NBER WORKING PAPER SERIES

DISTANCE TO HOSPITAL AND CHILDREN'S ACCESS TO CARE: IS BEING CLOSER BETTER, AND FOR WHOM?

Janet Currie
Patricia Reagan

Working Paper 6836
http://www.nber.org/papers/w6836

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
December 1998

We are grateful to David Cutler and Mark Duggan for helpful comments. We also thank Randy Olson for his support of the SLSY79 geocode project. Steve Mulherin, Fernando Bosco, and Chris Starrett provided excellent research assistance. Janet Currie thanks the Canadian Institute for Advanced Research, and NICHD for support under grant number R01-HD3101A2. The views expressed here are those of the author and do not reflect those of the National Bureau of Economic Research or any funding agency.

Distance to Hospital and Children's Access
to Care: Is Being Closer Better, and for Whom?
Janet Currie and Patricia Reagan
NBER Working Paper No. 6836
December 1998
JEL No. I1, H4, I3

ABSTRACT

Distance to hospital may affect the utilization of primary preventative care if children rely on hospitals for such routine care. We explore this question using matched data from the National Longitudinal Survey of Youth's Child-Mother file and the American Hospital Association's 1990 Hospital Survey. Our measure of preventative care is whether or not a child has received a regular checkup in the past year.

We find that distance to hospital has significant effects on the utilization of preventative care among central-city black children. For these children, each additional mile from the hospital is associated with a 3 percent decline in the probability of having had a checkup (from a mean baseline of 74 percent). This effect can be compared to the 3 percent increase in the probability of having a checkup which is associated with having private health insurance coverage. The size of this effect is similar for both the privately insured and those with Medicaid coverage, suggesting that even black urban children with private health insurance may have difficulty obtaining access to preventative care. In contrast, we find little evidence of a negative distance effect among white or Hispanic central-city children, suburban children, or rural children.

Janet Currie
Department of Economics
UCLA
405 Hilgard Ave.
Los Angeles, CA 90095-1477
and NBER
currie@simba.sscnet.ucla.edu

Patricia Reagan
Department of Economics
Ohio State University
1945 N. High St.
Columbus, OH 43210
reagan@pewter.chrr.ohio-state.edu

Many poor children rely on hospitals for their medical care. This pattern of use is inefficient because, in principal, preventive care can be delivered more cheaply in doctors' offices. Doctors' offices also provide greater continuity of care. In practice however, the use of hospitals for preventive care may reflect lack of access to other providers. Increased competition among hospitals in recent years has raised fears that hospitals will be forced to cut back on care to under-privileged groups, which may severely restrict access to medical care among children who are currently served by hospitals.[1]

This paper examines the way in which distance to hospital affects the utilization of preventive care among children, using matched data from the National Longitudinal Survey of Youth's Child-Mother file and the American Hospital Association's 1990 Hospital Survey. Using special geographical software, we measure the distance (as the crow flies) between a child's address and his or her nearest hospital.

Our measure of preventive care is whether or not a child has received a regular checkup in the past year. We examine differences in utilization patterns by race and ethnicity, insurance status, and location (rural, suburban or central-city). In order to control for unobserved maternal characteristics that could be related to use of preventive care and either location or insurance status, we estimate models that include maternal fixed effects. Where applicable, we also estimate models including city fixed effects in order to control for relevant characteristics of city health care delivery systems.

We find that distance to hospital has significant effects on access to preventive care among central-city black children. For these children, each additional mile from the hospital is associated with a 3 percent decline in the probability of having had a checkup (from a mean baseline of 74 percent). This effect can be compared to a 3 percent increase in the probability of having a

[1] The market for hospital services has changed rapidly in recent years. Technological changes have resulted in dramatically reduced hospital stays, and lower demands for hospital services. Managed care has mushroomed leading to greater scrutiny of hospital procedures by insurers--in 1980, only 5 percent of the privately insured were in some form of managed care, while by 1997, this fraction had increased to 75 percent (Cutler and Sheiner, 1998).

checkup which is associated with having private health insurance coverage. The size of this effect is similar for both the privately insured, and those with Medicaid, suggesting that even black urban children with private health insurance may have difficulty obtaining access to preventive care. In contrast, we find little evidence of a negative distance effect among white or Hispanic central-city children, suburban children, or rural children.

The rest of this paper is laid out as follows. Section II provides a review of the literature regarding the effects of access to hospitals on utilization of preventive care among "at risk" children. The model that underlies our estimating equations is presented in section III. Section IV gives an overview of the data. Results are shown in section V, and section VI concludes.

Section II: Children Who Rely on Hospitals For Primary Care

The previous literature suggests that four groups of children are especially likely to rely on hospitals for preventive care. The first group is central-city minority children. American cities are highly segregated by race and income (Massey and Denton, 1993). Urban black children often live in parts of the city that are shunned by physicians in private practice and hence are more likely to be served by large, urban, teaching hospitals. In Chicago, for example, there are twice as many children per office-based pediatrician in the inner city compared to the best-served neighborhoods, and there are 60 percent more children per child health care provider (Fossett *et al.*, 1992). Black children are twice as likely as white children to receive care in an institutional setting such as a clinic or emergency room, and they are more likely to be attended by residents than by staff physicians (Bloom, 1990).

Although there has been little investigation of access to health care among Hispanic children, similar arguments suggest that they may also rely on hospitals to a greater extent than non-Hispanic white children. Denton and Massey (1989) show that in many areas recent Hispanic immigrants are even more residentially segregated than blacks. Furthermore, language may create a barrier between these families and some doctors in private practice, whereas many hospitals have translation services available.

Second, children without health insurance may have difficulty finding private physicians who will treat them. Despite the existence of public programs to provide insurance for the poor, 10 million children (14 percent) have no health insurance coverage at all. Nine out of 10 of these children have parents who work, and 60 percent live in two-parent families (Children's Defense Fund, 1997).

Children without health insurance are less likely to have a regular provider of care and are five times more likely than other children to use an emergency room as a regular source of care--one in four uninsured children uses an emergency room as his or her regular source of care or has no regular provider. These children are less likely to seek routine preventive care and receive less care when they are sick (Currie and Thomas, 1995; Kogan *et al*, 1995).

Third, children with Medicaid (the main source of public health insurance for poor children) are also likely to have problems finding private doctors who will accept this coverage. For pediatric services Medicaid pays about half as much as private insurers for the same services (Rowland and Salganicoff, 1994). Twenty percent of U.S. pediatricians refuse to see Medicaid patients at all, and 40 percent limit the number of Medicaid patients in their practices. Moreover, both percentages have been growing over time, as more and more physicians opt out of the Medicaid program--in 1977, only 15 percent of physicians refused Medicaid patients and only 26 percent limited their numbers (Yudkowsky *et al.*, 1990).

The result is that while children on Medicaid are more likely than uninsured children to have a usual source of care, and to receive routine care on an appropriate time frame, they are less likely than privately insured children to be seen in doctors' offices. They are also more likely than privately insured children to lack continuity between usual sources of routine and sick care since they typically receive routine care at a clinic, and sick care in a hospital emergency room (St. Peter *et al.*, 1992).

Fourth, rural children may face shortages of providers in private practice, and hence be forced to rely on hospitals for primary care. In 1990, the Department of Health and Human Services surveyed the states and found that virtually all of them cited general shortages of primary care physicians, particularly in rural areas, as a serious concern (U.S. DHHS, 1990). Children living in counties in which the supply of primary care physicians was in the top 20 percent had half the odds of reporting emergency departments as their usual source of care as other children (Halfon *et al.*, 1996).

Closures of rural hospitals have attracted a great deal of negative publicity, in part because of possible effects on access to basic health services (c.f. Fleming *et al.*, 1995; Bindman, Keane and Lurie, 1990; U.S. General Accounting Office, 1991; McKay and Coventry, 1995). The evidence about the effects of closures on primary care comes primarily from case studies, and is generally mixed. In some cases other providers were able to pick up the slack, while in others cases patients lost access to care. We know little about the overall contribution of rural hospitals to access to primary preventive care, however.

Section III: A Model of the Demand for Child Health Inputs

In the standard economic model of the determinants of child health, parents are assumed to maximize an intertemporal utility function such as:[2]

(1) $\Sigma_{t=1}^{T} E_t(1/1+\sigma)^t U_t + B(A_{T+1})$,

where σ is the discount rate, B is a bequest function, A denotes assets, and U_t is given by:

(2) $U_t = U(Q_t, C_t, L_t,; X_t, u_1, \varepsilon_{1t})$,

where Q is the stock of child health, C is consumption of other goods, L is

[2] The model in this section is similar to Blau (1996).

leisure, X is a vector of exogenous taste shifters, u is a vector of permanent taste shifters, and ε denotes a shock to preferences. Utility is maximized subject to the following set of constraints:

(3) $Q_t = Q(Q_{t-1}, G_t, V_t; Z_t, u_2, \varepsilon_{2t})$,

(4) $C_t = Y_t + P_{gt}G_t - (A_{t+1} - A_t)$,

(5) $Y_t = I_t + w_tH_t + rA_t$,

(6) $L_t + V_t + H_t = 1$,

where G and V are material and time inputs into health production, Z is a vector of exogenous productivity shifters, u_2 are permanent productivity shifters, ε_{2t} is a productivity shock, Y is total income, P represents prices, I is unearned income, w is the wage, r is the interest rate, and endowments of health and assets, Q_0 and A_0 are assumed to be given. Equation (3) can be interpreted as a "production function" for child health which describes the way that inputs are can be converted into health. Equations (4), (5), and (6) are budget constraints.

Health inputs are valued by consumers not for their own sake, but because they affect child health, which in turn has a direct effect on parental utility. Non-market time is an input into both health production and the production of other valued non-market goods (i.e. leisure activities). This model is dynamic in the sense that the stock of child health today depends on past investments in health, and on the rate of depreciation of health capital (which is one of the elements of u_2).

The model can be solved to yield Frisch demand functions for G_t, and V_t of the following form:

(7) G_t, and $V_t = F(\lambda_t, X_t, Z_t, w_t, P_t, M_t, r, \sigma, u_1, u_2, \varepsilon_{1t}, \varepsilon_{2t})$,

where λ_t is the marginal utility of wealth and M_t is a vector of moments of the distribution of $\{X_k, Z_k, w_k, P_k, \varepsilon_{1k}, \varepsilon_{2k}\}$, and $k=t+1, \ldots, T$.

This model can be considerably simplified by assuming that the elements of M_t are functions of current and past realizations of the exogenous variables. In panel data, we can also control for w_t, r, σ, λ_t, u_1, u_2 by including a mother-specific fixed effect, η to yield the following reduced form demands for health inputs:

(8) G_t and $V_t = F(X_t, Z_t, P_t, \eta, \varepsilon_{1t}, \varepsilon_{2t})$,

In our empirical implementation of (8), the goods and time inputs into child health will be collapsed into one variable measuring whether or not the child has had a checkup in the past year. The taste and productivity shifters will be measured using background characteristics of the mother and child as well as city fixed effects (where applicable). Distance and insurance status will be treated as proxies for the price of health inputs, which is not directly observed.

Section IV: The Data

Our main source of data is the National Longitudinal Survey's Child-Mother file (NLSCM). This data set is based on the National Longitudinal Survey of Youth, which began in 1978 with 6,283 young women aged 14 to 21 (and a similar number of young men). These women have been followed up every year, and in 1986, the NSLCM began surveying the children born to them. To date, 10,042 children have been included in the NLSCM. The children have been followed up biennially. Thus, a good deal of information is available about both the mother and the child.

Our sample is composed of children drawn from the five waves of the survey conducted between 1986 and 1994, and consists of all children under 12 years old, excluding those whose mothers were in the "military" sample or in the "poor whites" oversample (which was dropped partway through our sample period).

Although the NLSCM is based on a nationally representative sample of young women who were in the United States in 1978, their children may not form a representative sample of U.S. children for several reasons. First, the youngest women in the NLSCM were 30 in 1994, and may not have completed their child bearing. Thus, the children of the NLSCM tend to be born to young mothers on average. Second, the composition of some groups, such as Hispanics, has changed dramatically since 1978 due to immigration. The authors' calculations using Current Population Survey Data suggest that about 8 percent of the 1957 to 1964 birth cohort currently living in the United States have immigrated since 1979. These limitations of the data should be kept in mind.

We focus on whether or not the child has had a routine checkup in the past year. The American Academy of Pediatrics recommends that all children in this age group receive at least one routine checkup per year, so children who lack this minimum contact with the medical establishment are going without recommended preventive care. Nevertheless, the child's probability of having had a checkup goes down with age, so we control for single year of age dummies in all of our models. The NLSCM data also includes information about whether a child was covered by private health insurance, Medicaid, or was uninsured in each wave.

In order to track respondents from year to year, the NLS must collect street addresses. However, prior to 1990, street addresses were recorded only for respondents who moved. Hence addresses for 1986 and 1988 have to be imputed for those who did not move. In order to do the imputation, we began in 1979 with the addresses for parents and spouses (since 1979 respondent addresses were not obtained). By using the household roster to identify respondents who lived with their parents or spouses, we obtained an address for about 70 percent of the mothers in the sample.[3] The remaining mothers were assigned an address at the center of their zip code, since 1979 zip codes were available for all mothers.

Until 1984, respondents were asked whether they had moved since the last

[3] In some cases addresses were recorded for siblings in the same household, and adding this information increased the fraction with addresses by a few percentage points. For respondents who were unmarried and away at school in 1979, we use the parent's address.

interview. Thus, in principal, we can start with the 1979 address. If the person moved subsequently, then the new address should be reported. If they report that they did not move and no new address is given, then we use the old address.[4] In 1984 through 1990, we assume that if no new address is reported and the MSA (metropolitan statistical area or city), county, and state remain the same, then the person did not move. Beginning in 1990, we have the street address for all respondents.[5]

This data base of street addresses was then fed into geographical software that determines the latitude and longitude of each address.[6] A first pass yielded a match rate of approximately 80 percent. When a match was not made we searched maps that were also included in the software for a likely location. For example, an address might have been recorded as "221 Morning Glory Circle, Cleveland, Ohio", while the map indicated that only numbers between 1000 and 2000 existed on Morning Glory Circle. If Morning Glory Circle was a reasonably short street, we would assign an address on the mid-section of the street. Alternatively, if the software found a "Morning Glory Court", rather than a circle, we would use "221 Morning Glory Court". When we could not come up with a sensible match then we assigned an address at the center of the zip code.

Further information about the construction of the data set is shown in the Data Appendix. Appendix Table 1 gives the number of observations in each wave of the survey (row 1). Subsequent rows show the numbers of observations lost due to missing data about checkups, location, family income (in 1986 dollars), or other missing information. The final row of the table indicates the number of

---

[4] One glitch in this procedure is that only zip codes are available for 1980. All of the exact street addresses have been lost.

[5] Exceptions occur when the respondent was in the military and living on a base or ship, or incarcerated. In these cases we have no address. In rural areas addresses are sometimes reported as "the third trailer on the right". In these cases, we assigned addresses at the center of the respondent's zip code.

[6] The geographical software that we used included Arcview, Arc Information and GDT. We used Geographic Data Technology's Matchmaker/2000 to geocode complete addresses and assign zipcode centroids when address information was incomplete. We used maps available in Arcview to check locations of incomplete addresses.

observations used from each wave of the survey. Appendix Table 2 shows the source of the location information by year for the observations used in this study (e.g. imputed, or assigned zipcode centers). Appendix Table 3 shows that the cases that were excluded due to missing data are similar in most respects to those that are included in our sample. For example, the mean of our dependent variable does not change when we exclude those who are missing other data.

Appendix Table 4 shows the number of observations, the number of individual children, and the number of mothers in each of our subsamples as well as for the sample as a whole. We have a sample of 16,746 observations on 3,173 mothers and 6,722 children in 232 different MSAs (in addition to rural locations). Since estimates from models that include mother fixed effects are identified by mothers who move, Appendix Table 4 also reports the number of moves that mothers make and the number of children affected by these moves for each of our subsamples. In the whole sample we observe mothers moving on 5,332 occasions, which affected 8,814 children.

This data set is matched to information about hospital location from the American Hospital Survey of 1990. This survey is a census of all hospitals. In addition to the exact street address, the survey tells us whether it is a hospital that treats children. For example tuberculosis clinics and psychiatric hospitals are excluded from our hospital sample. We determined hospital latitude and longitude using the methods described above. When a match could not be made, we examined paper maps, which often show hospitals in order to determine the address. All but 3 hospitals were successfully located. Our hospital sample consists of 5,731 general and childrens' hospitals. We found exact locations for 5,468 of these hospitals and used zipcode centroids as the location of the remaining 263 hospitals.[7]

Distance between respondents and hospitals was calculated as follows. All hospitals within a .8 degree radius of each respondent were identified. Distances from each of these hospitals to the respondent were calculated. We

[7] Some hospitals have multiple locations, but only one address is available from the American Hospital survey. Thus our numbers understate the true diversity of hospital locations.

then kept all hospitals within a 50 mile radius, sorted by distance, and identified the closest one. Everyone in our sample was within 50 miles of a hospital.

In addition to constructing the distance variable, we used the geographic software and address information to refine the "central city" variable that is on the public use NLSCM tape. The NLSY data set contains a "central city" variable that is defined using zip codes. If a zip code lies entirely within the city limits of the "main" city of an MSA (population more than 100,000) then the respondent is said to be living in a central city. If the zip is entirely in the MSA but not within the city limits then the respondent is coded "MSA-not central city". Finally, if the zip laps in and out of the city limits, then the respondent is coded on the tapes as "don't know central city". As a result, the central city variable is missing for many NLSY respondents. We improve on this measure using maps and street addresses in order to eliminate the "don't know central city" category.[8] However the reader should be aware that this "central city" variables is based on city limits. It includes, but is not restricted to, impoverished inner-city neighborhoods.

Table 1 gives an overview of our data, broken down into four categories: Central-city black, central-city white and hispanic, suburban, and rural. The choice of these four categories reflects the fact that we were unable to find any statistically significant differences in the effects of distance between central-city whites and hispanics, or between racial and ethnic groups outside of the central-city area.

Table 1 shows that out of our four groups, central-city black children are both most likely to get checkups and most likely to live close to hospitals. They are also less likely to be uninsured, since although they are less likely to have private health insurance coverage, central-city black children are more likely than other children to have Medicaid coverage.

In some respects, such as family income or not having a father present the

---

[8] Specifically, we used GDT's boundaries files to overlay central city boundaries on respondents' locations to identify those living in central cities.

black central-city children appear disadvantaged relative to others. However, their mothers are actually slightly more educated than the mothers of other central-city children or those of rural children, and are about equally likely to work. All of these characteristics are likely to be related to the probability that a child receives a checkup. Thus, we control for them when we estimate the relationship between checkups and distance, as discussed below. Models that excluded potentially endogenous characteristics such as measures of family structure and work status produced very similar estimates of the effects of distance.

Section V: Results

a) The Effect of Distance

Ordinary Least Squares (OLS) regressions of the effects of distance on the probability of a checkup are shown in Table 2 for each group. These linear probability models include all of the variables shown in Table 1, including some like marital status and employment status that may be viewed as endogenous. Our main results are robust to the exclusion of marital status, employment status, family size, and family income from the regressions.

These OLS estimates suggest that among central-city blacks, the probability of a checkup decreases by four percent for each mile of distance from a hospital. Among suburban residents, distance has a small though statistically significant effect. There is no significant effect of distance among white central-city residents, or among rural residents.

The next two rows of Table 2 show that insurance increases the probability that children in all four groups have had a checkup in the past year, and that the effect is as much as twice as big for Medicaid as for private health insurance coverage. This result is consistent with previous work on the effects of insurance coverage using the NSLCM (see Currie and Thomas, 1995). It is not surprising given that Medicaid checkups are free, while most private insurance policies have deductibles and copayments and many do not pay for preventive pediatric care at all.

Other notable results are that firstborn children are more likely to have checkups than their siblings; that hispanic central-city children are less likely than other white central-city children to have checkups (although there is no difference between hispanics and other whites outside the central city); and that for central-city whites and hispanics and for suburban residents, the probability of a checkup increases with maternal education. These results are in keeping with the literature. It is also interesting to note that having a mother who is employed full-time has a significant negative effect on the probability of a checkup among suburban and rural children.

We also find that car ownership has a significant negative effect on the probability of a checkup among non-black central-city residents, a finding which may reflect omitted variables bias since other things being equal one would expect a car to expand the available provider options. Omitted variables that are time-invariant or location-specific will be controlled for in the mother and city fixed effects estimates that are reported below.

We first turn however, to regressions that are similar to those reported in Table 2, except that they include fixed effects for each city. These dummy variables will control, for example, for differences in city transportation systems or in the geographical distribution of medical services across MSAs. Estimates of the key coefficients of this model are shown in Panel B of Table 3. For ease of comparison, the corresponding coefficients from Table 2 are repeated in Panel A. These estimates show that when characteristics of cities are controlled for, the effect of distance on the probability of a checkup among central-city blacks is reduced slightly from 4 to 3 percent for each mile of distance, but remains strongly statistically significant. Distance has no significant effect in any other group. The effects of health insurance and Medicaid are reduced by about one quarter among central-city residents, and only the effects of Medicaid remain statistically significant.

Estimates from models similar to those in Table 2 except that they control for mother fixed effects are shown in Panel C of Table 3. Fixed effects estimates are known to be biased towards zero in the presence of measurement error. While we believe that we have measured distance as carefully as possible given the data, it is likely that some error remains. Thus, it is remarkable that controlling for mother fixed effects has virtually no effect on the estimated distance coefficients.

We still find that among black central-city children, the probability of a checkup is reduced by about 3 percent for each mile of distance from a hospital. The effect of Medicaid coverage also remains statistically significant in all four groups, though the effect of private health insurance coverage does not. Finally, the anomalous coefficients on car ownership disappear once maternal fixed effects are added to the model, although this may be in part because there are relatively few women who change car ownership status--the percentages changing ownership status were 25, 14, 8, and 12 for the black central-city, white/hispanic central city, suburban, and rural groups, respectively.

b) Interactions Between Distance and Insurance Status

The estimates in Tables 2 and 3 support the hypothesis that black central-city children are more reliant on hospitals than other groups for their primary care. As was discussed above, the literature also suggests that uninsured children and children on Medicaid are more likely than others to rely on hospitals. This hypothesis is investigated in Table 4, which follows the same format as Table 3.

These estimates suggest that the only significant negative interactions between insurance status and distance occur among black central-city children. (There is a statistically significant on the interaction between private insurance and distance in the model for suburban children, but the coefficient is small in magnitude.) The effects of distance are greater among black central-city children with Medicaid than among those with private health insurance coverage. For example, in the models which include mother fixed effects, the probability of a checkup falls by 3.7 percent for each mile of distance in the former group, but by only 2.7 percent in the latter group although this difference is not statistically significant. These estimates suggest that many central-city black children rely on hospitals for primary care regardless of their source of insurance coverage.

Among white central-city and suburban residents, the interaction of private health insurance and distance is actually positive once mother fixed effects have been controlled for. A possible explanation is that the number of doctors in private practice increases with distance from central-city hospitals, and that these children are served by these doctors rather than by hospitals.

A surprising finding is that there is no significant interaction between lack of insurance coverage and distance to hospital for any group in any of our specifications. The fact that the probability of a checkup is not related to distance to hospital suggests either that the uninsured do not rely on hospitals for primary care, or alternatively, that they receive non-urgent care only from particular hospitals, so that distance to the nearest hospital is not the relevant concept for this group. As we have seen, the uninsured are less likely than insured children to get regular checkups, which suggests that they often do without primary care rather than being served by the hospitals clinics that take black central-city children who have some form of insurance.

Thus Table 4 suggests that many central-city blacks with insurance rely on hospitals for preventive care, while uninsured children often do without.

c) Interactions Between Distance and Car Ownership

If the estimates above truly reflect the effects of distance, then we should expect people with better transportation to be less affected. Hence, we have estimated models interacting distance and car ownership, and distance, car ownership, and insurance status. These estimates are shown in Tables 5 and 6, which follow the same format as Tables 3 and 4.

Panels A and B of Table 5 show that among central-city blacks, distance has negative effects on the probability of checkups among both car owners, and non-car owners, but that the effects are twice as large among those without cars. We reject the restricted model (distance with no car interactions) in favor of the unrestricted model (which includes distance*car and distance*no car interactions). There is also a small and statistically significant negative effect of distance among suburbanites who do not own cars. The OLS estimates of the main effects of car ownership are negative and statistically significant for central city residents. However, this result is greatly attenuated when city fixed effects are included in the model suggesting that people are more likely to own cars in cities where services are more spread out or where public transportation is poorer.

In contrast to our earlier estimates which were robust to changes in specification, Panel C shows that these results disappear when we control for mother fixed effects. The mother fixed effects are identified using mothers who changed either distance or car ownership status. A potential problem is that changes in these two factors could be related since someone who moves further away from the center of town and public transportation services is more likely to need a car. However, we found no significant correlations between changes in car ownership status and distance. A more serious problem is likely to be the small numbers of mothers who changed car ownership status that was noted above that was noted above.

Table 6 shows a similar set of patterns. Panels A and B show that the negative effects of distance are most pronounced among black central-city residents with insurance (either private or Medicaid) and without cars. For example, the -.032 interaction on Medicaid*no car*distance in Panel A is significantly more negative than the .018 coefficient on Medicaid*car*distance. However, the -.037 coefficient on the interaction of private, car, and distance is not significantly different than the -.053 coefficient on the private*no car*distance interaction.

Once again, a very small but statistically significant negative effect of distance among suburbanites without cars is found, and it is concentrated among those with Medicaid coverage. However, there is also a negative and statistically significant interaction between private, car, and distance for suburban residents, as well as a negative interactions between uninsured, car, and distance among rural residents.

Panel C indicates that when mother fixed effects are added to the model for central-city blacks, the interactions between Medicaid, car ownership status, and distance are reduced in size and become statistically insignificant, although the comparable interactions between private health insurance status and the other variables remain marginally significant and negative. Thus, while the OLS and city-fixed effects models support the hypothesis that distance to a hospital is a greater problem for black central-city children in families without cars, we hesitate to draw a firm conclusion given the imprecision of the mother-fixed effects estimates.

We also find a negative interaction between Medicaid, no car, and distance among suburban and rural dwellers, although it is only marginally statistically significant in the later group.

A more peculiar result is that we estimate relatively large positive coefficients on private*car*distance and private*no car*distance for white and hispanic central-city dwellers, as well as a small positive interaction between private, car, and distance among suburban residents. These results are consistent with those in Panel C of Table 4, where we found a positive and significant interaction between private health insurance coverage and distance for these two groups. As discussed above, a possible explanation is that the number of doctors in private practice who are willing to serve these children actually increases with distance from hospitals, so that access to care improves with distance.

Section VI: Extensions and Conclusions

We have estimated several other variants of the models discussed above. First, we have re-estimated these models using distance to the nearest hospital that accepts Medicaid patients, rather than distance to the nearest hospital as the independent variable of interest. We could not reject the null hypothesis of similar effects.[9]

Second, we estimated models that contained child fixed effects rather than mother fixed effects. As Appendix Table 4 shows, there are approximately two children per mother. The models with mother fixed effects use within-child variation in distance as well as variations in distance between siblings to achieve identification. Models with child fixed effects use only the within-child variation.

It is the mother (or parent) who determines whether or not a child will go for a checkup, so her unobserved characteristics are likely to be important. Nevertheless, there may also be characteristics of individual children that would lead them to be more or less likely to receive checkups. Hence, it could be argued that models with child fixed effects are preferred to those presented above. We found, however, that we could not precisely identify the effects of distance in these models. We have controlled for the age of the child (one of the more important determinants of checkup probabilities) as well as the child's gender, as discussed above.

A third issue we have addressed is whether it is appropriate to measure distance to hospital linearly. Non-parametric regressions of distance on the probability of a checkup, indicated that the assumption of linearity was a reasonable one over most of the range of our data.

In view of the literature, some of the things we do not find are as remarkable as those we do find. We find for example, that in the central city there are no significant differences in the effects of distance between hispanics and non-hispanic whites. There is little evidence that either group relies on

---

[9] The hospital survey asks how many inpatient days were paid for by Medicaid. We divided by total inpatient days to get a measure of the fraction of inpatient days paid for by Medicaid. We required the hospital to have at least one percent of patient days paid for by Medicaid to qualify as a hospital serving Medicaid patients. Some hospitals did not report in this section and some hospitals did not serve Medicaid patients. Average distance to a hospital serving Medicaid patients for central-city blacks is .25 miles farther away than distance to nearest hospital. The coefficient estimates for black central city residents become slightly smaller when using distance to nearest hospital serving Medicaid patients. In the simplest OLS specification the coefficient fell from -.04 to -.035. Thus, the ball park estimate of a 3% decline in the probability of a checkup for each mile from a hospital is robust to this change in variable definition.

hospitals for primary care. One caveat is that the hispanics in the NLSCM sample are children of mothers who were in the United States in 1978, and are of predominately Mexican origin. Hence, it is not clear that these results can be extended to the current American population of Hispanics, many of whom are recent immigrants and some of whom are from other countries of origin.

Other surprising negative findings are that there is no relationship between distance and checkups among rural residents, or among uninsured children. It is important to note that these results do not imply that these groups are receiving adequate preventive care. Our point estimates suggest that these children are significantly less likely to receive checkups than other children, but that this poor showing is independent of distance to hospital.

Our central finding is that among central-city black children, a longer distance to the nearest hospital reduces the probability of checkups. Although the effects are greatest for children on Medicaid, they are also present for children with private health insurance coverage. These results suggest that among blacks, even many children with private health insurance rely on hospitals for primary care.

We find little evidence of interactions between distance and insurance status among other groups. It is possible that previous findings that children on Medicaid tend to rely on hospitals for primary preventive care reflect the fact that children on Medicaid are disproportionately likely to be black, rather than an effect of Medicaid *per se*.

Our results suggest that hospital mergers and closures, as well as competitive pressures that cause hospitals to cut back on services to under-privileged groups are likely to have their greatest effects on central-city black children. Hence, this group may merit special attention by policy makers seeking to mitigate the societal effects of consolidation in the hospital industry.

References

Bindman, A., D. Keane, and N. Lurie. "A Public Hospital Closes," Journal of the American Medical Association, 264 (Dec. 12, 1990) 2899-2904.

Bloom, Barbara, "Health Insurance and Medical Care," Advance Data from Vital and Health Statistics of the National Center for Health Statistics, #188 (Washington D.C.: Public Health Service, October 1, 1990).

Blau, David. "The Effect of Income on Child Development," Dept. of Economics, University of North Carolina at Chapel Hill, June 1996.

Children's Defense Fund, 14 Things You Should Know About the New Child Health Program, (Washington D.C.: Children's Defense Fund, Sept. 4, 1997).

Currie, Janet and Duncan Thomas, "Medical Care for Children: Public Insurance, Private Insurance and Racial Differences in Utilization," Journal of Human Resources, 30 #1 (Winter, 1995) 135-162.

Cutler, David and Louise Sheiner, "Managed Care and the Growth of Medical Expenditures," (Cambridge MA: National Bureau of Economic Research, April 1998) working paper #6140.

Denton, Nancy and Douglas Massey. "Hypersegregation in U.S. Metropolitan Areas: Black and Hispanic Segregation Along Five Dimensions," Demography, 26 #3 (August, 1989) 373-391.

Fleming, Steven, Harold Williamson, Lanis Hicks, Isabel Rife. "Rural Hospital Closures and Access to Services," Hospital and Health Services Administration, 40 #2 (Summer, 1995) 247-262.

Fossett, J.W. *et al.*, "Medicaid and Access to Child Health Care in Chicago," Journal of Health Politics, Policy, and Law, 17 #2 (Summer, 1992) 273-298.

Halfon, Neal, Paul Newacheck, David Wood and Robert St. Peter, "Routine Emergency Department Use for Sick Care by Children in the United States," Pediatrics, 98 #1 (1996) 28-34.

Kogan, Michael *et al.*, "The Effect of Gaps in Health Insurance on Continuity of a Regular Source of Care Among Preschool-Aged Children in the United States," Journal of the American Medical Association, 274 #18 (Nov. 8,

1995) 1429-1435.

Massey, Douglas S. and Nancy Denton, American Apartheid, (Cambridge MA: Harvard University Press, 1993).

McKay, Niccie and John Coventry. "Access Implications of Rural Hospital Closures and Conversions," Hospital and Health Services Administration, 40 #2 (Summer 1995) 227-246.

Rowland, Diane and Alina Salganicoff, "Commentary: Lessons from Medicaid--Improving Access to Office-Based Physician Care for the Low-Income Population," Public Health Policy Forum, 84 #4 (April 1994) 550-552.

St. Peter, Robert F., Paul Newacheck and Neal Halfon, "Access to Care for Poor Children: Separate and Unequal?," Journal of the American Medical Association, 267 #20 (May 27, 1992) 2760-2764.

U.S. Dept. of Health and Human Services, States' Assessment of Health Personnel Shortages, Issues and Concerns, (Washington D.C.: Government Printing Office, 1990) HRS-P-OD-90-6.

U.S. General Accounting Office. Rural Hospitals: Federal Efforts Should Target Areas Where Closures Would Threaten Access to Care, (Washington D.C.: Government Printing Office, 1991).

Yudkowsky, Beth K., Jennifer Cartland, and Samuel Flint, "Pediatrician Participation in Medicaid: 1978 to 1989," Pediatrics, 85 #4 (April 1990) 567-577.

Table 1: Means by Race and Location

	Black Central City	White/Hispanic Central City	Suburban	Rural
Checkup	.74	.72	.69	.66
past year	(.44)	(.45)	(.46)	(.47)
Distance to	1.51	1.64	4.35	7.31
hospital	(1.09)	(1.36)	(4.36)	(6.77)
Child Characteristics				
Private Health	.46	.61	.72	.58
insurance	(.50)	(.49)	(.45)	(.49)
Medicaid	.43	.24	.15	.27
	(.49)	(.43)	(.36)	(.45)
Uninsured	.11	.15	.13	.15
Hispanic	0	.53	.22	.07
		(.50)	(.42)	(.25)
Black	1	0	.22	.33
			(.41)	(.47)
Male	.49	.53	.51	.50
	(.50)	(.50)	(.50)	(.50)
First born	.40	.48	.46	.43
	(.49)	(.50)	(.50)	(.50)
Age (years)	6.26	5.63	5.62	6.01
	(3.47)	(3.39)	(3.37)	(3.37)
Mother Characteristics				
Age @ birth	22.69	23.86	24.06	22.03
	(3.99)	(4.04)	(4.04)	(4.01)
Education	12.39	12.15	12.52	12.04
	(1.67)	(2.39)	(2.21)	(2.17)
Car	.54	.81	.88	.79
	(.50)	(.39)	(.32)	(.41)
Married, spouse	.31	.66	.72	.63
present	(.46)	(.48)	(.45)	(.48)
Full time	.45	.46	.51	.43
employment	(.50)	(.50)	(.50)	(.49)
Family size	5.14	5.22	5.28	5.36
	(1.57)	(1.44)	(1.39)	(1.40)
Family income	15,912	29,486	32,967	22,992
	(24,660)	(57,066)	(56,351)	(47,204)
# Observations	2734	3158	8230	2624
# Cities	103	163	202	—
# Mothers	625	806	1885	567
# Children	1316	1571	3839	1206

Notes: Standard deviations in parentheses.

Table 2: OLS Regressions of Checkups on Distance

	Black C. City	White/Hispanic C. City	Suburban	Rural
Distance	-.040	-.004	-.002	.000
	(5.34)	(.76)	(2.20)	(.09)
Private health insurance	.039	.108	.038	.065
	(1.42)	(4.71)	(2.51)	(2.44)
Medicaid	.103	.171	.091	.150
	(3.67)	(6.51)	(4.62)	(4.91)
First born	.070	.028	.032	.077
	(3.68)	(1.62)	(2.85)	(3.81)
Black	-	-	.078	.021
			(6.01)	(.93)
Hispanic	-	-.032	-.005	.043
		(1.93)	(.41)	(1.22)
Male	.017	-.025	-.004	.020
	(1.04)	(1.66)	(.38)	(1.15)
Age mother @ birth	.007	-.003	-.001	.002
	(2.25)	(1.29)	(.73)	(1.78)
Highschool dropout	.025	.015	-.051	-.034
	(.28)	(.42)	(1.79)	(.83)
Highschool graduate	.040	.021	-.027	-.016
	(.44)	(.65)	(1.02)	(.44)
Some college	.058	.070	-.001	-.007
	(.63)	(1.93)	(.046)	(.15)
College graduate	.068	.036	.022	.014
	(.69)	(.86)	(.71)	(.27)
Car	-.027	-.106	.003	-.009
	(1.35)	(4.52)	(.15)	(.31)
Married, spouse present	-.013	-.038	-.017	-.028
	(.60)	(1.77)	(1.17)	(1.05)
Fulltime employment	-.016	-.024	-.025	-.087
	(.75)	(1.41)	(2.40)	(4.45)
Family size	-.001	.012	-.023	-
.005	(.090)	(1.88)	(5.51)	(5.83)
(.78)				
log family income	-.012	.010	.007	.006
	(1.61)	(1.45)	(1.50)	(.60)
Intercept	.47	.46	.56	.39
	(3.60)	(4.67)	(8.51)	(3.49)
R-squared	.121	.153	.144	.152
# Observations	2734	3158	8230	2624

Notes: T-statistics in parentheses.

Table 3: Regressions of Checkups on Distance

	Black C. City	White/Hispanic C. City	Suburban	Rural
Panel A: Ordinary Least Squares				
Distance	-.040	-.004	-.004	.000
	(5.34)	(.76)	(2.20)	(.09)
Private health insurance	.039	.108	.038	.065
	(1.42)	(4.71)	(2.51)	(2.44)
Medicaid	.103	.171	.091	1.50
	(3.67)	(6.51)	(4.62)	(4.91)
Car	-.027	-.106	.003	-.009
	(1.35)	(4.52)	(.15)	(.31)
R-squared	.121	.153	.144	.152
Panel B: City Fixed Effects				
Distance	-.032	-1.01	-.001	
	(3.52)	(.08)	(.96)	
Private health insurance	.032	.105	.034	
	(1.12)	(4.30)	(2.20)	
Medicaid	.082	.145	.086	
	(2.78)	(5.35)	(4.31)	
Car	.008	-.058	.020	
	(.39)	(2.28)	(1.07)	
R-squared	.204	.244	.177	
Panel C: Mother Fixed Effects				
Distance	-.034	.011	.002	.003
	(2.98)	(.98)	(1.19)	(1.03)
Private health insurance	.033	.038	.020	.049
	(1.02)	(1.28)	(1.00)	(1.52)
Medicaid	.061	.082	.059	.141
	(1.95	(2.68)	(2.56)	(3.83)
Car	.014	-.047	.035	.084
	(.55)	(1.51)	(1.39)	(2.23)
R-squared	.467	.482	.453	.475

Notes: T-statistics in parentheses. Aside from the mother and/or city dummies, these regression models are of the same form as those shown in Table 2.

Table 4: Interactions of Distance and Insurance Status

	Black C. City	White/Hispanic C. City	Suburban	Rural
Panel A: Ordinary Least Squares				
Private health insurance	.115	.082	.066	.031
	(2.34)	(2.39)	(3.26)	(.80)
Private health * distance	-.039	.002	-.004	-.000
	(4.49)	(.23)	(2.54)	(.036)
Medicaid	.175	.152	.123	.103
	(3.48)	(4.01)	(4.81)	(2.36)
Medicaid * distance	-.030	-.003	-.004	.002
	(2.36)	(.27)	(1.40)	(.81)
Uninsured * distance	.012	-.014	.002	-.005
	(.48)	(1.06)	(.89)	(1.27)
R-squared	.121	.153	.144	.152
Panel B: City Fixed Effects				
Private health insurance	.093	.075	.054	
	(1.87)	(2.05)	(2.62)	
Private health * distance	-.027	.007	-.002	
	(2.69)	(.88)	(1.34)	
Medicaid	.158	.126	.114	
	(3.10)	(3.30)	(4.39)	
Medicaid * distance	-.032	-.001	-.003	
	(2.44)	(.07)	(1.29)	
Uninsured * distance	.015	-.011	.002	
	(.58)	(.77)	(.81)	
R-squared	.204	.245	.177	
Panel C: Mother Fixed Effects				
Private health insurance	.079	-.027	.005	.011
	(1.44)	(.62)	(.20)	(.24)
Private health * distance	-.027	.028	.005	.001
	(2.40)	(2.56)	(2.24)	(.44)
Medicaid	.127	.081	.080	.132
	(2.34)	(1.96)	(2.62)	(2.54)
Medicaid * distance	-.037	-.012	-.005	-.003
	(2.18)	(.71)	(1.41)	(.79)
Uninsured * distance	.005	-.009	.001	-.004
	(.18)	(.52)	(.29)	(.84)
R-squared	.468	.483	.453	.475

Notes: T-statistics in parentheses. Aside from the mother and/or city dummies and interaction terms, these regression models are of the same form as those shown in Table 2.

Table 5: Interactions of Distance and Car Ownership

	Black C. City	White/Hispanic C. City	Suburban	Rural
Panel A: Ordinary Least Squares				
Car ownership	-.070	-.140	-.028	.040
	(2.35)	(4.16)	(1.26)	(1.06)
Car * distance	-.028	-.001	-.001	-.002
	(3.01)	(.21)	(1.41)	(1.07)
No car * distance	-.058	-.025	-.009	.004
	(4.83)	(1.58)	(3.08)	(.76)
Private health insurance	.038	.107	.038	.061
	(1.35)	(4.66)	(2.50)	(2.31)
Medicaid	.104	.168	.090	.144
	(3.71)	(6.38)	(4.59)	(4.71)
R-squared	.122	.153	.145	.153
Panel B: City Fixed Effects				
Car ownership	-.027	-.069	-.005	
	(.85)	(1.90)	(.022)	
Car * distance	-.022	-.001	-.000	
	(2.03)	(.8)	(.23)	
No car * distance	-.046	-.07	-.006	
	(3.51)	(.43)	(2.16)	
Private health insurance	.031	.105	.034	
	(1.09)	(4.29)	(2.20)	
Medicaid	.083	.144	.086	
	(2.81)	(5.31)	(4.30)	
R-squared	.204	.244	.177	
Panel C: Mother Fixed Effects				
Car ownership	.06	-.048	.022	.099
	(.22)	(1.39)	(.83)	(2.46)
Car * distance	-.005	.005	.002	-.000
	(.76)	(.96)	(1.82)	(.28)
No car * distance	-.014	.004	-.002	.004
	(1.12)	(.27)	(.44)	(1.25)
Private health insurance	.031	.034	.020	.051
	(.93)	(1.14)	(1.04)	(1.58)
Medicaid	.049	.090	.063	.148
	(1.52)	(2.82)	(2.67)	(3.90)
R-squared	.468	.482	.459	.475

Notes: T-statistics in parentheses. Aside from the mother and/or city dummies and interaction terms, these regression models are of the same form as those shown in Table 2.

Table 6: Interactions of Distance, Insurance Status, and Car Ownership

	Black C. City	White/Hispanic C. City	Suburban	Rural
Panel A: Ordinary Least Squares				
Car	-.081	-.120	-.028	.036
	(2.85)	(3.76)	(1.22)	(.95)
Private health ins.	.123	.083	.069	.025
	(2.49)	(2.43)	(3.40)	(.64)
Medicaid	.143	.159	.115	.115
	(2.85)	(4.19)	(4.71)	(2.70)
Private * car * distance	-.037	.001	-.003	-.001
	(3.70)	(.16)	(2.25)	(.63)
Medicaid * car * distance	.018	.001	-.000	.001
	(1.44)	(.16)	(.05)	(.34)
Uninsured * car * distance	.016	-.016	.003	-.008
	(.60)	(1.13)	(1.13)	(2.05)
Private * no car * distance	-.053	.011	-.008	.005
	(3.47)	(.58)	(1.46)	(1.30)
Medicaid * no car * distance	-.032	-.030	-.009	.002
	(2.52)	(1.59)	(2.81)	(.90)
Uninsured * car * distance	.005	-.004	-.001	.007
	(.13)	(.14)	(.21)	(1.18)
R-squared	.123	.154	.145	.155
Panel B: City Fixed Effects				
Car	-.034	-.051	-.002	
	(1.14)	(1.48)	(.071)	
Private health ins.	.101	.077	.056	
	(2.01)	(2.13)	(2.70)	
Medicaid	.124	.134	.107	
	(2.43)	(3.59)	(4.32)	
Private * car * distance	-.023	.006	-.002	
	(2.08)	(.69)	(1.23)	
Medicaid * car * distance	.014	-.002	-.000	
	(1.10)	(.18)	(.072)	
Uninsured * car * distance	.019	-.012	.002	
	(.75)	(.85)	(.94)	
Private * no car * distance	-.038	.024	-.004	
	(2.39)	(1.20)	(.65)	
Medicaid * no car * distance	-.025	-.016	-.008	
	(1.90)	(.84)	(2.38)	
Uninsured * car * distance	.014	.007	.000	
	(.37)	(.24)	(.03)	
R-squared	.204	.245	.178	

Table 6, continued

	Black C. City	White/Hispanic C. City	Suburban	Rural
Panel C: Mother Fixed Effects				
Car	-.06	-.023	.013	.051
	(.19)	(.56)	(.45)	(1.14)
Private health ins.	.090	-.016	.011	.005
	(1.62)	(.39)	(.46)	(.12)
Medicaid	.095	.089	.077	.120
	(1.76)	(2.15)	(2.70)	(2.44)
Private * car	-.026	.025	.005	.002
* distance	(2.00)	(2.17)	(2.27)	(.66)
Medicaid * car	-.001	-.005	-.002	.003
* distance	(.08)	(.67)	(1.35)	(1.28)
Uninsured * car	.026	-.008	.004	-.006
* distance	(.87)	(.53)	(1.25)	(1.26)
Private * no car	-.030	.043	.007	.000
* distance	(1.78)	(1.98)	(1.11)	(.001)
Medicaid * no car	-.022	-.013	-.010	-.008
* distance	(1.44)	(.67)	(2.20)	(1.80)
Uninsured * car	-.080	.022	-.008	.005
* distance	(.21)	(.78)	(1.38)	(.75)
R-squared	.468	.484	.454	.475

Notes: T-statistics in parentheses. Aside from the mother and/or city dummies and interaction terms, these regression models are of the same form as those shown in Table 2.

Data Appendix

Appendix Table 1

Sample Sizes and Number of Observations Lost to Missing Information by Year

	1986	1988	1990	1992	1994	Total
# children <= 12	4115	5020	5311	5524	5263	25233
# children <= 12 lost due to missing checkup	54	73	99	59	18	303
# children <= 12 with valid checkup lost due to missing location	426	559	1362	204	185	2736
# children <= 12 with valid checkup and location lost due to missing income	516	683	625	729	1081	3634
# children <= 12 with valid checkup, location and income lost due to other missing information	403	404	295	393	319	1814
# children <= 12 with complete information	2716	3301	2930	4139	3660	16746

Appendix Table 2

Source of Location Information by Year

	1986	1988	1990	1992	1994
No new address information available:					
Location imputed from previous geocoded address	1554	1876			
Location imputed from previous zip centroid	423	357			
New address information available:					
Location geocoded to address	605	921	2373	3270	2963
Location geocoded to zip centroid	134	147	557	869	697
Total sample size	2716	3301	2930	4139	3660

Note: Prior to 1990, interviewers were instructed to record addresses only for respondents who moved. Thus, a blank address field suggests that the respondent has not moved since the last interview. Beginning 1990, interviewers were instructed to record addresses of all respondents.

Appendix Table 3
Means of Selected Variables by Sample Restrictions
[standard deviation of continuous variables]
(sample size)

	Checkup	**Distance**	**Private Ins.**	**Medicaid**	**Ed.**	**Income**
Raw data	0.70 (24930)	3.80 [4.57] (22194)	0.62 (25080)	0.24 (25060)	12.22 [2.22] (25089)	27299 [49263] (21150)
Valid checkup	0.70 (24930)	3.80 [4.57] (22194)	0.62 (24860)	0.24 (24840)	12.23 [2.22] (24791)	27337 [49308] (20913)
Valid checkup and location	0.70 (22194)	3.80 [4.57] (22194)	0.62 (22131)	0.24 (22117)	12.27 [2.21] (22104)	28132 [51948] (18560)
Valid checkup, location and family income	0.70 (18560)	3.84 [4.56] (18560)	0.64 (18508)	0.23 (18498)	12.32 [2.18] (18483)	28132 [51948] (18560)
Valid responses to all variables used in analysis	0.70 (16746)	3.84 [4.57] (16746)	0.64 (16746)	0.23 (16746)	12.35 [2.17] (16746)	27963 [51605] (16746)

Appendix Table 4

Sample Sizes and Counts of Mothers, Children, MSAs and Moves

	Black C. City	White/ Hisp. C. City	Suburb	Rural	Total
# observations	2734	3158	8230	2624	16746
# children	1316	1571	3839	1206	6722
# mothers	625	806	1885	567	3173
# mother moves	867	970	2668	827	5332
# child moves	1418	1587	4391	1418	8814
# MSAs	103	163	202	NA	232

Note: The total number of children and number of mothers is less than the sum of the columns because some children and mothers contribute to more than one sample. For example, if a woman moves from a central city to a suburb, she contributes observations to the central city sample for those years when she lives in the central city and she contributes to the suburban sample for those years when she lives in the suburbs. The reported total number of times a mother or child moves is the sum of the columns and excludes movements across geographic units, such as a move from a central city to a suburb. The total number of MSAs is less than the sum across the columns because the MSAs in each column are not mutually exclusive.