered at family group level in parentheses. Number of observations given in braces. First-stage given for in-borough placement indicator. First-stage F-stat, in brackets, given for log length of stay regressions. * $p < 0.10$, ** $p < 0.05$

Table A.17: Regression Discontinuity Robustness: Distance Treatment

	Full Sample				Non-DV Sample				Pre-2015 Sample				One School Age Sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
A. Stays and Returns																
Log Length of Stay	-0.266**	-0.199**	-0.054	-0.114**	-0.141	-0.121**	-0.014	-0.075**	-0.270*	-0.176**	-0.025	-0.082**	-0.195**	-0.160**	-0.081**	-0.138**
	(0.118)	(0.037)	(0.033)	(0.032)	(0.101)	(0.035)	(0.032)	(0.022)	(0.151)	(0.039)	(0.038)	(0.040)	(0.092)	(0.033)	(0.033)	(0.055)
	{7,028}	{13,639}	{13,639}	{46,282}	{4,611}	{8,928}	{8,928}	{33,311}	{4,938}	{9,577}	{9,577}	{32,635}	{6,807}	{12,073}	{12,073}	{29,280}
Subsidized Exit	-0.057	-0.084**	-0.043**	-0.041**	-0.025	-0.072**	-0.035**	-0.030**	-0.039	-0.065**	-0.039**	-0.034**	-0.041	-0.058**	-0.038**	-0.064**
	(0.036)	(0.015)	(0.013)	(0.013)	(0.039)	(0.017)	(0.014)	(0.010)	(0.042)	(0.014)	(0.015)	(0.015)	(0.030)	(0.013)	(0.013)	(0.022)
	{6,910}	{13,377}	{13,377}	{45,228}	{4,523}	{8,735}	{8,735}	{32,511}	{4,918}	{9,524}	{9,524}	{32,405}	{6,699}	{11,846}	{11,846}	{28,644}
Returned to Shelter	0.002	0.034**	0.026**	0.011	-0.020	0.019*	0.012	0.009	0.005	0.022**	0.021*	0.008	0.004	0.031**	0.021**	-0.006
	(0.027)	(0.010)	(0.011)	(0.011)	(0.032)	(0.011)	(0.011)	(0.009)	(0.034)	(0.010)	(0.012)	(0.012)	(0.024)	(0.010)	(0.011)	(0.019)
	{6,211}	{12,114}	{12,114}	{40,829}	{4,078}	{7,892}	{7,892}	{29,354}	{4,819}	{9,319}	{9,319}	{31,707}	{6,034}	{10,755}	{10,755}	{25,947}
B. Year Post-Shelter Entry																
Cash Assistance	-0.035	-0.003	-0.021**	-0.019**	-0.067*	-0.007	-0.017*	-0.022**	-0.041	-0.006	-0.018*	-0.012	-0.033	-0.008	-0.020**	-0.035**
	(0.030)	(0.010)	(0.010)	(0.009)	(0.040)	(0.012)	(0.010)	(0.007)	(0.038)	(0.011)	(0.011)	(0.011)	(0.026)	(0.009)	(0.009)	(0.016)
	{7,028}	{13,639}	{13,639}	{46,282}	{4,611}	{8,928}	{8,928}	{33,311}	{4,938}	{9,577}	{9,577}	{32,635}	{6,807}	{12,073}	{12,073}	{29,280}
Food Stamps	-0.009	0.017**	-0.002	0.002	-0.014	0.018**	0.004	0.002	-0.017	0.014*	0.003	0.008	-0.009	0.008	-0.006	-0.006
	(0.020)	(0.008)	(0.006)	(0.005)	(0.022)	(0.008)	(0.006)	(0.004)	(0.025)	(0.008)	(0.006)	(0.007)	(0.017)	(0.007)	(0.006)	(0.009)
	{7,028}	{13,639}	{13,639}	{46,282}	{4,611}	{8,928}	{8,928}	{33,311}	{4,938}	{9,577}	{9,577}	{32,635}	{6,807}	{12,073}	{12,073}	{29,280}
Employed	0.002	0.032**	0.008	0.015	-0.023	0.028*	0.007	0.016*	0.032	0.040**	0.011	0.022	-0.006	0.000	-0.000	-0.010
	(0.034)	(0.013)	(0.012)	(0.011)	(0.041)	(0.015)	(0.013)	(0.009)	(0.045)	(0.014)	(0.014)	(0.014)	(0.030)	(0.012)	(0.012)	(0.018)
	{7,028}	{13,639}	{13,639}	{46,282}	{4,611}	{8,928}	{8,928}	{33,311}	{4,938}	{9,577}	{9,577}	{32,635}	{6,807}	{12,073}	{12,073}	{29,280}
Log Avg. Quarterly Earnings	-0.142	0.127	-0.002	0.070	-0.338	0.124	0.008	0.107*	0.048	0.223**	0.040	0.107	-0.186	-0.094	-0.042	-0.126
	(0.250)	(0.091)	(0.084)	(0.081)	(0.317)	(0.106)	(0.091)	(0.063)	(0.310)	(0.097)	(0.096)	(0.101)	(0.224)	(0.086)	(0.082)	(0.132)
	{7,028}	{13,639}	{13,639}	{46,282}	{4,611}	{8,928}	{8,928}	{33,311}	{4,938}	{9,577}	{9,577}	{32,635}	{6,807}	{12,073}	{12,073}	{29,280}
C. Year Post-Shelter Exit																
Cash Assistance	-0.073*	-0.015	-0.026**	-0.039**	-0.091**	-0.017	-0.020*	-0.027**	-0.069	-0.009	-0.017	-0.026*	-0.065**	-0.019*	-0.025**	-0.074**
	(0.038)	(0.011)	(0.012)	(0.014)	(0.046)	(0.013)	(0.012)	(0.009)	(0.046)	(0.012)	(0.013)	(0.013)	(0.033)	(0.011)	(0.012)	(0.028)
	{5,743}	{11,166}	{11,166}	{37,616}	{3,774}	{7,254}	{7,254}	{26,999}	{4,751}	{9,184}	{9,184}	{31,229}	{5,603}	{9,913}	{9,913}	{23,882}
Food Stamps	-0.034	0.015*	-0.003	-0.006	-0.036	0.011	-0.003	-0.002	-0.016	0.019**	0.007	0.007	-0.032	0.004	-0.008	-0.022
	(0.024)	(0.008)	(0.007)	(0.009)	(0.026)	(0.009)	(0.008)	(0.006)	(0.027)	(0.008)	(0.008)	(0.008)	(0.021)	(0.007)	(0.007)	(0.015)
	{5,743}	{11,166}	{11,166}	{37,616}	{3,774}	{7,254}	{7,254}	{26,999}	{4,751}	{9,184}	{9,184}	{31,229}	{5,603}	{9,913}	{9,913}	{23,882}
Employed	0.019	0.033**	0.006	0.019	-0.006	0.035**	0.009	0.020**	0.048	0.032**	0.003	0.023	0.011	0.007	0.001	-0.011
	(0.035)	(0.014)	(0.013)	(0.015)	(0.039)	(0.015)	(0.014)	(0.010)	(0.047)	(0.014)	(0.014)	(0.015)	(0.031)	(0.012)	(0.013)	(0.026)
	{5,743}	{11,166}	{11,166}	{37,616}	{3,774}	{7,254}	{7,254}	{26,999}	{4,751}	{9,184}	{9,184}	{31,229}	{5,603}	{9,913}	{9,913}	{23,882}
Log Avg. Quarterly Earnings	0.102	0.163*	0.021	0.124	-0.091	0.185*	0.033	0.152**	0.233	0.176*	0.013	0.159	0.058	-0.000	0.004	-0.075
	(0.255)	(0.098)	(0.097)	(0.110)	(0.291)	(0.110)	(0.100)	(0.073)	(0.329)	(0.101)	(0.104)	(0.109)	(0.231)	(0.090)	(0.095)	(0.186)
	{5,743}	{11,166}	{11,166}	{37,616}	{3,774}	{7,254}	{7,254}	{26,999}	{4,751}	{9,184}	{9,184}	{31,229}	{5,603}	{9,913}	{9,913}	{23,882}
First Stage	-0.350**	-0.706**	-0.645**	-0.520**	-0.368**	-0.745**	-0.734**	-0.545**	-0.329**	-0.796**	-0.680**	-0.553**	-0.402**	-0.813**	-0.718**	-0.504**
	(0.110)	(0.080)	(0.074)	(0.114)	(0.134)	(0.095)	(0.089)	(0.141)	(0.129)	(0.092)	(0.086)	(0.132)	(0.112)	(0.086)	(0.079)	(0.117)
	[10.1]	[78.7]	[75.5]	[80.2]	[7.5]	[61.0]	[67.7]	[74.1]	[6.5]	[74.4]	[63.2]	[56.9]	[12.9]	[89.7]	[82.3]	[49.1]
Order	Wald	Wald	Wald	Linear	Wald	Wald	Wald	Linear	Wald	Wald	Wald	Linear	Wald	Wald	Wald	Linear
Bandwidth	{-1,0}	{-2,-1,1,2}	{-2,-1,1,2}	[-3,12]	{-1,0}	{-2,-1,1,2}	{-2,-1,1,2}	[-3,12]	{-1,0}	{-2,-1,1,2}	{-2,-1,1,2}	[-3,12]	{-1,0}	{-2,-1,1,2}	{-2,-1,1,2}	[-3,12]
Threshold	Yes	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes
Covariates	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes

This table extends the fuzzy regression discontinuity analysis for distance treatment, measured in miles between origin and shelter address. Supercolumns give samples. Each cell reports the coefficient on placement distance from a separate 2SLS regression of the row-delineated outcome on distance treatment, using as the instrument an indicator for whether a family's oldest child's grade year (end-of-school-year age year minus five) is zero (i.e., in-school) or greater. The first three columns for each sample present Wald estimates for varying bandwidths, while the fourth fits a linear regression on the running variable for the given bandwidths, allowing for different slopes on either side of the threshold. The first two columns for each sample have no covariates; the last two control for Main RD covariates. Standard errors clustered at family group level in parentheses. Number of observations given in braces. First-stage given for distance treatment. First-stage F-stat, in brackets, given for log length of stay regressions. * $p < 0.10$, ** $p < 0.05$

Table A.18: Regression Discontinuity Baseline Covariates

	Wald				Linear	
	(1)	(2)	(3)	(4)	(5)	(6)
Month Entered Shelter	-1.284	0.965	0.656	1.068*	-1.870	0.188
	(1.506)	(1.049)	(0.628)	(0.642)	(2.321)	(1.040)
Year Entered Shelter	2.147*	2.206**	1.862**	1.950**	2.003	2.778**
	(1.108)	(0.770)	(0.462)	(0.470)	(1.643)	(0.837)
Manhattan Origin	-0.112	-0.033	-0.062	-0.065	0.071	0.018
	(0.152)	(0.103)	(0.063)	(0.063)	(0.233)	(0.106)
Bronx Origin	-0.243	0.084	-0.038	0.043	-0.283	-0.107
	(0.230)	(0.148)	(0.092)	(0.092)	(0.352)	(0.155)
Brooklyn Origin	0.107	-0.044	0.081	0.056	0.056	0.060
	(0.208)	(0.141)	(0.087)	(0.087)	(0.313)	(0.144)
Queens Origin	0.205	-0.004	0.031	-0.011	0.159	0.032
	(0.156)	(0.098)	(0.061)	(0.061)	(0.231)	(0.101)
Staten Island Origin	0.044	-0.002	-0.013	-0.023	-0.004	-0.003
	(0.073)	(0.046)	(0.029)	(0.029)	(0.107)	(0.048)
Family Size	2.227**	3.311**	4.096**	4.487**	-0.949	1.140**
	(0.685)	(0.599)	(0.425)	(0.463)	(0.759)	(0.402)
Family Members Under 18	2.441**	3.240**	4.105**	4.412**	-0.672	1.901**
	(0.660)	(0.556)	(0.408)	(0.439)	(0.597)	(0.434)
Health Issue Present	0.135	0.216	0.173**	0.202**	-0.033	-0.078
	(0.200)	(0.140)	(0.085)	(0.087)	(0.299)	(0.136)
Eligibility: Eviction	0.474**	0.647**	0.709**	0.798**	0.010	0.074
	(0.216)	(0.161)	(0.100)	(0.106)	(0.297)	(0.136)
Eligibility: Overcrowding	0.263	0.021	0.069	0.011	0.219	0.103
	(0.178)	(0.115)	(0.070)	(0.070)	(0.264)	(0.116)
Eligibility: Conditions	-0.158	-0.305**	-0.126**	-0.160**	-0.184	-0.190**
	(0.137)	(0.098)	(0.055)	(0.055)	(0.208)	(0.095)
Eligibility: Domestic Violence	-0.348	-0.292**	-0.515**	-0.539**	0.025	0.098
	(0.216)	(0.145)	(0.094)	(0.094)	(0.325)	(0.151)
Eligibility: Other	-0.231	-0.071	-0.141**	-0.113*	-0.074	-0.086
	(0.150)	(0.096)	(0.060)	(0.059)	(0.215)	(0.099)
Female	-0.061	-0.031	-0.058	-0.062	0.047	-0.076
	(0.113)	(0.076)	(0.048)	(0.048)	(0.171)	(0.081)
Age	16.141**	24.170**	27.804**	31.521**	0.138	-1.438
	(4.616)	(4.190)	(2.839)	(3.173)	(4.779)	(2.547)
Partner/Spouse Present	-0.266	-0.073	-0.053	-0.012	-0.307	0.094
	(0.205)	(0.135)	(0.082)	(0.082)	(0.313)	(0.138)
Pregnant	-0.390**	-0.143*	-0.169**	-0.130**	-0.314	-0.114
	(0.144)	(0.084)	(0.052)	(0.051)	(0.205)	(0.086)
Obs.	7,679	7,430	18,655	14,925	26,046	50,480
Order	Wald	Wald	Wald	Wald	Linear	Linear
Bandwidth	{-1,0}	{-1,1}	[-2,2]	{-2,-1,1,2}	[-3,3]	[-3,12]
Threshold	Yes	No	Yes	No	Yes	Yes
Covariates	No	No	No	No	No	No

This table assesses the plausibility of the fuzzy regression discontinuity design by checking whether baseline covariates are similar on both sides of the treatment threshold (oldest child of school-starting age). Each cell reports the coefficient on in-borough shelter placement from a separate 2SLS regression of the row-delineated characteristic on the treatment indicator, using as the instrument an indicator for whether a family's oldest child's grade year (end-of-school-year age year minus five) is zero or greater. The first four columns present Wald estimates (pooled instrumented mean comparisons), while the last two present linear estimates, allowing for different slopes on either side of the threshold. Within these groups, columns vary by bandwidth and whether the threshold itself is included. Standard errors clustered at family group level in parentheses. * $p < 0.10$, ** $p < 0.05$

Table 18 (Cont.): Regression Discontinuity Baseline Covariates

	Wald				Linear	
	(1)	(2)	(3)	(4)	(5)	(6)
Black	0.060	-0.035	-0.017	-0.049	0.344	0.165
	(0.219)	(0.150)	(0.093)	(0.093)	(0.347)	(0.157)
Hispanic	-0.104	-0.011	0.022	0.059	-0.405	-0.228
	(0.215)	(0.147)	(0.090)	(0.091)	(0.348)	(0.159)
White	0.042	0.040	-0.001	-0.015	0.071	0.007
	(0.068)	(0.047)	(0.028)	(0.027)	(0.104)	(0.046)
Asian	0.024	0.024	0.017	0.016	0.050	0.046**
	(0.026)	(0.020)	(0.012)	(0.012)	(0.044)	(0.020)
No Degree	0.278	0.089	-0.080	-0.136	0.365	-0.025
	(0.226)	(0.150)	(0.093)	(0.094)	(0.350)	(0.154)
High School Grad	-0.260	-0.322**	-0.083	-0.087	-0.331	-0.243
	(0.215)	(0.150)	(0.088)	(0.089)	(0.329)	(0.151)
Some College or More	0.049	0.131*	0.094**	0.110**	0.010	0.111*
	(0.093)	(0.068)	(0.040)	(0.042)	(0.140)	(0.067)
Unknown Education	-0.067	0.102	0.069	0.112**	-0.043	0.157**
	(0.102)	(0.073)	(0.043)	(0.045)	(0.156)	(0.075)
On Cash Assistance	0.161	0.137	0.010	-0.007	0.199	0.215
	(0.221)	(0.150)	(0.090)	(0.091)	(0.337)	(0.154)
On Food Stamps	0.142	0.048	-0.074	-0.124	0.331	0.123
	(0.193)	(0.131)	(0.080)	(0.082)	(0.311)	(0.134)
Employed Year Pre	0.086	-0.038	-0.017	-0.081	0.087	-0.092
	(0.225)	(0.153)	(0.094)	(0.095)	(0.351)	(0.164)
Log AQ Earnings Year Pre	0.931	0.215	0.887	0.513	0.662	-0.689
	(1.597)	(1.090)	(0.670)	(0.674)	(2.487)	(1.167)
Tier II Shelter	-0.282	-0.207	-0.326**	-0.338**	-0.720*	-0.392**
	(0.229)	(0.154)	(0.096)	(0.097)	(0.401)	(0.172)
Commercial Hotel	-0.028	-0.211	-0.245**	-0.279**	0.767**	0.199
	(0.201)	(0.137)	(0.085)	(0.085)	(0.390)	(0.161)
Family Cluster Unit	0.275*	0.405**	0.563**	0.614**	-0.085	0.195*
	(0.162)	(0.120)	(0.079)	(0.084)	(0.233)	(0.110)
Mahattan Shelter	-0.122	-0.275**	-0.475**	-0.531**	0.031	-0.404**
	(0.174)	(0.117)	(0.076)	(0.077)	(0.275)	(0.123)
Bronx Shelter	-0.026	0.178	0.406**	0.454**	-0.248	0.156
	(0.216)	(0.143)	(0.089)	(0.090)	(0.348)	(0.147)
Brooklyn Shelter	0.421**	0.302**	0.438**	0.431**	0.196	0.324**
	(0.206)	(0.136)	(0.085)	(0.086)	(0.295)	(0.137)
Queens Shelter	-0.303*	-0.227**	-0.358**	-0.342**	-0.040	-0.089
	(0.167)	(0.110)	(0.071)	(0.070)	(0.249)	(0.116)
Staten Island Shelter	0.029	0.023	-0.011	-0.011	0.060	0.013
	(0.039)	(0.027)	(0.017)	(0.017)	(0.063)	(0.027)
Obs.	7,679	7,430	18,655	14,925	26,046	50,480
Order	Wald	Wald	Wald	Wald	Linear	Linear
Bandwidth	{-1,0}	{-1,1}	[-2,2]	{-2,-1,1,2}	[-3,3]	[-3,12]
Threshold	Yes	No	Yes	No	Yes	Yes
Covariates	No	No	No	No	No	No

This table assesses the plausibility of the fuzzy regression discontinuity design by checking whether baseline covariates are similar on both sides of the treatment threshold (oldest child of school-starting age). Each cell reports the coefficient on in-borough shelter placement from a separate 2SLS regression of the row-delineated characteristic on the treatment indicator, using as the instrument an indicator for whether a family's oldest child's grade year (end-of-school-year age year minus five) is zero or greater. The first four columns present Wald estimates (pooled instrumented mean comparisons), while the last two present linear estimates, allowing for different slopes on either side of the threshold. Within these groups, columns vary by bandwidth and whether the threshold itself is included. Standard errors clustered at family group level in parentheses. * $p < 0.10$, ** $p < 0.05$

Table A.19: Complier Characteristics: Ineligibility Rate Instrument

	Compliers	Non-Compliers	Diff.
Manhattan Origin	0.00	0.14	-0.13
	(0.003)	(0.000)	[-2.56]
Bronx Origin	0.57	0.39	0.18
	(0.006)	(0.000)	[2.28]
Brooklyn Origin	0.25	0.32	-0.07
	(0.005)	(0.000)	[-0.99]
Queens Origin	0.10	0.13	-0.02
	(0.003)	(0.000)	[-0.45]
Staten Island Origin	0.02	0.03	-0.00
	(0.000)	(0.000)	[-0.33]
Health Issue Present	0.33	0.30	0.04
	(0.004)	(0.000)	[0.61]
Eligibility: Eviction	0.29	0.34	-0.05
	(0.005)	(0.000)	[-0.67]
Eligibility: Overcrowding	0.16	0.18	-0.02
	(0.003)	(0.000)	[-0.34]
Eligibility: Conditions	0.11	0.08	0.03
	(0.002)	(0.000)	[0.67]
Eligibility: Domestic Violence	0.30	0.30	0.00
	(0.004)	(0.000)	[0.01]
Eligibility: Other	0.08	0.11	-0.03
	(0.003)	(0.000)	[-0.67]
Female	0.97	0.91	0.06
	(0.002)	(0.000)	[1.26]
Partner/Spouse Present	0.31	0.25	0.06
	(0.004)	(0.000)	[0.99]
Pregnant	0.04	0.07	-0.03
	(0.001)	(0.000)	[-0.86]
Black	0.43	0.57	-0.14
	(0.006)	(0.000)	[-1.79]
Hispanic	0.46	0.37	0.09
	(0.006)	(0.000)	[1.18]
White	0.06	0.02	0.04
	(0.001)	(0.000)	[1.57]
No Degree	0.61	0.57	0.05
	(0.005)	(0.000)	[0.67]
High School Grad	0.30	0.32	-0.02
	(0.005)	(0.000)	[-0.29]
Some College or More	0.06	0.05	0.01
	(0.001)	(0.000)	[0.21]
Unknown Education	0.02	0.07	-0.05
	(0.001)	(0.000)	[-1.27]
On Cash Assistance	0.30	0.36	-0.06
	(0.005)	(0.000)	[-0.78]
On Food Stamps	0.75	0.73	0.02
	(0.006)	(0.000)	[0.29]
Employed Year Pre	0.39	0.44	-0.05
	(0.005)	(0.000)	[-0.67]
Tier II Shelter	0.63	0.54	0.08
	(0.004)	(0.000)	[1.27]
Commercial Hotel	0.08	0.29	-0.21
	(0.005)	(0.000)	[-3.08]
Family Cluster Unit	0.19	0.16	0.02
	(0.003)	(0.000)	[0.46]
Family Size 1–3	0.54	0.64	-0.11
	(0.006)	(0.000)	[-1.43]
Family Size 4–5	0.39	0.28	0.11
	(0.004)	(0.000)	[1.68]
Family Size 6+	0.07	0.08	-0.01
	(0.002)	(0.000)	[-0.27]
Age	31.69	31.53	0.16
	(1.350)	(0.013)	[0.14]
Log AQ Earnings Year Pre	2.73	3.03	-0.30
	(0.259)	(0.002)	[-0.60]

Main sample. Treatment is in-borough placement. Instrument is 15-day moving average of the initial ineligibility rate for 30-day application period. Compliers are families placed in-borough when the ineligibility rate is high, but not otherwise. Non-compliers consist of always-takers and never-takers. Compiler and non-complier characteristics, adjusted for year and month of shelter entry, are estimated from the algorithm described in the Cassidy (2019). Standard errors (in parentheses) and differences in means (with t-stats in brackets) are calculated from 200 bootstrap replications, clustering by family.

Table A.20: Complier Characteristics: Aversion Ratio Instrument

	Compliers	Non-Compliers	Diff.
Manhattan Origin	0.09	0.13	-0.04
	(0.001)	(0.000)	[-1.18]
Bronx Origin	0.55	0.39	0.16
	(0.004)	(0.000)	[2.67]
Brooklyn Origin	0.20	0.33	-0.13
	(0.003)	(0.000)	[-2.29]
Queens Origin	0.12	0.13	-0.01
	(0.002)	(0.000)	[-0.17]
Staten Island Origin	0.03	0.03	0.01
	(0.000)	(0.000)	[0.51]
Health Issue Present	0.35	0.29	0.06
	(0.002)	(0.000)	[1.27]
Eligibility: Eviction	0.33	0.34	-0.01
	(0.003)	(0.000)	[-0.13]
Eligibility: Overcrowding	0.15	0.18	-0.03
	(0.002)	(0.000)	[-0.61]
Eligibility: Conditions	0.11	0.08	0.02
	(0.001)	(0.000)	[0.73]
Eligibility: Domestic Violence	0.27	0.30	-0.03
	(0.002)	(0.000)	[-0.59]
Eligibility: Other	0.10	0.11	-0.01
	(0.001)	(0.000)	[-0.28]
Female	0.94	0.91	0.03
	(0.001)	(0.000)	[0.82]
Partner/Spouse Present	0.28	0.25	0.03
	(0.002)	(0.000)	[0.61]
Pregnant	0.05	0.07	-0.02
	(0.001)	(0.000)	[-0.66]
Black	0.47	0.57	-0.09
	(0.004)	(0.000)	[-1.51]
Hispanic	0.43	0.37	0.06
	(0.003)	(0.000)	[0.98]
White	0.05	0.02	0.03
	(0.000)	(0.000)	[1.46]
No Degree	0.59	0.57	0.02
	(0.003)	(0.000)	[0.41]
High School Grad	0.31	0.32	-0.01
	(0.002)	(0.000)	[-0.21]
Some College or More	0.07	0.05	0.02
	(0.001)	(0.000)	[0.76]
Unknown Education	0.02	0.07	-0.04
	(0.001)	(0.000)	[-1.47]
On Cash Assistance	0.23	0.37	-0.14
	(0.003)	(0.000)	[-2.43]
On Food Stamps	0.70	0.74	-0.04
	(0.003)	(0.000)	[-0.63]
Employed Year Pre	0.39	0.44	-0.05
	(0.003)	(0.000)	[-0.91]
Tier II Shelter	0.59	0.55	0.04
	(0.003)	(0.000)	[0.82]
Commercial Hotel	0.14	0.29	-0.16
	(0.003)	(0.000)	[-2.83]
Family Cluster Unit	0.19	0.16	0.02
	(0.001)	(0.000)	[0.63]
Family Size 1–3	0.60	0.64	-0.04
	(0.003)	(0.000)	[-0.76]
Family Size 4–5	0.35	0.28	0.06
	(0.003)	(0.000)	[1.26]
Family Size 6+	0.05	0.08	-0.02
	(0.001)	(0.000)	[-0.82]
Age	32.20	31.47	0.73
	(0.949)	(0.014)	[0.74]
Log AQ Earnings Year Pre	2.76	3.03	-0.27
	(0.147)	(0.002)	[-0.71]

Main sample. Treatment is in-borough placement. Instrument is 15-day moving average of the aversion ratio. Compliers are families placed in-borough when the aversion ratio is high, but not otherwise. Non-compliers consist of always-takers and never-takers. Compiler and non-complier characteristics, adjusted for year and month of shelter entry, are estimated from the algorithm described in the Cassidy (2019). Standard errors (in parentheses) and differences in means (with t-stats in brackets) are calculated from 200 bootstrap replications, clustering by family.

Table A.21: Compliance Type Shares: Regression Discontinuity

	1%	1.5%	2%
Compliers	0.01	0.01	0.01
Always-Takers	0.67	0.67	0.67
Never-Takers	0.33	0.33	0.33

Main sample. Results from linear first-stage, controlling for year and month of shelter entry. Percentages in second row refer to percentiles used as thresholds to define low and high instrument values. See Cassidy (2019) for estimation method details.

Table A.22: Complier Characteristics: Regression Discontinuity

	Compliers	Non-Compliers	Diff.
Manhattan Origin	-0.03	0.13	-0.16
	(0.000)	(0.000)	[-13.42]
Bronx Origin	0.56	0.41	0.16
	(0.000)	(0.000)	[8.37]
Brooklyn Origin	0.50	0.31	0.19
	(0.000)	(0.000)	[9.94]
Queens Origin	-0.07	0.13	-0.20
	(0.000)	(0.000)	[-14.23]
Staten Island Origin	0.01	0.03	-0.02
	(0.000)	(0.000)	[-4.54]
Health Issue Present	0.28	0.30	-0.02
	(0.000)	(0.000)	[-1.69]
Eligibility: Eviction	0.26	0.34	-0.08
	(0.000)	(0.000)	[-4.89]
Eligibility: Overcrowding	0.16	0.18	-0.02
	(0.000)	(0.000)	[-1.38]
Eligibility: Conditions	0.07	0.08	-0.01
	(0.000)	(0.000)	[-1.66]
Eligibility: Domestic Violence	0.20	0.30	-0.10
	(0.000)	(0.000)	[-6.34]
Eligibility: Other	0.09	0.11	-0.02
	(0.000)	(0.000)	[-1.85]
Female	0.91	0.92	-0.01
	(0.000)	(0.000)	[-0.98]
Partner/Spouse Present	0.27	0.26	0.01
	(0.000)	(0.000)	[0.86]
Pregnant	0.08	0.07	0.01
	(0.000)	(0.000)	[0.94]
Black	0.58	0.56	0.02
	(0.000)	(0.000)	[1.27]
Hispanic	0.36	0.38	-0.02
	(0.000)	(0.000)	[-1.08]
White	0.02	0.03	-0.00
	(0.000)	(0.000)	[-0.83]
No Degree	0.59	0.57	0.02
	(0.000)	(0.000)	[0.88]
High School Grad	0.32	0.32	-0.00
	(0.000)	(0.000)	[-0.22]
Some College or More	0.06	0.05	0.01
	(0.000)	(0.000)	[1.14]
Unknown Education	0.04	0.06	-0.02
	(0.000)	(0.000)	[-2.09]
On Cash Assistance	0.39	0.35	0.03
	(0.000)	(0.000)	[1.90]
On Food Stamps	0.77	0.73	0.04
	(0.000)	(0.000)	[2.39]
Employed Year Pre	0.46	0.43	0.02
	(0.000)	(0.000)	[1.16]
Tier II Shelter	0.64	0.55	0.09
	(0.000)	(0.000)	[4.69]
Commercial Hotel	0.16	0.28	-0.11
	(0.000)	(0.000)	[-7.49]
Family Cluster Unit	0.08	0.17	-0.09
	(0.000)	(0.000)	[-5.68]
Family Size 1–3	0.86	0.63	0.23
	(0.000)	(0.000)	[10.71]
Family Size 4–5	0.20	0.29	-0.09
	(0.000)	(0.000)	[-5.05]
Family Size 6+	-0.00	0.08	-0.08
	(0.000)	(0.000)	[-5.23]
Age	27.87	32.38	-4.51
	(0.118)	(0.008)	[-12.74]
Log AQ Earnings Year Pre	3.06	3.00	0.06
	(0.017)	(0.001)	[0.45]

Main sample. Treatment is in-borough placement. Instrument is 15-day moving average of the initial ineligibility rate for 30-day application period. Compliers are families placed in-borough when the ineligibility rate is high, but not otherwise. Non-compliers consist of always-takers and never-takers. Compiler and non-complier characteristics, adjusted for year and month of shelter entry, are estimated from the algorithm described in Cassidy (2019). Standard errors (in parentheses) and differences in means (with t-stats in brackets) are calculated from 200 bootstrap replications, clustering by family.

D Supplementary Figures

Figure A.1

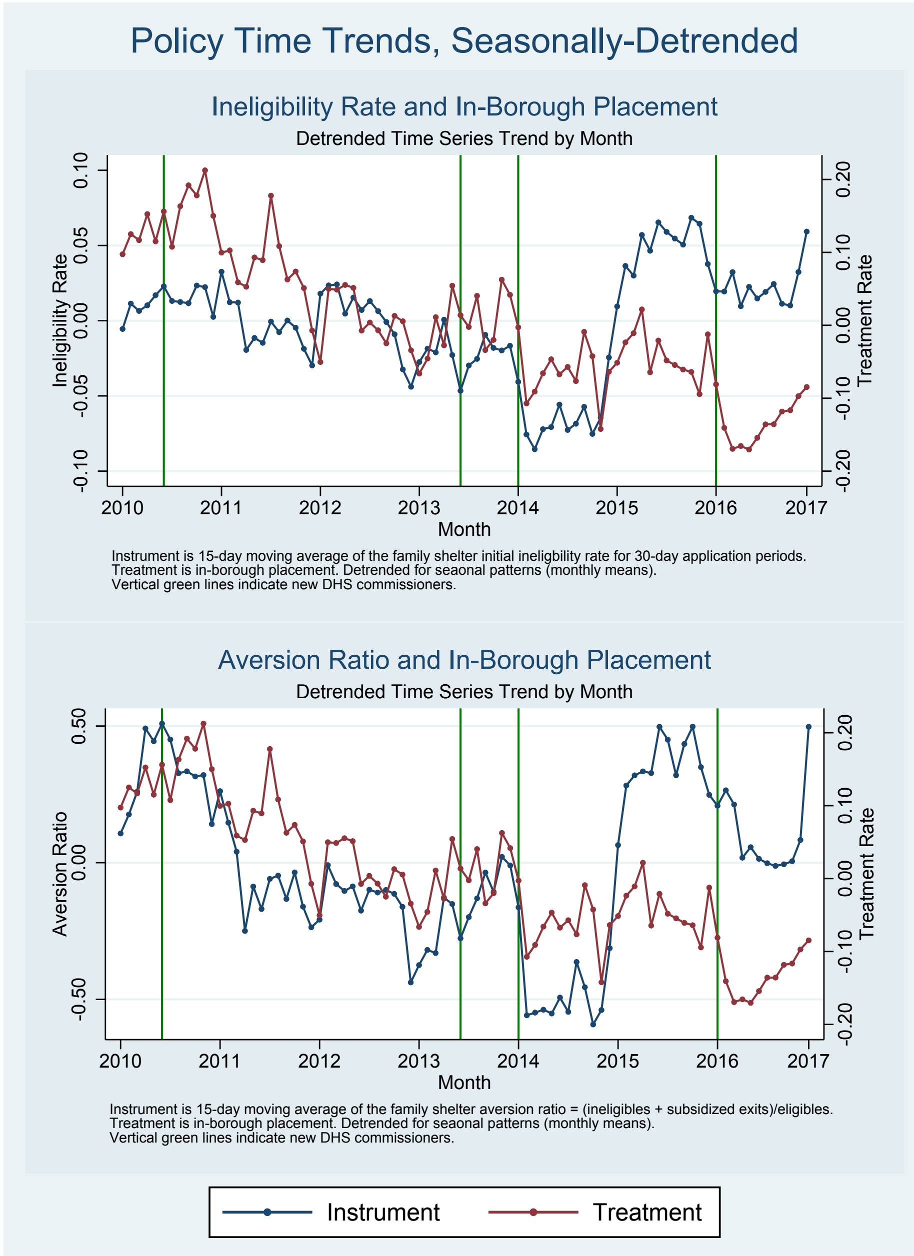
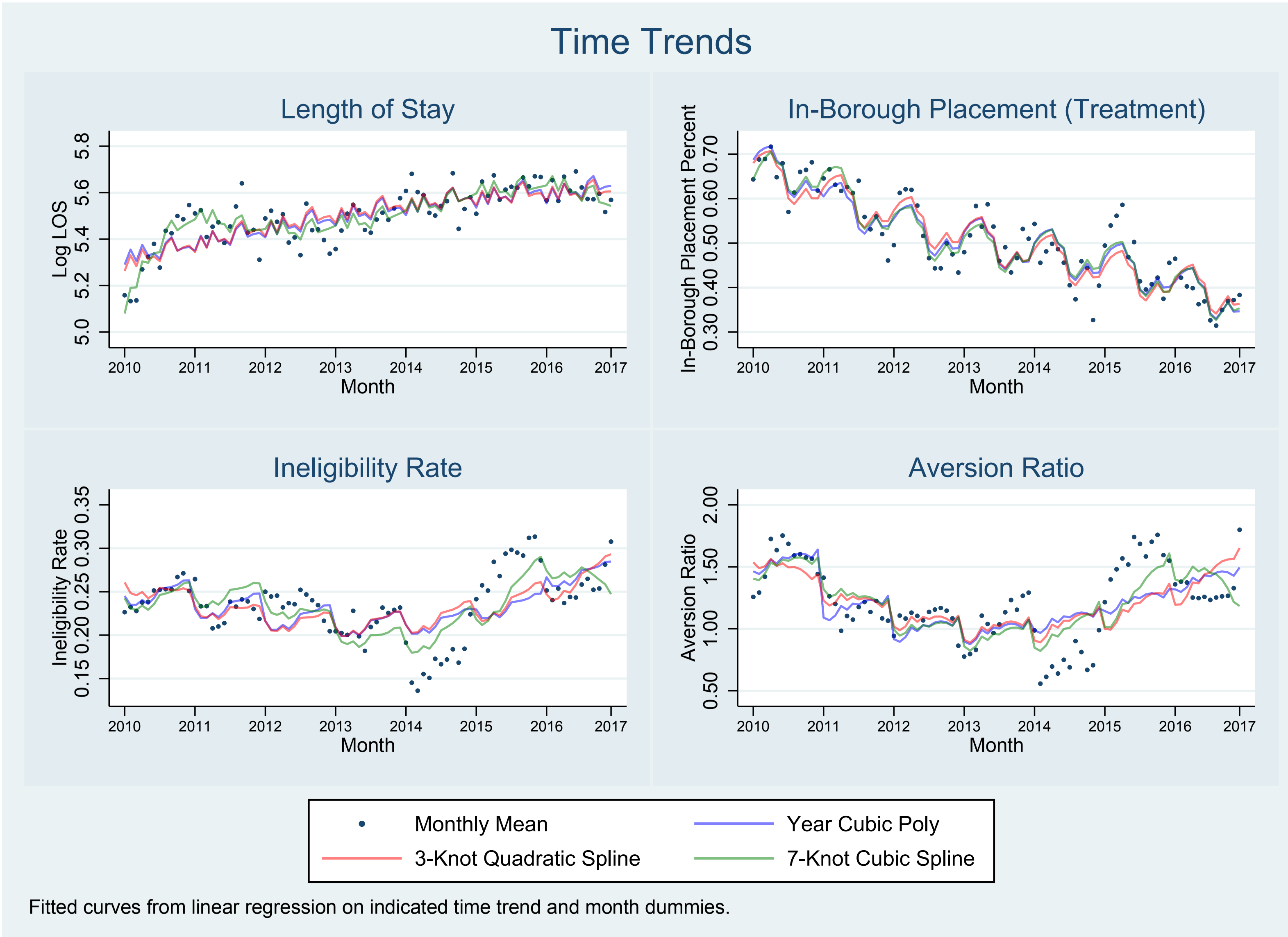
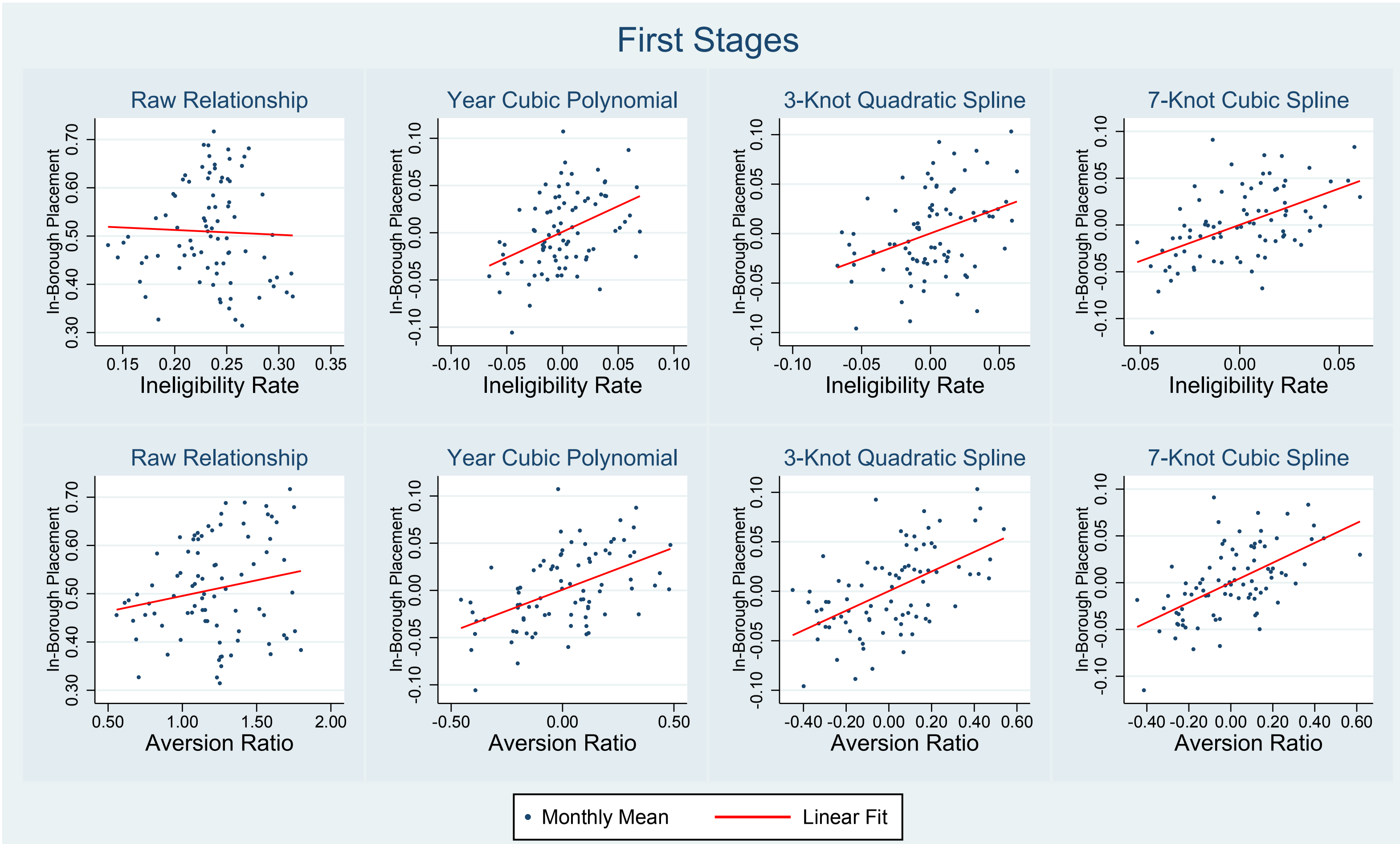


Figure A.2



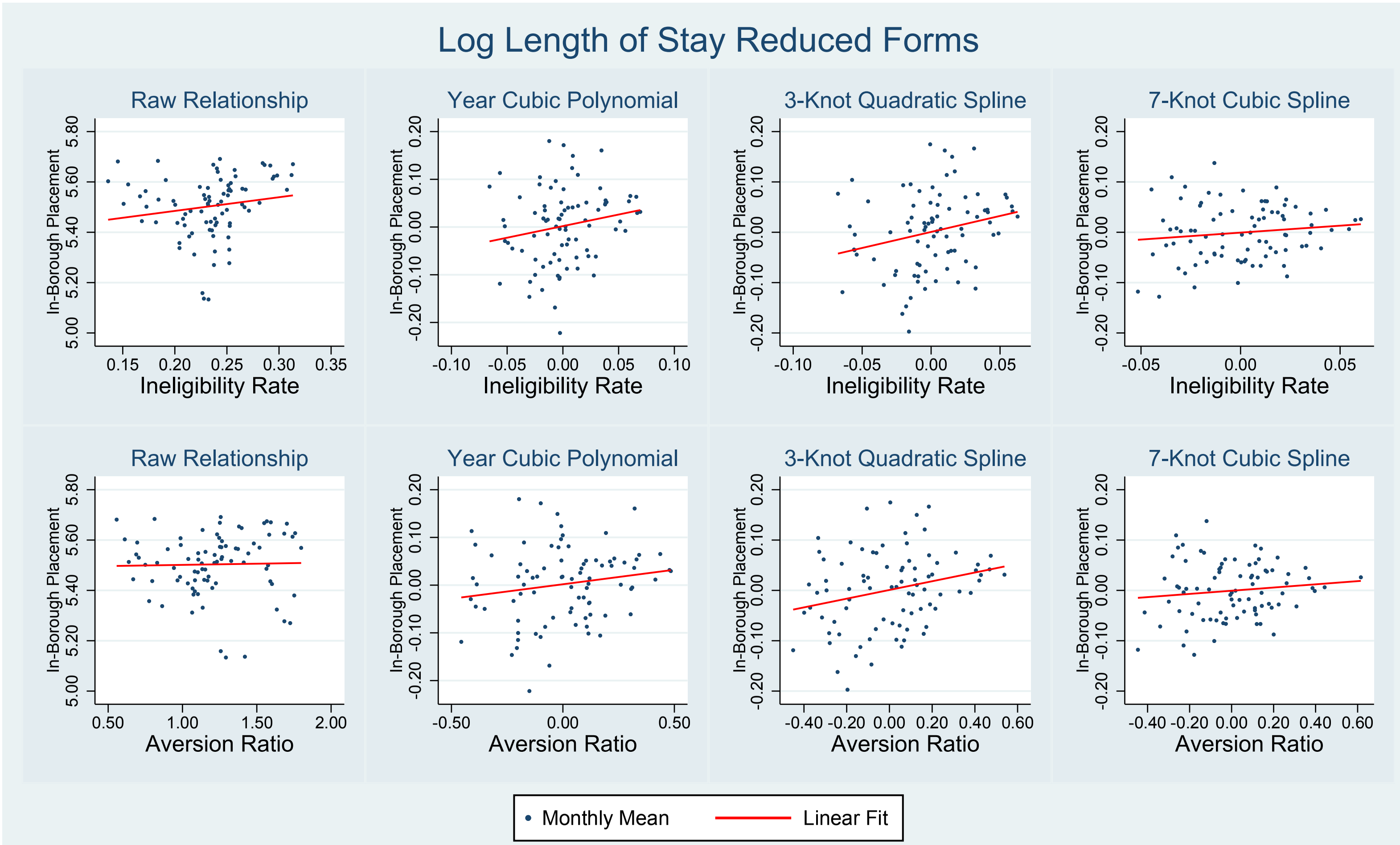
Time Trends
Length of Stay
Log LOS
5.0
5.2
5.4
5.6
5.8
In-Borough Placement (Treatment)
In-Borough Placement Percent
0.30 0.40 0.50 0.60 0.70
Ineligibility Rate
Ineligibility Rate
0.15 0.20 0.25 0.30 0.35
Aversion Ratio
Aversion Ratio
0.50 1.00 1.50 2.00
2010 2011 2012 2013 2014 2015 2016 2017
Month
Monthly Mean
Year Cubic Poly
3-Knot Quadratic Spline
7-Knot Cubic Spline
Fitted curves from linear regression on indicated time trend and month dummies.

Figure A.3



Panels are detrended by title time trend and month.

Figure A.4



Panels are detrended by title time trend and month.

Figure A.5

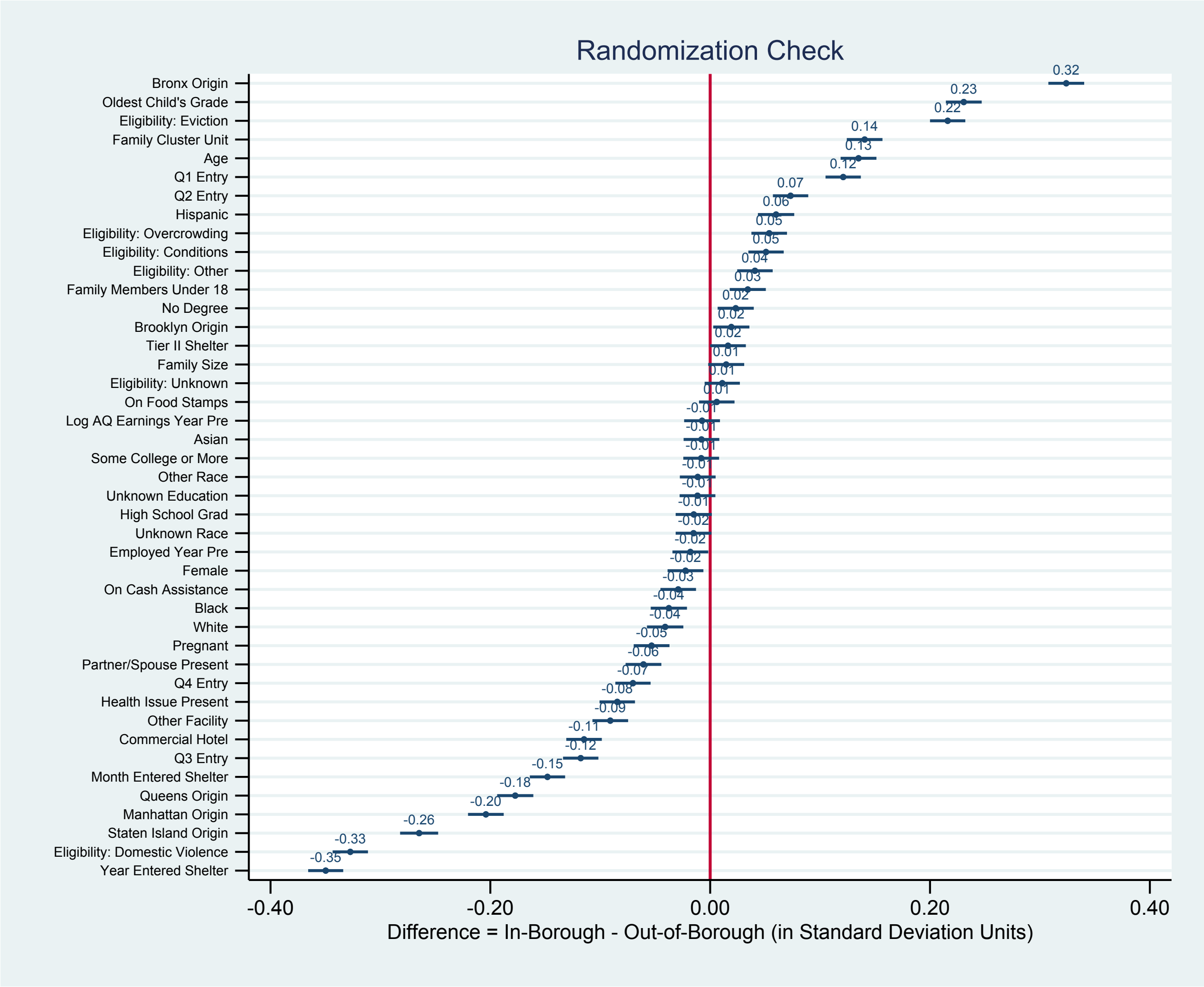

Randomization Check
Bronx Origin
Oldest Child's Grade
Eligibility: Eviction
Family Cluster Unit
Age
Q1 Entry
Q2 Entry
Hispanic
Eligibility: Overcrowding
Eligibility: Conditions
Eligibility: Other
Family Members Under 18
No Degree
Brooklyn Origin
Tier II Shelter
Family Size
Eligibility: Unknown
On Food Stamps
Log AQ Earnings Year Pre
Asian
Some College or More
Other Race
Unknown Education
High School Grad
Unknown Race
Employed Year Pre
Female
On Cash Assistance
Black
White
Pregnant
Partner/Spouse Present
Q4 Entry
Health Issue Present
Other Facility
Commercial Hotel
Q3 Entry
Month Entered Shelter
Queens Origin
Manhattan Origin
Staten Island Origin
Eligibility: Domestic Violence
Year Entered Shelter
0.32
0.23
0.22
0.14
0.13
0.12
0.07
0.06
0.05
0.05
0.04
0.03
0.02
0.02
0.02
0.01
0.01
0.01
-0.01
-0.01
-0.01
-0.01
-0.01
-0.01
-0.02
-0.02
-0.02
-0.03
-0.04
-0.04
-0.05
-0.06
-0.07
-0.08
-0.09
-0.11
-0.12
-0.15
-0.18
-0.20
-0.26
-0.33
-0.35
-0.40
-0.20
0.00
0.20
0.40
Difference = In-Borough - Out-of-Borough (in Standard Deviation Units)

Figure A.6

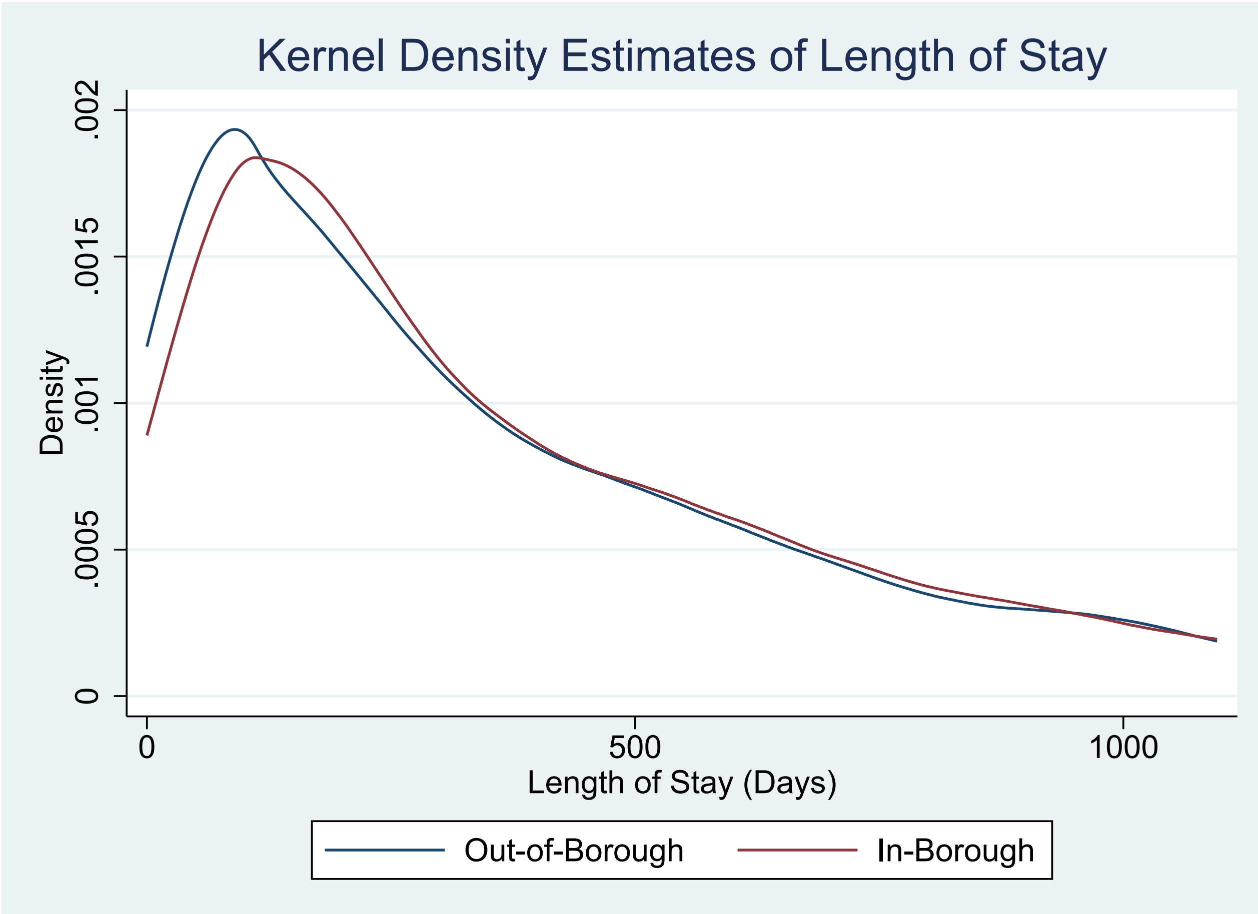

Kernel Density Estimates of Length of Stay
Density
0
.0005
.001
.0015
.002
0
500
1000
Length of Stay (Days)
Out-of-Borough
In-Borough

Figure A.7

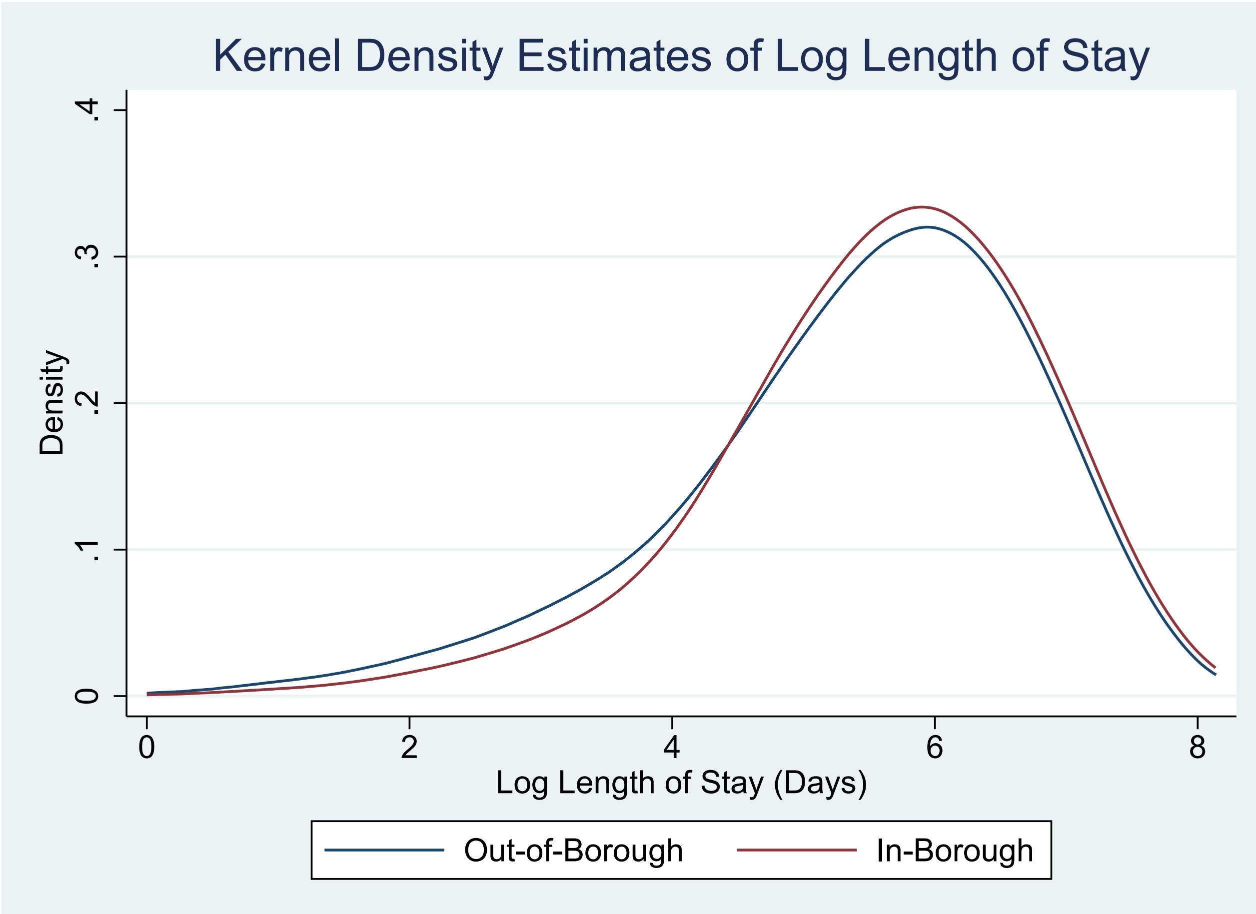

Kernel Density Estimates of Log Length of Stay
Density
0
.1
.2
.3
.4
0
2
4
6
8
Log Length of Stay (Days)
Out-of-Borough
In-Borough

Figure A.8

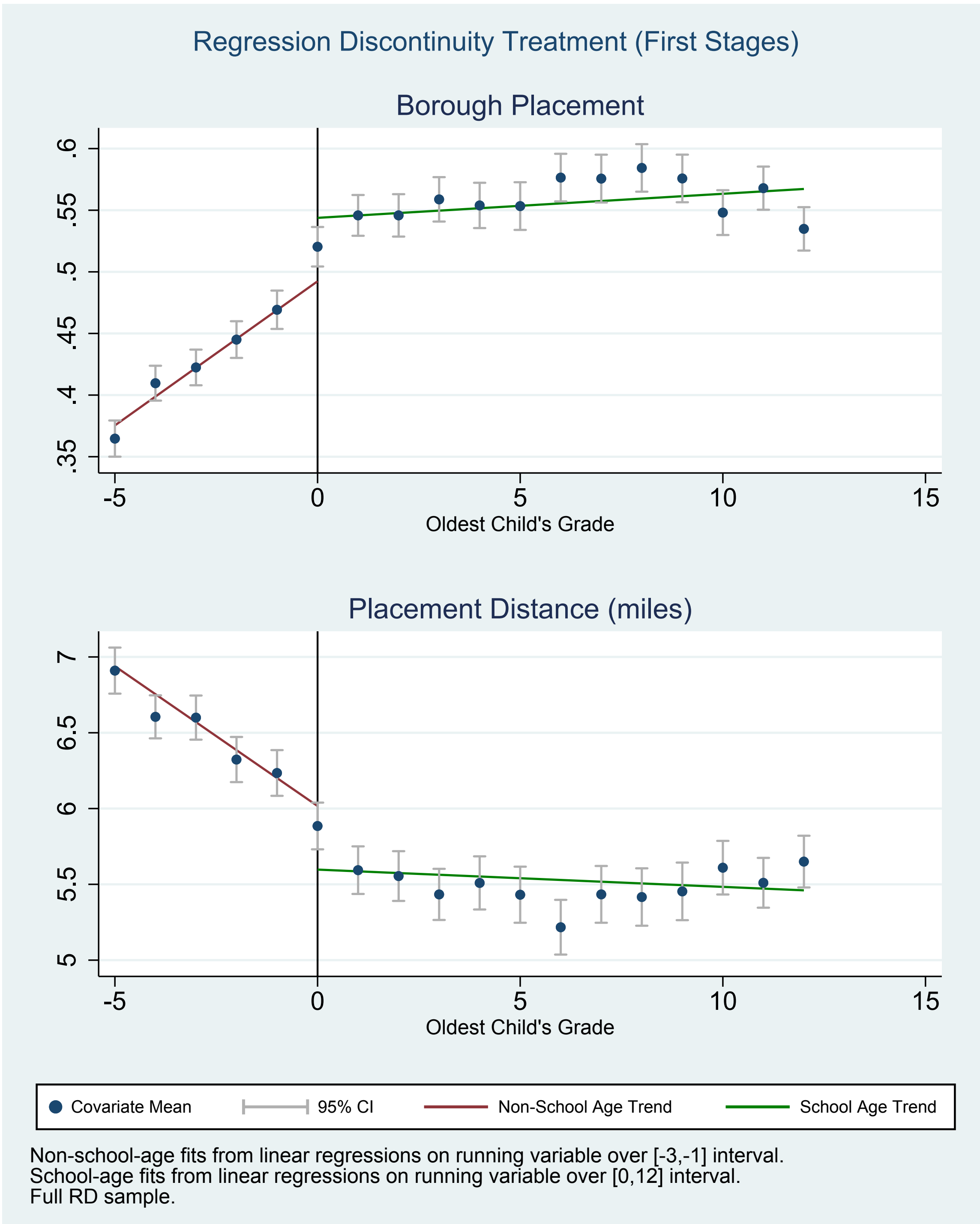
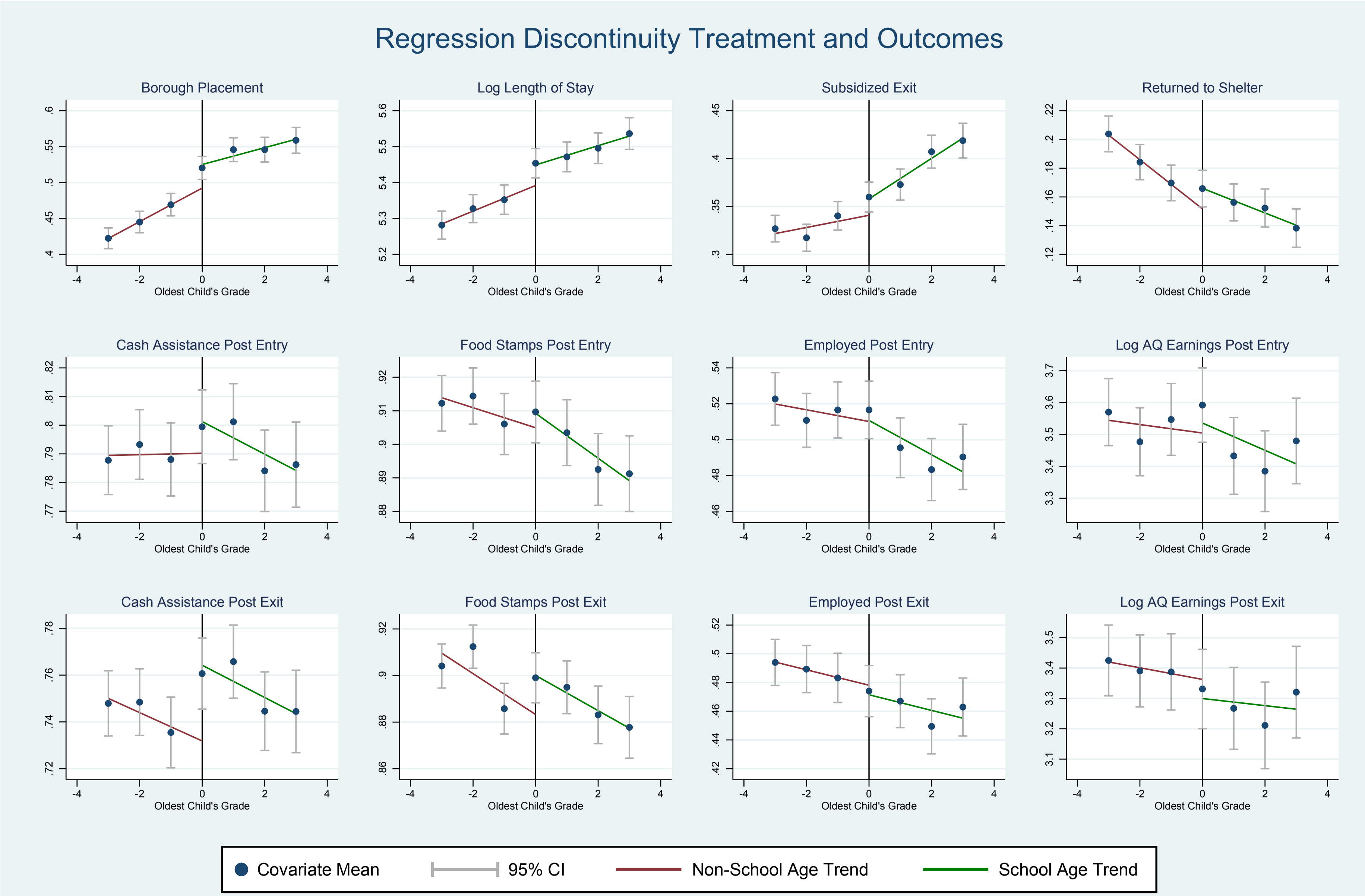
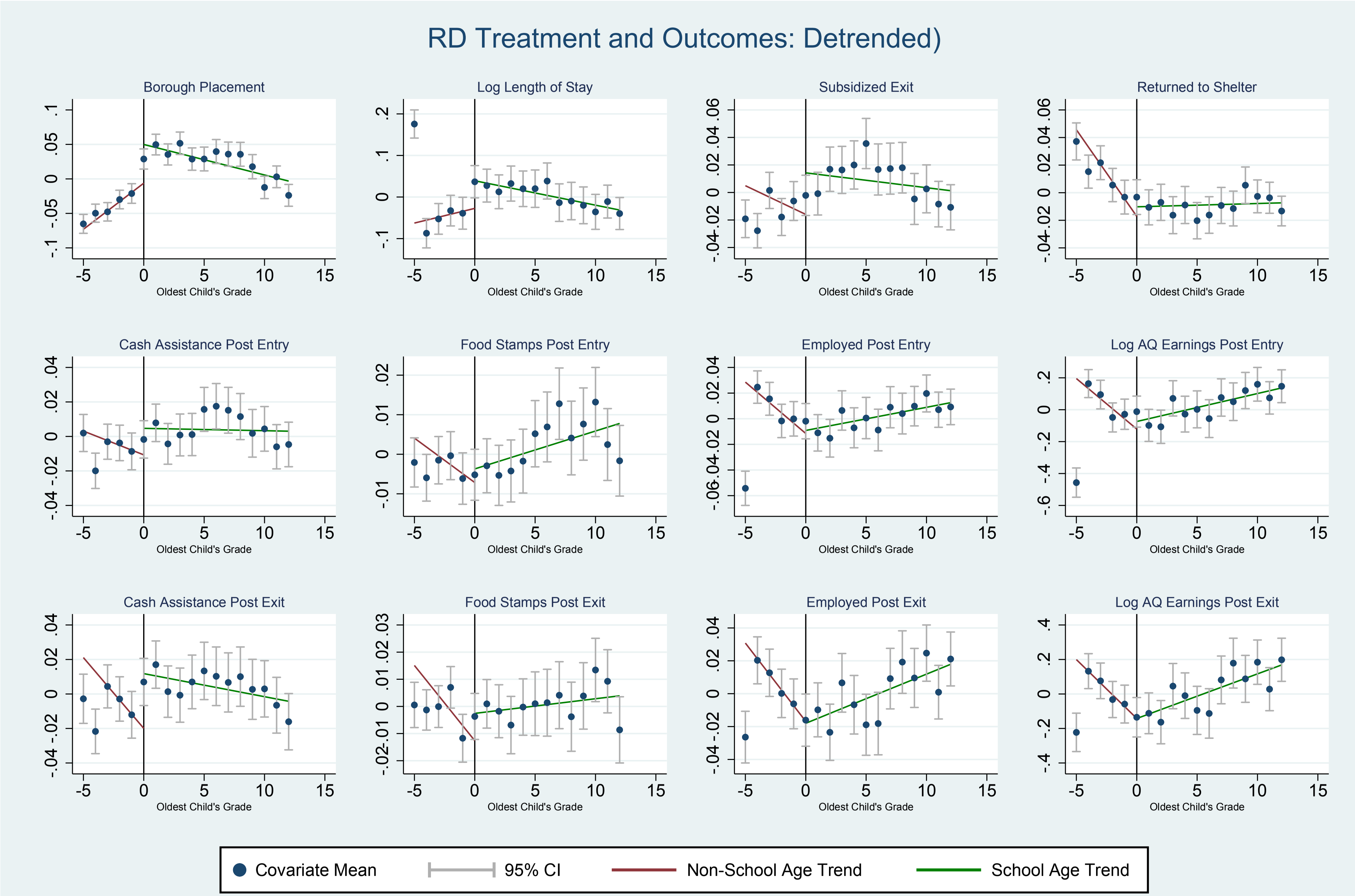

Regression Discontinuity Treatment (First Stages)
Borough Placement
.35
.4
.45
.5
.55
.6
-5
0
5
10
15
Oldest Child's Grade
Placement Distance (miles)
5
5.5
6
6.5
7
-5
0
5
10
15
Oldest Child's Grade
Covariate Mean
95% CI
Non-School Age Trend
School Age Trend
Non-school-age fits from linear regressions on running variable over [-3,-1] interval.
School-age fits from linear regressions on running variable over [0,12] interval.
Full RD sample.

Figure A.9



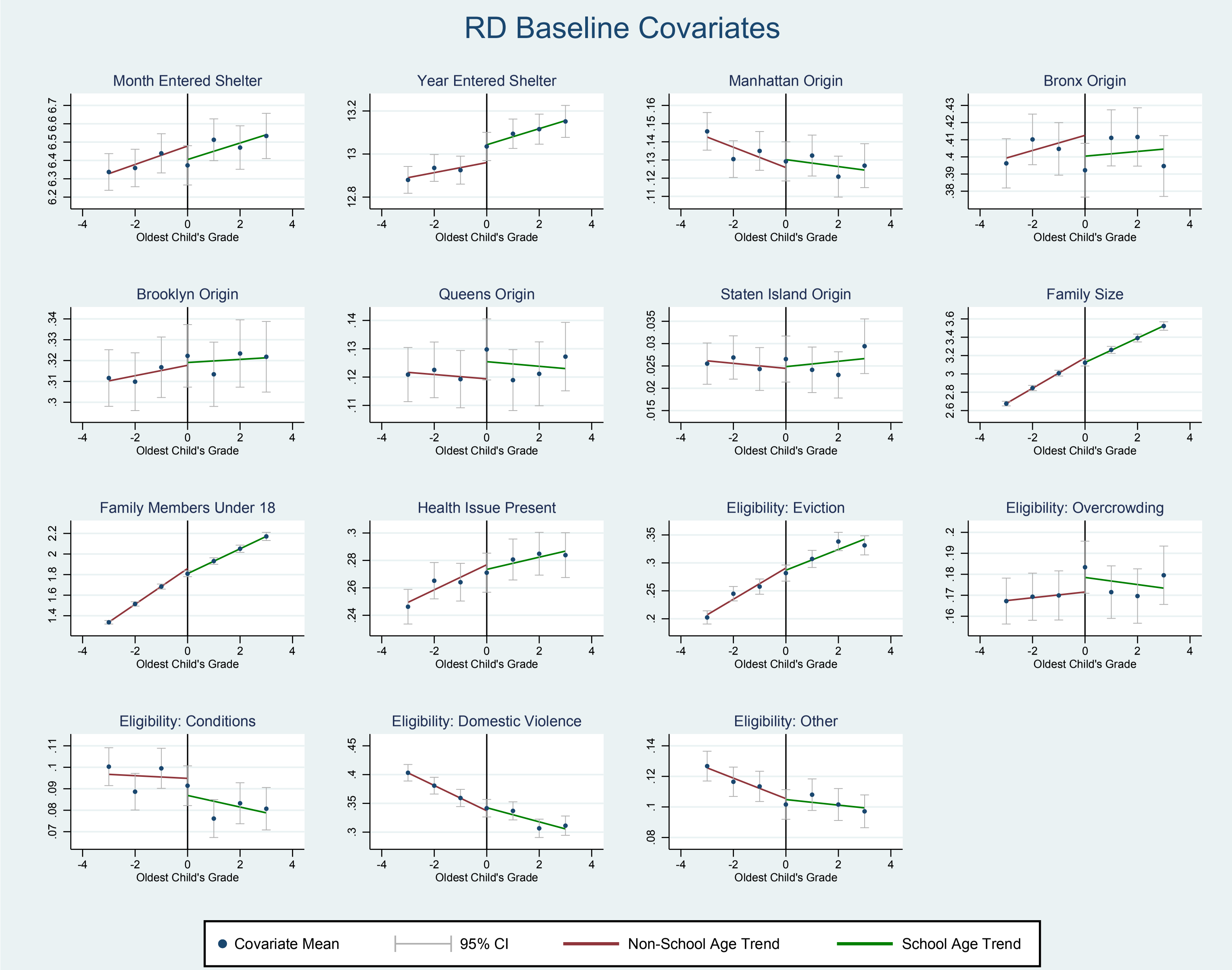
Non-school-age fits from linear regressions on running variable over [-3,-1] interval.
School-age fits from linear regressions on running variable over [0,3] interval.
Full RD sample.

Figure A.10



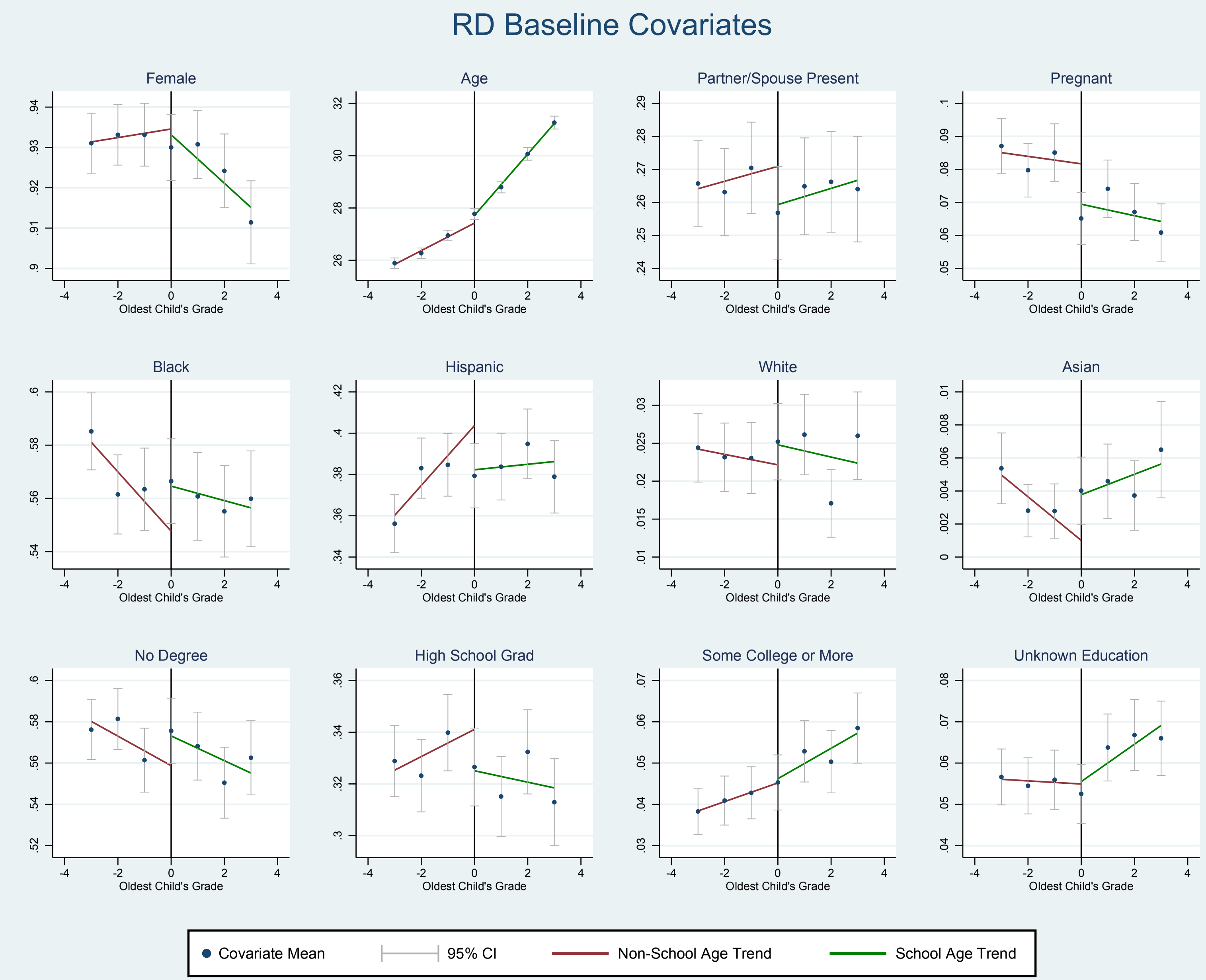
Non-school-age fits from linear regressions of detrended outcome on running variable over [-3,-1] interval.
School-age fits from linear regressions of detrended outcome on running variable over [0,12] interval.
Detrended outcomes are residuals from a linear regression on Main RD covariates.
Full RD sample.

Figure A.11



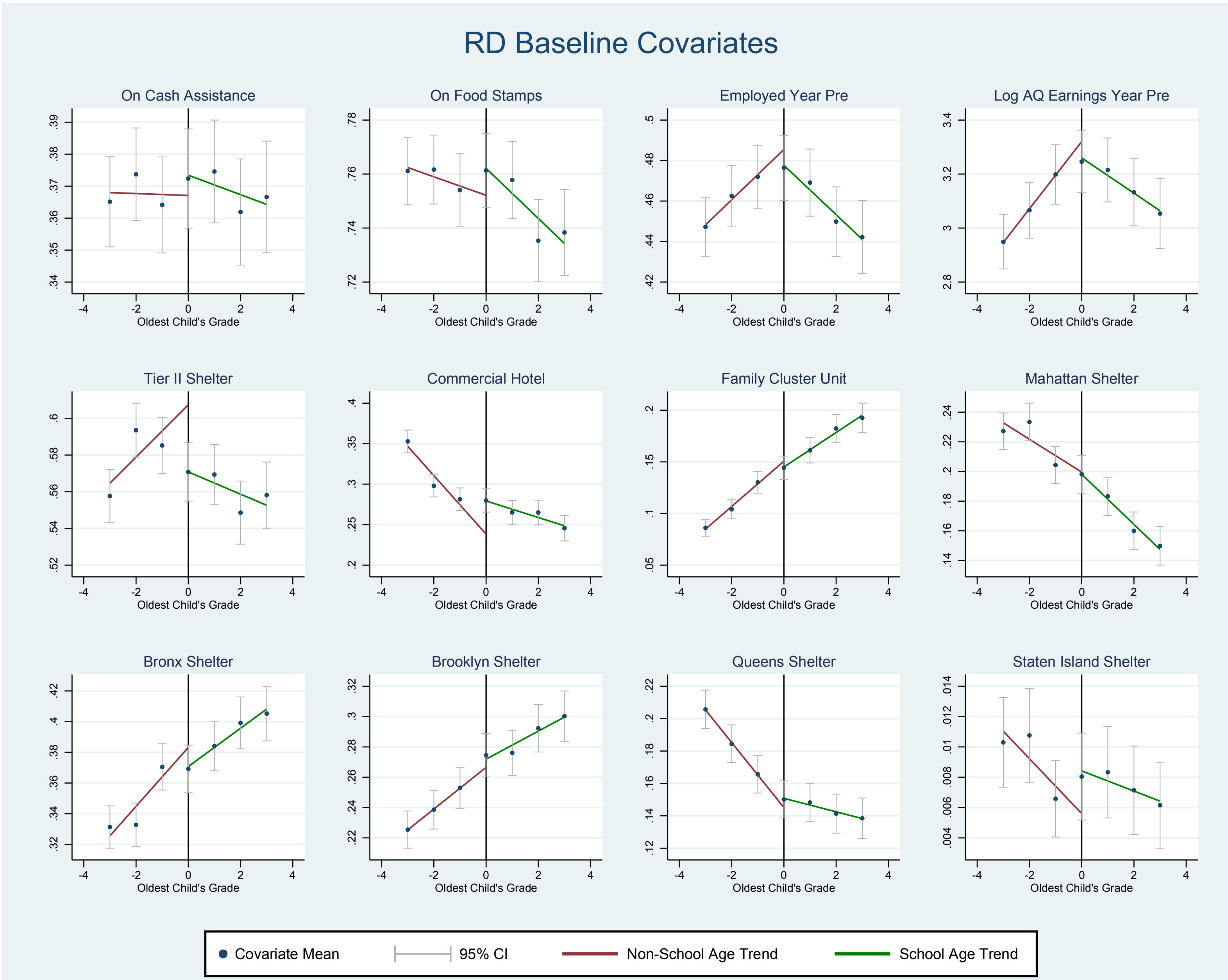
Non-school-age fits from linear regressions of detrended outcome on running variable over [-3,-1] interval.
School-age fits from linear regressions of detrended outcome on running variable over [0,3] interval.
Full RD sample.

Figure A.12



Non-school-age fits from linear regressions of detrended outcome on running variable over [-3,-1] interval.
School-age fits from linear regressions of detrended outcome on running variable over [0,3] interval.
Full RD sample.

Figure A.13



Non-school-age fits from linear regressions of detrended outcome on running variable over [-3,-1] interval.
School-age fits from linear regressions of detrended outcome on running variable over [0,3] interval.
Full RD sample.