Supplemental Security Income and Child Outcomes: Evidence from Birth Weight Eligibility Cutoffs [a,b]

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Abstract:
Low birth weight infants born to mothers with low educational attainment have a double hurdle to overcome in the production of human capital. We examine whether income transfers, in the form of Supplemental Security Income (SSI) payments, can help close the gap in outcomes due to this initial health and environmental disadvantage. We exploit a discontinuity in SSI eligibility at 1200 grams and, using a regression discontinuity approach, produce plausibly causal estimates of the effects of SSI eligibility. We find that it increases SSI enrollment, improves child outcomes, and shifts maternal labor supply from full to part time.

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I. Introduction

Individuals born to mothers of lower socio-economic status (SES) experience worse outcomes than children born to mothers with greater resources. These differences across SES are immediate, persist over time, and contribute to the growing divide in the outcomes of children of high- versus low-SES mothers (Currie, 2011; Kalil, Ryan, and Corey, 2012; Aizer and Currie, 2014; Autor et al., 2016; Economic Report of the President, 2016, ch. 4). Irrespective of financial resources, low birth weight alone contributes to diminished economic and health outcomes (Behrman and Rosenzweig, 2004; Black, Devereux, and Salvanes, 2007; Oreopolous et al., 2008). Low birth weight infants born into low-SES families face a particularly steep uphill climb to achieve outcome equality. Fortunately, prior research has shown that both public and private investment can improve outcomes by alleviating credit constraints, improving access to health or education services, and reducing home and family stress (Almond and Currie, 2011; Aizer, 2014; Akee et al., 2015; Currie and Rossin-Slater, 2015; Jones, Milligan, and Stabile, 2015; Aizer et al., 2016). In this paper we study a population that is particularly vulnerable—infants born at very low birth weights, below 1200 grams, to mothers with a high school degree or less. We explore whether public investment in these infants in the form of Supplemental Security Income (SSI) mitigates the detrimental impact of being born at double disadvantage.

The SSI program provides means-tested income support to individuals with disabilities in the United States. SSI payments make up 48% of income for families of child recipients, and SSI has been shown to reduce poverty among those families (Duggan and Kearney, 2007). In addition to the income transfer, most SSI recipients also receive publicly-provided health insurance through the

Medicaid program.[1] Although only 4% of children under 200% of the federal poverty line receive SSI (Wittenburg et al., 2015), the public resources allocated to SSI are nontrivial; eleven states have more child SSI recipients than child Temporary Assistance to Needy Families (TANF) and expenditures on child SSI currently exceed federal and state expenditures on the cash benefit portion of TANF (Tambornino, Crouse, and Winston, 2015; Wittenburg et al., 2015). Both the cash transfers and the accompanying health insurance could have important implications for child outcomes. However, despite tremendous public expenditure on the program, little is known about the relationship between SSI payments and infant or early child outcomes.

To fill this research gap, we exploit discontinuous changes in SSI eligibility to analyze the relationship between SSI and child outcomes. According to Social Security Administration (SSA) rules, a child can qualify for SSI based on extremely low birth weight defined as either weighing less than 1200 grams at birth or falling below cutoffs based on birth weight for gestational age (SSA Program Operations Manual System). To estimate plausibly causal effects, we use a regression discontinuity approach to compare outcomes for infants born just under the SSI eligibility cutoffs to those for infants born just above the cutoffs. We use the Early Childhood Longitudinal Study, Birth Cohort (ECLS-B) to show that the likelihood of SSI receipt increases discontinuously at the 1200g cutoff. Next, we estimate the relationship between SSI eligibility and a number of important outcomes for children including measures of health, infant mortality, hospitalizations, cognitive and socio-emotional development, and maternal labor supply using data from the Healthcare Cost and Utilization Project State Inpatient

[1] In fact, in 33 states plus the District of Columbia, receiving SSI automatically enrolls an individual into the state Medicaid program.

Database (HCUP-SID), the Vital Statistics Linked Birth-Infant Death Detail file (VS-L), and the ECLS-B.

Our results suggest that SSI eligibility for low birth weight infants reduces length of hospital stay for infants and is associated with reduced infant mortality in the hospital, although we find little evidence that it affects infant mortality in general. We examine child outcomes and find that SSI eligibility significantly improves child development of motor skills and parenting behaviors. Finally, we explore labor market choices and find that SSI eligibility reduces maternal labor supply on the intensive margin, which could imply that parents reallocate their time towards investments in children.

Our findings contribute to a growing body of evidence linking public investments in children to improved outcomes (e.g. Aizer, 2014; Almond and Currie, 2011). SSI eligibility is shown to improve outcomes most markedly for children of the least educated parents -- parents who likely have the fewest private resources to tap into when caring for a child in a fragile health state. Our results suggest that providing income to these doubly disadvantaged families improves non-cognitive measures, such as parenting behaviors. Since greater non-cognitive ability has been shown to augment cognitive ability (Cunha and Heckman, 2008), our results provide additional evidence that targeted public programs such as SSI may be one way to mitigate the growing divide between children of high- and low- educated parents (Kalil, Ryan, and Corey, 2012). The development of human capital in the presence of self-productivity and dynamic complementarities suggests that investments made at certain points in time, like these investments in vulnerable infants, could be particularly cost-effective (Cunha and Heckman, 2007).

II. Background and Institutional Context

A. Income Transfers and Child Outcomes

There are two key channels through which income transfers can improve child outcomes. First, income transfers alleviate credit constraints. Even when families realize that the benefits of investing in a child outweigh the costs, these investments may not be made if the family is credit constrained. Direct income transfers enable families to invest more optimally. This mechanism is referred to as the "resource" channel (Mayer, 1997; Yeung, Linver, and Brooks-Gunn, 2002; Milligan and Stabile, 2011). Second, income transfers can reduce a stressful household environment which in turn improves outcomes. This mechanism is referred to as the "family process" channel (Mayer, 1997; Yeung, Linver, Brooks-Gunn, 2002; Milligan and Stabile, 2011). Understanding the effects of income transfers, however, is difficult since exogenous variation to identify the effects is not easy to come by.

In prior work, authors have identified several useful sources of variation to show income transfers to be effective in improving outcomes through these channels. For example, Aizer et al. (2016) examine the Mother's Pension Program and find that it reduces the likelihood of being under weight, improves life expectancy, and increases education and adult earnings. Hoynes, Miller and Simon (2015) show that the Earned Income Tax Credit improves infant health at birth. Others have shown that the distribution of casino revenues to tribal members improves education and crime outcomes (Akee et al., 2010); behavior and mental health (Akee et al., 2015); and it affects body mass index (Akee et al., 2013). Milligan and Stabile (2011) show that the Canadian Child Benefit improves educational attainment as well as mental and physical health of the affected children. In follow-up work, Jones, Milligan, and Stabile (2015) evaluate the same benefit to examine spending patterns and their findings suggest that the additional income works through both the resource and family process channels.

Across these studies, the evidence suggests income transfers are effective, particularly for families with the highest credit constraints.

B. Supplemental Security Income for Children

The Supplemental Security Income program was enacted in 1972 to provide means-tested income support to individuals with disabilities and the elderly in the United States. Since its inception, SSI has paid benefits to children with disabilities ages 0-17. Although relatively few children received benefits in the early years of the program, SSI for children has become an increasingly important part of the safety net (Aizer, Gordon, and Kearney, 2013; Duggan, Kearney, and Rennane, 2015; National Academies, 2015). However, only a handful of studies have focused on the effects of the program on child and family outcomes.

Through the resource channel, increases in income resulting from SSI could relax the budget constraint faced by low income parents of children with disabilities. Duggan and Kearney (2007) show that child participation in SSI reduces the likelihood of family poverty. SSI could also enable parents to purchase goods or services for their disabled child that they would forgo in absence of the transfer (Duggan, Kearney and Rennane 2015), but no causal evidence exists on this mechanism.[2] Through the family process channel, SSI receipt could alleviate stress if, for example, it allows a parent to reduce time in the labor market in exchange for time spent with the child. Work by Deshpande (2015) suggests that in response to child SSI parents adjust their labor earnings, presumably by reallocation of their labor market time. Additionally, stress could

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[2] The Social Security Administration (SSA) requires the child SSI payments be spent exclusively on the child, listing medical expenses as an appropriate use (https://www.ssa.gov/pubs/EN-05-10076.pdf), although parents may reallocate family resources, including time or monetary resources, when the child receives SSI.

also be reduced since many infants who receive SSI automatically qualify for Medicaid.

In related work, Deshpande (2016) finds that removal of a child from SSI at age 18 significantly reduces future income and increases income volatility, and Levere (2015) shows that increased exposure to SSI benefits during childhood reduces cumulative labor earnings through age 30. While these studies point to effects for later outcomes, whether SSI for low birth weight infants affects early child development or other family outcomes during early childhood is not yet known.

C. Child SSI eligibility for Low Birth Weight Infants

The typical procedure to determine eligibility for SSI is twofold. First, the SSA determines a child's financial eligibility. Next, the Disability Determination Services (DDS) assesses the child's impairment and determines whether the child is classified as disabled according to the SSA rules (Wixon and Strand, 2013).[3] In 1991, SSA deemed low birth weight to be a condition "functionally equivalent" to meeting a listing, and infants below certain birth weight cutoffs would be classified as disabled.[4]

The medical community defines low birth weight (LBW) as weight less than 2,500 grams or 5.5 pounds, and very low birth weight (VLBW) as less than 1,500 grams or 3.25 pounds (Maternal and Child Health Bureau, 2013).[5] Infants born below 2,500 grams are at greater risk of diminished short- and long-run health (e.g. Hack et al., 1995; MMWR, 2004; IOM, 2006) and worse economic

[3] See Duggan, Kearney, and Rennane (2015) for a detailed discussion of the disability determination process.
[4] When birth weight is used to determine disability, the individual would still face the means test when no longer in a medical institution.
[5] This low birth weight designation has been used since the 1930s and the very low birth weight designation since at least the 1980s (Almond et al., 2010).

outcomes (e.g. Oreopoulos et al., 2008; Aarnoudse-Moens et al., 2009). Furthermore, the risk increases non-linearly the lower the birth weight and/or the earlier the gestation. This finding suggests that interventions targeting infants in more precarious states at birth may have the largest effects (Alexander et al., 2003).[6] The fraction of all live births in the United States that are low birth weight or very low birth weight has risen over the past thirty years, suggesting a growing number of individuals are at risk of experiencing worse health at birth and beyond.[7]

SSA evaluates low birth weight from birth to age one using one of two rules defining this condition.[8] The first, 100.04A, defines low birth weight as weighing less than 1200 grams regardless of gestational age. The second, 100.04B, considers gestational age together with birth weight. As shown in Appendix Table 1, infants light for their gestational age qualify as low birth weight. SSA low birth weight criteria are more restrictive than the medical community's definitions for low (<2500g) and very low (<1500g) birth weight.[9] SSA included low birth weight to target infants at risk of longer term disability,

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[6] The cost of treating low birth weight infants is tremendous; in 2001, while only 8% of all hospitalized infants had a preterm or low birth weight diagnosis, these infants accounted for 47% of the hospitalization costs (Russell et al., 2007).

[7] The rise in multiple births and increases in obstetric interventions (e.g. C-section births) have contributed to the rise in low and very low birth weight babies (Maternal and Child Health Bureau, 2013). We note that rates of low birth weight births rose until about 2005, and have fallen since then (see Buckles and Guldi, 2015 for a discussion and possible explanations).

[8] In this paper, when discussing SSI birth weight eligibility we will use “low birth weight” to indicate that an infant falls below SSI’s low birth weight cutoffs as described below.

[9] Low birth weight is documented by an original or certified copy of the infant's birth certificate or by a medical record signed by a physician. Birth weight is the first weight recorded after birth. Gestational age is the infant's age based on the date of conception. The Childhood Disability Interview checklist prompts parents to bring the child's birth certificate with them when applying. However, getting a birth certificate may take several months. In 2009, a nationally uniform form, SSA Form 3830 went into use to expedite the application process for low birth weight applicants. SSA staff use the Form 3830 to request birth weight and other information directly from hospital staff. See https://www.ssa.gov/disability/professionals/bluebook/100.00-GrowthImpairment-Childhood.htm accessed 12-4-15.

writing in the preamble to the final rule (SSA 1991), "[o]ur case experience has shown that infants who demonstrate the kinds of functional deficits that will be required to establish disability [as low birth weight]… are likely to continue to demonstrate that they are disabled when they are older." The fraction of low birth weight child SSI awards has increased since then and, as of 2015, accounted for over 10 percent of all child SSI awards (see Figure 1).[10]

We study a population particularly suited to benefit from income transfers. First, a given health intervention can be expected to have a higher marginal benefit if initial health is worse. The infants we study are well below average in terms of initial infant health. The birth weight threshold we study is below the first percentile of the birth weight distribution.[11] Second, based on prior work, the positive benefits of income transfers exhibit the largest effects for individuals from low-SES families.[12] Since SSI payments are means tested, benefits will target families with fewer resources and we expect the effects of these transfers to be concentrated among lower SES families.

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[10] Individuals who receive SSI are typically eligible for state Medicaid. While most SSI recipients receive publicly-provided insurance through the Medicaid program, the way in which the two programs are linked varies by state. In 33 states plus the District of Columbia, qualifying for SSI automatically enrolls an individual into the state Medicaid program (the 1634 or "auto-enroll" states). In seven states, Medicaid and SSI eligibility standards are identical, but require that recipients file a separate application (the criteria states). (Indiana became a 1634 state in 2014.) In the remaining ten states Medicaid eligibility criteria are more restrictive in at least one aspect than those used for SSI (the 209b states). Finally, each state determines the generosity of services covered by its program.

[11] Using the 2001 natality data, the 1200 gram threshold is just below the bottom 1% of the birth weight distribution.

[12] Above, we discuss several studies that specifically show this for income transfers. In addition, a number of studies examine other programs and show stronger effects for low SES groups. For example, the WIC program (Hoynes, Page, Stevens, 2011); the Food Stamp program (Hoynes, Schanzenbach, and Almond, 2016); childcare (Herbst, forthcoming); and early childhood education (Kearney and Levine, 2015).

III. Data

A. Early Childhood Longitudinal Study, Birth Cohort (ECLS-B)

The Early Childhood Longitudinal Study, Birth Cohort (ECLS-B) is a nationally representative longitudinal data set collected by the National Center for Education Statistics (NCES). The ECLS-B oversamples low and very low birth weight children.[13] Births to mothers less than age 15, or children who died or were adopted before the 9 month assessment are not included in the base sample.[14] The ECLS-B follows children from birth through kindergarten with data collection occurring at approximately 9 months of age, 2 years of age (2003), 4 years of age (at pre-school, Fall 2005), and at kindergarten entry. The 9-month data collection also includes variables from infants' birth certificates. A sample of 10,700 children born in 2001 participated in the first wave of the ECLS-B.[15]

We also limit the sample to infants born at 32 weeks gestation or less. The variation we are using is the SSI birth weight eligibility cutoff. We exclusively explore the 1200g cutoff in this study, since we do not have enough sample mass around SSA's other thresholds for infants with longer gestations. In addition, infants at higher gestations could potentially be treated by medical interventions aimed at very low birthweight infants (e.g. Almond et al., 2010).[16] Restricting the

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[13] The ECLS-B also oversamples Asian and American Indian children and twins.

[14] This leads to selection of healthier infants, on average into the ECLS-B. Our results using the linked birth-infant death data, discussed below, do not suggest that SSI alters infant mortality, so it does not appear that selection into the ECLS-B sample is related to SSI receipt.

[15] All ECLS-B reported sample sizes have been rounded to the nearest 50 per NCES restrictions regarding disclosure of restricted use data. However, the analyses and statistics presented in the tables and text are generated using all observations in each subsample.

[16] We also omit infants born at 32 weeks gestation with birth weights between 1200 and 1250 grams. The SSI eligibility cutoff for infants at 32 weeks is birth weight of 1250 grams or less, so these infants would be incorrectly classified as ineligible in our current set-up. In total, this eliminates 7 observations from our ECLS-B sample. If we include these, our results are similar, likely because they represent a relatively small portion of the mass above the 1200g cutoff. See Appendix Table 1 for a list of the SSI birth weight–gestation eligibility cutoffs.

sample to infants of these gestational ages gives us the most power to identify effects and is also the cleanest sample to examine.

We examine a number of different child and family outcomes from the 9-month wave. Importantly, our measure of SSI receipt is from the 2-year wave and asks "Since the last interview, has anyone in the household received SSI/SSDI?" This variable proxies for child SSI receipt, but with significant measurement error, since it includes receipt from family members other than the focal infant, includes Social Security Disability Insurance (SSDI) as well as SSI, and is from an interview taking place a full year after LBW SSI recipients must go through a 1-year Continuing Disability Review to reestablish eligibility. We examine measures of health insurance coverage (any, private, and public (Medicaid or the Children's Health Insurance Program (CHIP)). We examine measures of maternal labor supply (whether the mother works, works part time, works full time, or is not in the labor force).

We then look at a number of different child and family outcomes. The Bayley Short Form Research edition (BSF-R) measures children's cognitive development as well as the development of their fine and gross motor skills. We include both the mental and motor scale, and use standardized t-scores (with a mean of 50 and a standard deviation of 10) that adjust for prematurity. The Nursing Child Assessment Teaching Scale (NCATS) assesses parent-child interactions, and we include both the parent and child scores.

We expect the impact of SSI to be the largest for low-SES children. For our analysis we define low SES by mother's education and focus on the subsample of 5,350 children whose mother has a high school degree or less.[17] Panel A of Table 1 presents summary statistics for our ECLS-B sample. These

[17] Although we could define our low SES sample by parental income in the ECLS-B, reported income might be endogenous to SSI receipt.

statistics show just how disadvantaged our sample is, as 31% of our sample report receipt of disability benefits. Our sample also has near universal health insurance coverage (98%). This suggests that even though the Medicaid that accompanies SSI receipt could be an important benefit of the program, it is unlikely to play much of a role in our sample.

B. The Healthcare Cost and Utilization Project State Inpatient Databases (HCUP-SID)

The HCUP-SID is a data set of inpatient discharge abstracts from participating states sponsored by the Agency for Healthcare Research and Quality. The data are drawn from 97% of all U.S. hospital discharges. The data set contains one record per hospital admission ending in discharge or death. Each state-year HCUP-SID database contains a slightly different set of variables. We used the HCUP-SID databases that report birth weight, month of birth, year of birth, and unique person identifiers; therefore our data come from Arizona 2006-2007, North Carolina 2006-2010, and New York 2006-2012.[18] Our sample includes all children for whom we observe their birth hospitalization and whose gestational age was 32 weeks or less at birth.

As with the ECLS-B, we expect the effects of the SSI program to be strongest for the group of individuals with the fewest resources. However, our HCUP-SID database does not include individual level variables that could proxy for household resources like mother's education. Instead, we restrict our sample to infants whose birth residence is in zip codes with low median household income. The HCUP-SID reports quartile classifications of the estimated median household income for patients' residence zip code. We present results for infants

[18] The SID data partners are the Arizona Department of Health Services, New York State Department of Health, and the North Carolina Department of Health and Human Services.

whose birth residence is in the lowest three quartiles or who are homeless at birth. In 2012, for example, this includes all zip codes with median household income less than \$63,000.[19] Our final analysis sample includes 20,673 births/infants.[20]

As we describe in Section II, increases in household resources due to SSI may alter children's healthcare use or type of health insurance (Duggan, Kearney and Rennane 2015). We use the HCUP-SID databases to investigate this possibility. The HCUP-SID records the primary, secondary and tertiary expected payer of the birth hospitalization distinguishing between Medicaid, private health insurance, self-pay and other federal or local programs. We also analyze the number of hospital readmissions (not including transfers from one hospital to another) after birth as children age. We look at the number of hospital readmissions at 1 month, at 9 months, at one year, and at two years.[21] The child's birth month and year are used to determine their "risk" of a hospital readmission over time.[22] That is, the possibility they could show up in the data years available.

We also construct the number of days spent in the hospital at birth and as the child ages. For infants transferred from one hospital to another at birth, we include the total number of days spent in the hospital across all transfers. Finally, we examine what fraction of hospital readmissions for children under age two occur because of potentially avoidable reasons. Table 1, Panel B presents summary statistics for the HCUP-SID analysis sample.

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[19] We have reason to believe that even in the third quartile of the zip code by income distribution a non-trivial proportion of infants may be SSI eligible. While in the second quartile 52% of births in our HCUP sample reported Medicaid as the primary expected payer, in the 3rd quartile still 42% reported Medicaid. This proportion drops to 21% in the highest quartile.

[20] We create our analysis sample of people born between 2006 and 2012 and drop observations that cannot be followed after birth; that is infants with missing unique identifiers, who were born out of state, or who were transferred out of the hospital at birth but who do not have a transfer in record. These sample restrictions do not qualitatively change our results.

[21] These points in time correspond to standard infant mortality measures and for times represented in the ECLS-B data.

[22] Since, for instance, infants born in January of a state's first year of data are more likely to be observed for the longer-term outcomes.

C. Linked Birth/infant Death Birth Cohort Data Set

We also use the National Center for Health Statistics (NCHS) birth cohort linked birth/infant death files (VS-L), containing information from birth certificates and death certificates for infants who died within one year including: birth weight, gestational age, age in days at death, mother's education at birth and other mother and child characteristics. We limit our sample to infants born in 2001 and born at 32 weeks gestation or less.

We use the VS-L dataset to assess the validity of the regression discontinuity design by testing whether predetermined characteristics move discontinuously at the 1200 gram threshold for SSI program eligibility. The predetermined characteristics include the mother's level of education, mother's race, mother's age at birth, marital status, whether the mother drank or smoked during pregnancy or had a pregnancy risk factor, whether the child was male or a singleton birth.

We also examine infant mortality in the neonatal period less than 28 days old, in the post-neonatal period between 28 days and one year old, and during the first year of life. In the analysis of infant mortality the sample is restricted to infants whose mother has a high school degree or less to match the ECLS-B analysis sample. This sample includes 60,460 live births. Table 1, Panel C presents summary statistics for this sample.

IV. Methods

We use a regression discontinuity (RD) approach to estimate the impact of SSI eligibility for low birth weight infants on SSI receipt and outcomes for infants by comparing those born just under the 1200 gram cutoff for SSI eligibility to those born just above the cutoff. Infants whose birth weight falls below the 1200 gram cutoff are categorically eligible for SSI. Although individuals below 1200 grams are eligible, not everyone enrolls in the program. Furthermore, individuals above the 1200 gram cutoff may be deemed eligible for SSI depending on their birth weight for gestational age or other qualifying medical conditions. Therefore, conceptually we would like to implement a fuzzy regression discontinuity design as the probability of SSI enrollment increases at the 1200 gram cutoff, but not necessarily from 0 to 1. However, as described above, our measure of infant SSI enrollment is quite noisy. As a result, we have not scaled up our estimates of the effect of SSI receipt on infant outcomes by the first stage, so our estimates should be interpreted as intention to treat effects (e.g. Ludwig and Miller, 2007).

We use both parametric models (linear and quadratic) and a local linear regression model to estimate the discontinuity in SSI receipt and outcomes at the 1200 gram birth weight cutoff. The parametric models use ad-hoc bandwidth choices of 200 grams and 150 grams and bootstrapped standard errors. The local linear regression model is weighted using a triangular kernel, and run within the optimal bandwidth chosen by the Calonico et al. (2016) procedure (CCFT procedure). Using the CCFT procedure, we present bias-corrected estimates with robust standard errors. Both types of specifications allow the regression slope to differ on either side of the 1200g cutoff.

A key assumption of the RD design is that potential outcomes change smoothly at the cutoff. Although not directly testable, we believe the SSA birth weight eligibility thresholds provide a setting in which the RD design is likely valid and, to the extent possible, we test for and fail to find empirical evidence of violations of this assumption.

First, birth weight itself is partially, but not precisely controlled. However, reported birth weight may be precisely controlled, which would call into question the validity of our design if those who report birth weight know the SSA cutoffs and strategically report weight. We investigate this possibility by examining histograms of birth weights from the ECLS-B around the 1200g threshold, presented in Figure 2. The first graph is for the entire distribution of birth weights to mothers with a high school degree or less, making clear the extent to which the ECLS-B oversamples very low birth weight infants. The second ECLS-B histogram is for our analysis sample (births with gestational age less than or equal to 32 weeks and maternal education of high school or less), and zooms in on the smaller range of birthweights from 500g to 2000g. Neither histogram shows evidence of manipulation of birth weights just below the threshold.

However, substantial heaping of births at round numbers of ounces, and, to a lesser degree at 100 gram intervals, is apparent (Barreca et al., 2011). Most of the mass in our sample is at round number ounce heaps.[23] Our identification strategy might be compromised if a) those infants at the heaps were systematically different than those not at the heaps, or b) if the composition of infants heaping at ounces changes at the threshold. Appendix Table 2 shows how summary statistics for the full analysis sample (Column 1) compare to those for the sample without infants at ounce heaps (Column 2), without those at 100-gram heaps (Column 3), and without those at either type of heap (Column 4). Overall, the characteristics of the sample are remarkably robust across these four groups. Appendix Table 3 tests whether infants' characteristics differ significantly between the ounce heap on the left of the threshold (1191g (42 oz)) and the ounce heap on the right of the threshold (1219g (43 oz)). For the ECLS-B (Appendix Table 3a), we show that infants born at 1191 grams do not differ statistically from infants born at 1219 grams along the dimensions of gender, race, mother's marital status, or Apgar score. Admittedly, these samples are tiny, so we do the same analysis with births from the VS-L (Appendix Table 3b), which also indicate no statistical difference between the two heaps. If anything, it appears that the infants at the 42oz heap just below the cutoff are worse off along observable

[23] In the ECLS-B, only 250 of the 650 infants in our analysis sample are NOT at ounce heaps.

characteristics. This suggests that any heaping-induced bias would make it more difficult to find positive effects of SSI for the outcomes we consider in this paper.

In Figure 3, we display the results of testing the continuity of the density of the running variable around the threshold (McCrary, 2008). The graph does show evidence of a discontinuity. However, the heaping of the distribution appears to the right of the threshold, which is on the “wrong" side to indicate advantageous manipulation. In addition, this discontinuity in the density of the running variable appears to be related to the ounce heaping issue described above. When we run the McCrary test on only the ounce heaped data, where most of the mass is, we find no evidence of a discontinuity.

Finally, we test for discontinuous changes in infants’ baseline characteristics around the cutoff to further probe the assumption that birth weight is locally as good as randomly assigned. Table 2 examines whether a wide variety of predetermined characteristics exhibit a discontinuity at the 1200g cutoff. We do this across all three data sources and characteristics include: race, child’s gender, child’s plurality, Apgar score, mother’s marital status, and mother’s pregnancy risk factors. For most variables, we find no evidence of such a discontinuity, suggesting that infants born just below the cutoff are a good counterfactual for infants born just above the cutoff.[24]

Furthermore, as far as we are aware, no other program or intervention begins at the 1200 gram mark. Importantly, the 1200g SSA low birth weight cutoff is not the same as the medical VLBW cutoff, which can involve significant medical interventions (Almond et al., 2010). Had the two thresholds coincided,

[24] Exceptions include mother’s marital status in the ECLS-B (infants just under the cutoff are more likely to have unmarried mothers), child gender in the VL-S data (infants just under the cutoff are less likely to be male), and state of residence in the HCUP-SID data (infants just under the cutoff are more likely to be from AZ).

we would be unable to disentangle the effect of SSI receipt on outcomes from the effect of medical intervention.

V. Results

A. SSI Eligibility and SSI Enrollment, ECLS-B

We first establish that a discontinuity exists in SSI receipt at the 1200g cutoff. Figure 4 illustrates this graphically, and Table 3 presents estimated RD coefficients and robust standard errors. For each outcome, the first two rows present results from the linear polynomial models and the second two rows present results from the quadratic polynomial models. Within each set of polynomial results, we first present a bandwidth of 200g and then 150g. Finally, the last row of results presents estimates from the local linear regression model with optimal bandwidth choice. We present all five sets of estimates to show the stability of our results.

Column 1 shows that infants born just under the 1200g cutoff are significantly more likely to be in families that reported SSI or SSDI receipt in the 2-year ECLS-B wave. Estimates from the linear polynomial model with 200g bandwidth imply that low birth weight SSI eligibility increases the likelihood of family disability benefit receipt by 25 percentage points, significant at the 5-percent level. The point estimates are fairly stable across the five specifications, ranging from 23 to 32 percentage points. These effects are large in magnitude, given that the baseline rate of disability receipt in our sample is 32%.[25] Columns 2-4 present results for any health insurance coverage, private health insurance coverage, and public health insurance coverage (Medicaid plus CHIP). We find

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[25] In results not presented here, we estimated the effect of SSI eligibility on participation in other social safety net programs (TANF, Food Stamps, and WIC) and found no significant cross-program effects.

no effects of SSI eligibility on overall health insurance coverage or coverage by type. The lack of effects on health insurance coverage may be specific to our sample – with 98% of our sample reporting health insurance coverage, there may be no room for any measurable effect.[26] These results are also consistent with Duggan and Kearney (2007), who find no effects of SSI for children on health insurance coverage.

B. Post-Birth Hospital Outcomes, HCUP-SID

In Table 4 we examine the relationship between the primary expected payer of the birth around the SSI eligibility threshold using the HCUP-SID data. These infants are all born at 32 weeks gestation or less, living in lower income zip codes. We expect that since SSI eligibility is tightly linked with Medicaid eligibility we may observe an increase in Medicaid as the primary payer for infants who are SSI eligible. Some hospitals record the primary expected payer at hospital admission (likely before SSI eligibility is known) and others report the payer from the hospital claims (likely after SSI eligibility is known). We find evidence that the SSI program reduces the likelihood that parents self-pay for their infant's birth (column 4). However, as in the ECLS-B, we find no statistically significant effects of SSI for Medicaid as the primary payer (column 1), Medicaid or any government program (column 2) or private (column 3).

Table 5 investigates the intention to treat effects of the SSI program on the number of days children spend in the hospital at birth and cumulatively over their first two years of life. Infants in our analysis sample (those born at 32 weeks gestation or less who live in lower income zip codes) spend on average about 40 days in the hospital at birth. Column 1 reports the effects of SSI eligibility on the length of stay at birth which includes the length of stay for infants transferred

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[26] We have also estimated these regressions separately for the 1634 (auto-enroll) states and the 209b (more restrictive states) and find no significant differences.

from their originating birth hospital. Columns 2-4 show the differential effect of being below the 1200 gram threshold on the cumulative number of days spent in the hospital within 27 days, 9 months, 1 year, and 2 years since birth. This cumulative measure captures the total number of days spent in the hospital, summing the length of stay at birth as well as any hospital readmissions later in childhood. Taken together, the results of this table offer suggestive evidence that the SSI program reduces the number of days children spend in the hospital.

Next we explore whether SSI eligibility influences the number of hospital readmissions. Ambulatory Care Sensitive (avoidable with proper preventative care) (ACS) hospitalization may be affected by the increase in household resources from the SSI program. Appendix Table 4 shows the top ten reasons for a hospital readmission in our sample of infants born at 32 weeks gestation or less living in lower income zip codes. These top ten reasons account for over 50 percent of all hospital readmissions. Hospital revisits for ACS conditions such as asthma and dehydration are among the most common. We report estimates for hospital readmission in Table 6. Although we cannot rule out positive effects, these estimates are small in magnitude with large standard errors and seem to suggest that SSI does not alter readmission. Taken together with the results in Table 5, it appears that the reduction in length of stay comes primarily from a decreased number of days spent in the hospital at birth rather than for hospital readmissions.

Infants may spend fewer days in the hospital (at birth) for many reasons. One possibility is that parents may substitute away from in-hospital care to other venues for care. Table 7 examines the reasons for hospital discharge at birth. Column 1 explores whether infants whose birth weight falls below the 1200-gram threshold are more likely to have a routine discharge and Column 2 examines the possibility of substituting towards other venues for care such as a Home Health Care, Skilled Nursing Facility or Intermediate Care Facility. Finally Column 3 examines whether infants below the threshold are less likely to die in their originating birth hospital. We find no statistical support to suggest that eligible infants have differential routine discharges or that parents substitute other forms of care for hospital care. Our estimates for death suggest that SSI eligible infants are less likely to have death as a reason for discharge. Taken together with the length of stay results in Table 5, these estimates suggest that the true effect of SSI on length of stay may be even larger (greater reduction) since the estimated decrease in the length of stay at birth is likely offset by increases in stay lengths due to fewer infant in-hospital deaths.[27]

C. Infant Mortality, VS-L

We examine the effects of SSI on infant mortality further using the linked birth and infant death data from 2001 for all states and report these estimates in Table 8. These results examine infant mortality (Column 1), neonatal infant mortality (Column 2), and post-neonatal infant mortality (Column 3). The direction of the estimates is mixed and only one estimate is statistically significant. In Appendix Table 5 we perform the analysis for a period that overlaps our HCUP-SID analysis and in Appendix Table 6 we report the analysis for 2001 on the subset of states also available for our HCUP-SID analysis. These estimates are similarly mixed in sign and only one estimate is statistically significant. Taken together these estimates offer little evidence of a relationship between SSI and infant mortality. Together with the HCUP-SID results, our findings suggest that SSI may decrease discharge due to death, but we do not find evidence of an effect for infant mortality overall.

D. Early Child Development, ECLS-B

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[27] Infants who are most likely to die presumably have the longest hospital stays.

Table 9 examines the effects of SSI participation on the Bayley Mental and Motor tests, as well as on the NCATS parent and child scores. We find no significant effects on cognitive development as measured by the Bayley Mental test, but we do find positive and significant effects of SSI eligibility on T-Scores for the Bayley Motor Test. These results suggest an increase of between 4 and 8 points – roughly half of a standard deviation increase. We also find significant positive effect on parent-child relationships as measured by the NCATs parent test, with coefficients across the specifications suggesting an increase of 3-4 points, or about a standard deviation increase.

E. Maternal Labor Supply, ECLS-B

The results presented above suggest that the income associated with SSI has positive effects on health, on early childhood development, and on parenting behaviors. One possibility for these findings, (as discussed in Section II), is that SSI alters the time allocation of mothers. In Table 10, we examine the intention to treat effects of SSI receipt on maternal labor supply. We find no significant effects of SSI receipt on the extensive margin of labor supply – there is no effect on the probability that the mother works at all, or on her probability of being out of the labor force. However, mothers of infants just under the 1200g cutoff are significantly less likely to work full time and significantly more likely to work part time. Results from the linear polynomial model with 200g bandwidth suggest a decrease in full time work of 21 percentage points (on a baseline likelihood of 23%), and an increase in part time work of 19 percentage points (on a baseline probability of 19%). These results suggest that one way SSI eligibility could affect family outcomes is by freeing up some time for mothers of these particularly vulnerable infants. These results accord with Desphande (2015) who finds that parents increase their earnings when their child loses SSI. We offer symmetric evidence that parents reduce their work time when their child receives SSI.

VI. Discussion and Conclusion

Low birth weight infants born to mothers with low educational attainment have a double hurdle to overcome in the production of human capital. In this paper we examine whether income transfers, in the form of SSI payment, can help close the gap in outcomes due to this initial health and environmental disadvantage.

Using a regression discontinuity approach, we find that SSI eligibility for low birth weight infants increases receipt of family disability benefits, but has no effect on health insurance coverage (perhaps unsurprising given the near universal coverage in our sample). SSI eligibility reduces infants' length of stay in the hospital and reduces the chance that the infant dies in the hospital. In addition, SSI eligibility significantly improves infant development of early motor skills and parenting behaviors, and reduces maternal labor supply on the intensive margin.

Many of our key results are attributable to the ECLS-B. As such, the usual caveats of studies on a single cohort, in this case individuals born in 2001, apply. We also caution that while these results are credible for the target group, very low birth weight infants in families with few resources, we would not necessarily expect to find similar effects for individuals of higher birth weight or for individuals born into families with greater resources.

Our results are important for several reasons. First, they provide credible estimates of the effect of SSI on child outcomes. This is an important contribution since a large number of public dollars are spent on SSI each year yet the benefits of this expenditure are not well understood. Second, they provide further evidence that post-birth investment made early in childhood, before age 5, can have meaningful effects on immediate and later outcomes. Third, they show that the effects appear to be concentrated among the segment of the population with the fewest resources.

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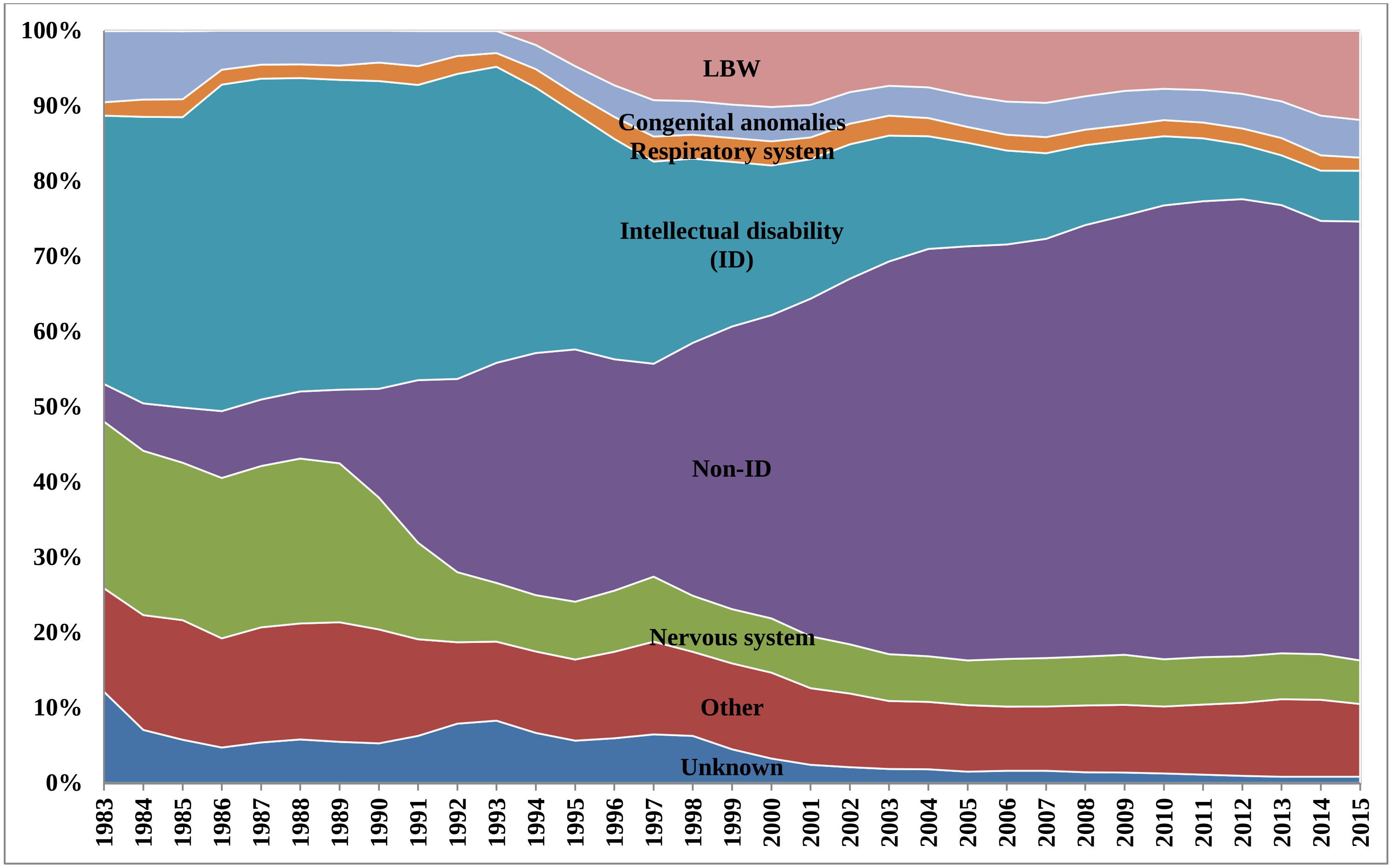
Figure 1: Percentage distribution of diagnostic group among child SSI awardees, 1983-2015



Source: Social Security Administration

Figure 2: Heaping (Panel ECLS-B)

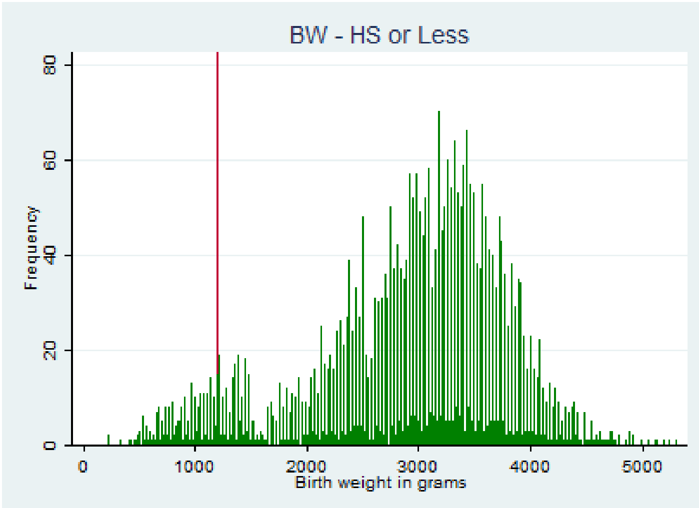
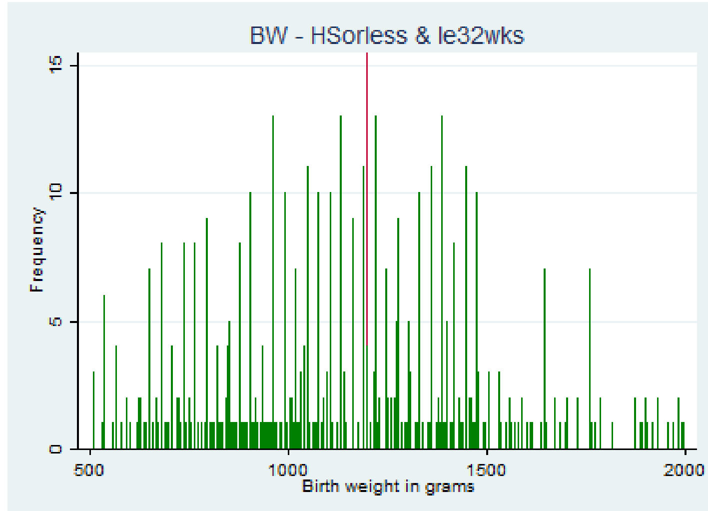
ECLS-B, Full sample with high school or less	ECLS-B Analysis sample between 500g-2000g
	

Figure 3: McCrary Density

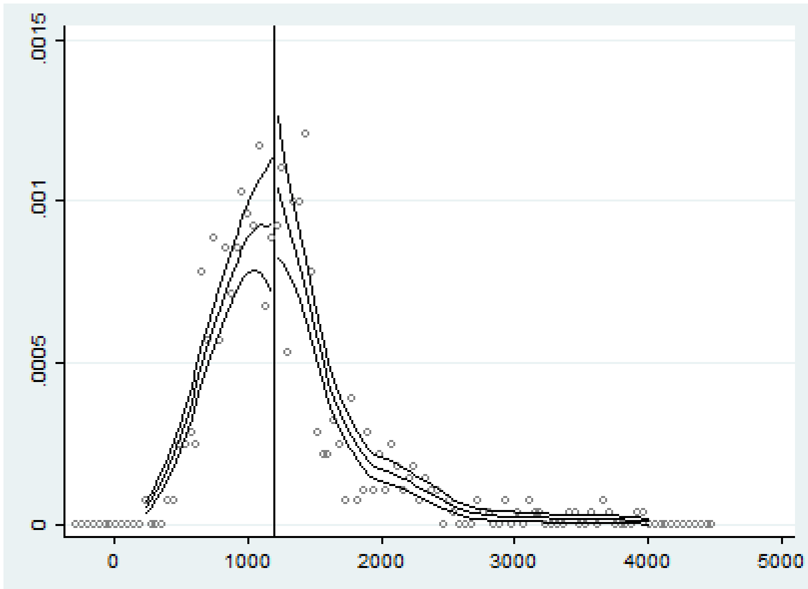


Figure 4: First Stage/ECLS-B

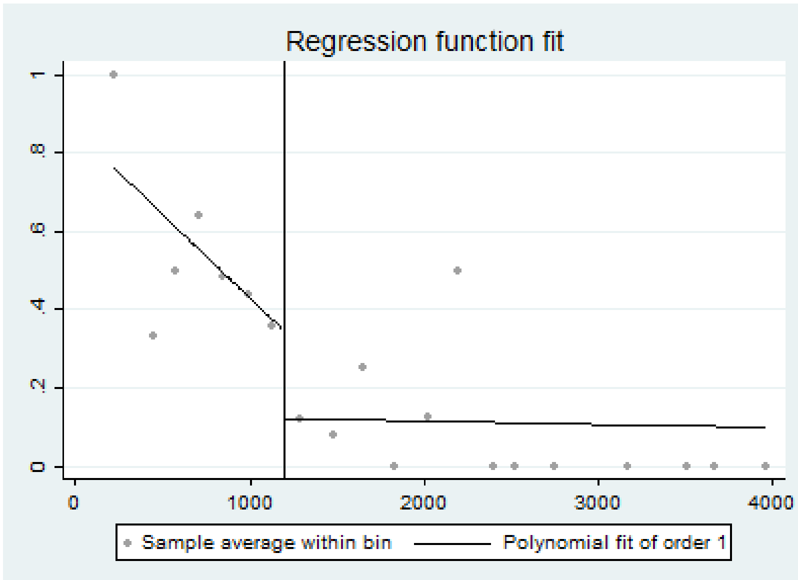


Table 1: Summary Statistics

	Mean	SD	Min	Max
Panel A: ECLS-B[a]				
SSI/SSDI receipt	0.311	0.463	0.0	1.0
Any health insurance coverage	0.980	0.139	0.0	1.0
Private health insurance coverage	0.281	0.450	0.0	1.0
Public health insurance coverage	0.772	0.420	0.0	1.0
Child is male	0.503	0.500	0.0	1.0
Child is nonwhite	0.651	0.477	0.0	1.0
Mother not married	0.608	0.489	0.0	1.0
Apgar score	7.667	1.517	1.0	10.0
Mother works	0.356	0.479	0.0	1.0
Mother works full time	0.234	0.424	0.0	1.0
Mother works part time	0.121	0.326	0.0	1.0
Mother not in labor force	0.525	0.500	0.0	1.0
Bayley mental t-score	43.167	14.262	-16.7	92.6
Bayley motor t-score	45.017	11.654	-9.3	80.0
Nursing child assessment teaching scale – parent	33.010	4.503	17.0	48.0
Nursing child assessment teaching scale – child	14.729	2.781	7.0	23.0
Panel B: HCUP-SID[b]				
Primary Expected Payer Birth: Medicaid□	0.604	0.489	0	1
Primary Expected Payer Birth: Medicaid + Other Gov.□	0.623	0.485	0	1
Primary Expected Payer Birth: Private Insurance	0.326	0.469	0	1
Primary Expected Payer Birth: Self Pay	0.049	0.216	0	1
Num. of Hospital Revisits: Neonatal Period	0.030	0.182	0	3
Num. of Hospital Revisits: 9 months	0.187	0.562	0	9
Num. of Hospital Revisits: 1 Year	0.211	0.628	0	12
Num. of Hospital Revisits: 2 Years	0.261	0.785	0	18
Days in Hospital: At Birth	40.970	33.620	0	354
Days in Hospital: Neonatal Period	21.721	8.908	0	27
Days in Hospital: 9 months	43.581	34.924	0	270
Days in Hospital: 1 Year	43.828	35.514	0	365
Days in Hospital: 2 Years	44.464	35.897	0	503
Birth Discharge Reason: Routine	0.558	0.497	0	1

Birth Discharge Reason: Transfer	0.309	0.462	0	1
Birth Discharge Reason: Death	0.132	0.339	0	1
Birth weight in grams	1321.84	563.87	230	9000
Child is male	0.522	0.500	0	1
Child is singleton	0.786	0.410	0	1
Child is nonwhite	0.683	0.465	0	1
Arizona	0.097	0.296	0	1
North Carolina	0.035	0.183	0	1
New York	0.869	0.338	0	1
Year	2008.8	2.032	2006	2012
Panel C: Linked Birth/infant Death Birth Cohort Data Set[c]				
Infant mortality	0.135	0.342	0	1
Post neonatal mortality	0.020	0.141	0	1
Neonatal mortality	0.114	0.318	0	1
Birth weight in grams	1732.017	941.744	227	5387
Gestational age	28.804	3.213	20	32
Child is male	0.535	0.499	0	1
Child is singleton	0.837	0.369	0	1
Apgar score	7.435	2.398	0	10
Mom is nonwhite	0.615	0.487	0	1
Mom's age	24.836	6.550	14	45
Mom is nonmarried	0.609	0.488	0	1
Mom drank during pregnancy	0.018	0.133	0	1
Mom smoked during pregnancy	0.206	0.405	0	1
Any pregnancy risk	0.487	0.500	0	1

Notes:

[a]All variables from the ECLS-B 9-month wave, with the exception of SSI/SSDI receipt. SSI/SSDI receipt asked in the 2-year wave (“Has anyone in the household received SSI/SSDI since the 9-month wave?”) Observations rounded to the nearest 50 as per NCES confidentiality restrictions. Sample limited to infants with mother with a high school degree or less and gestational age <=32 weeks. Infants born at 32 weeks between 1200g and 1250g were dropped from the sample. Total number of observations is 650.

[b]All variables from the HCUP-SID AZ 2006-2007, NC 2006-2010 and NY 2006-2012 databases. Sample limited to infants living in the bottom 3 quartiles of the zip code income distribution and gestational age <=32 weeks. Infants born at 32 weeks between 1200g and 1250g were dropped from the sample. Total number of observations is 20,673.

[c]All variables from NCHS 2001 Linked Birth/infant Death Birth Cohort Data Set . Sample limited to infants with mother with a high school degree or less and gestational age <=32 weeks. Infants born at 32 weeks between 1200g and 1250g were dropped from the sample. Total number of observations is 60460.

Table 2: Pretreatment Characteristics at the 1200g Cutoff

Panel A: ECLS-B[a]

	(1) Male	(2) Nonwhite	(3) Mom Unmarried	(4) Apgar score
Parametric Model - within 200g window				
Flexible linear	-0.036	0.063	0.237*	0.027
	(0.131)	(0.122)	(0.124)	(0.248)
Flexible quadratic	-0.011	0.177	0.219	-0.006
	(0.212)	(0.182)	(0.186)	(0.497)
Observations	250	250	250	200
Parametric Model - within 150g window				
Flexible linear	-0.010	0.109	0.213	0.152
	(0.153)	(0.109)	(0.187)	(0.270)
Flexible quadratic	-0.035	0.078	0.220	-0.233
	(0.252)	(0.191)	(0.232)	(0.454)
Observations	150	150	150	150
Nonparametric - local linear within CCFT window				
	-0.021	0.145	0.249*	-0.069
	(0.150)	(0.149)	(0.147)	(0.299)
Observations	650	650	650	550
Eff obs left	200	150	150	150
Eff obs right	150	150	150	150
BW Local Poly	278.9	224.7	263.1	343.7

Panel B: HCUP-SID[b]	(1) Child is male	(2) Child is singleton	(3) Child is nonwhite	(4) Arizona	(5) North Carolina	(6) New York	(7) Year
Parametric Model - within 200g window							
Flexible linear	-0.0447	-0.0163	0.0047	0.0332**	-0.0081	-0.0251	0.0302
	(0.0279)	(0.0257)	(0.0259)	(0.0154)	(0.0086)	(0.0192)	(0.1090)
Flexible quadratic							
	-0.0541	-0.0039	0.0305	0.0469**	-0.0017	-0.0452	-0.0558
	(0.0465)	(0.0388)	(0.0400)	(0.0214)	(0.0149)	(0.0323)	(0.1688)
Observations	5202	4609	4903	5202	5202	5202	5202
Parametric Model - within 150g window							
Flexible linear							
	-0.0465	-0.0023	0.0268	0.0367**	-0.0051	-0.0316	0.0586
	(0.0318)	(0.0260)	(0.0325)	(0.0161)	(0.0107)	(0.0230)	(0.1334)
Flexible quadratic							
	-0.0731	-0.0437	0.0025	0.0520*	-0.0125	-0.0395	-0.1113
	(0.0572)	(0.0430)	(0.0439)	(0.0297)	(0.0186)	(0.0351)	(0.1959)
Observations	3847	3408	3634	3847	3847	3847	3847
Nonparametric - local linear within CCFT window							
	-0.0441	-0.0177	0.0166	0.0356**	-0.0055	-0.0358*	0.0588

	(0.0298)	(0.0283)	(0.0300)	(0.0159)	(0.0116)	(0.0203)	(0.1156)
Observations	20673	18532	19538	20673	20673	20673	20673
Eff obs left	4443	3205	3761	4458	3608	3598	4448
Eff obs right	3986	2929	3416	4008	3346	3339	3995
BW Local Poly	321	266	291	324	269	266	321

Panel C:VS-L [c]

	(1) Mom is nonwhite	(2) Mom's Age	(3) Mom is unmarried	(4) Mom drank while pregnant	(5) Mom smoked while pregnant	(6) Any preg risk	(7) Child is male	(8) Child is single-ton	(9) Apgar score
Parametric Model - within 200g window									
Flexible linear	0.0243	-0.4623**	0.0048	-0.0023	-0.0333**	0.0103	-0.0445**	0.0061	-0.0319
	(0.0242)	(0.2355)	(0.0206)	(0.0057)	(0.0165)	(0.0239)	(0.0204)	(0.0143)	(0.0799)
Flexible quadratic	0.0752**	-0.4720	0.0340	-0.0094	-0.0293	-0.0258	-0.1043***	-0.0023	-0.1374
	(0.0313)	(0.4545)	(0.0314)	(0.0068)	(0.0283)	(0.0307)	(0.0317)	(0.0226)	(0.1220)
Observations	9880	9880	9880	8893	8921	9751	9880	9880	7946
Parametric Model - within 150g window									
Flexible linear	0.0531**	-0.6539**	0.0188	-0.0087	-0.0341*	-0.0010	-0.0626***	-0.0023	-0.0804
	(0.0254)	(0.2768)	(0.0219)	(0.0066)	(0.0195)	(0.0253)	(0.0212)	(0.0250)	(0.0842)

Flexible quadratic	0.0501	-0.0086	0.0206	-0.0011	-0.0263	-0.0319	-0.1058***	0.0141	-0.1345
	(0.0344)	(0.4625)	(0.0370)	(0.0119)	(0.0308)	(0.0309)	(0.0332)	(0.0361)	(0.1503)
Observations	7223	7223	7223	6496	6518	7134	7223	7223	5814
Nonparametric - local linear within CCFT window									
	0.0318	-0.5754*	0.0122	-0.0069	-0.0321*	-0.0018	-0.0587***	0.0061	-0.1163
	(0.0214)	(0.3366)	(0.0207)	(0.0068)	(0.0172)	(0.0231)	(0.0214)	(0.0204)	(0.1032)
Observations	60460	60460	60460	54042	54184	59817	60460	60460	47513
Eff obs left	7022	4894	7939	4367	7768	5623	7069	5751	3339
Eff obs right	7123	4997	8035	4436	7770	6233	7176	6349	3434
BW Local Poly	275	202	316	197	334	239	280	242	170

Notes:
[a] Data from the ECLS-B. All regressions limited to infants with mother with a high school degree or less and gestational age <=32 weeks. Infants born at 32 weeks between 1200 and 1250 grams were dropped from the sample. All sample sizes rounded to nearest 50 as per NCES confidentiality restrictions. Parametric regressions have bootstrapped and non-parametric regressions have robust standard errors in parentheses.
[b] Data from the HCUP-SID AZ 2006-2007, NC 2006-2010 and NY 2006-2012 databases. All regressions limited to infants living in bottom 3 zip code income quartiles and gestational age <=32 weeks. Infants born at 32 weeks between 1200g and 1250g were dropped from the sample. Parametric regressions have bootstrapped and non-parametric regressions have robust standard errors in parentheses.
[c] Data from the NCHS 2001 Linked Birth/infant Death Birth Cohort Data Set. All regression limited to infants with mother with a high school degree or less and gestational age <=32 weeks. Infants born at 32 weeks between 1200g and 1250g were dropped from the sample. Parametric regressions have bootstrapped and non-parametric regressions have robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 3: First Stage, ECLS-B

VARIABLES	(1) Received SSI/SSDI since last interview	(2) Any Health Insurance Coverage	(3) Private Health Insurance Coverage	(4) Public Health Insurance Coverage
Parametric Model - within 200g window				
Flexible linear	0.248**	0.005	0.012	-0.044
	(0.126)	(0.043)	(0.111)	(0.086)
Flexible quadratic	0.322	-0.042	-0.171	0.041
	(0.200)	(0.092)	(0.143)	(0.145)
Observations	250	250	250	250
Parametric Model - within 150g window				
Flexible linear	0.296**	-0.021	-0.074	-0.054
	(0.142)	(0.060)	(0.108)	(0.084)
Flexible quadratic	0.230	-0.014	-0.161	0.163
	(0.167)	(0.110)	(0.149)	(0.197)
Observations	150	150	150	150
Nonparametric - local linear within CCFT window				
	0.320**	-0.005	-0.100	-0.041
	(0.155)	(0.065)	(0.144)	(0.115)
Observations	600	650	650	650
Eff obs left	100	150	100	200
Eff obs right	100	150	100	200
BW Local Poly	207	268.7	205.9	375.2

Notes: Data source is ECLS-B 9-month wave, except SSI receipt which is measured at 2-years. All regressions limited to infants with mother with a high school degree or less and gestational age <=32 weeks. Infants born at 32 weeks between 1200 and 1250 grams were dropped from the sample.
All sample sizes rounded to nearest 50 as per NCES confidentiality restrictions. Parametric regressions have bootstrapped and non-parametric regressions have robust standard errors in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

Table 4: Primary Expected Payer of Birth, HCUP-SID

	(1)	(2)	(3)	(4)
Primary Expected Payer of Birth	Medicaid	Gov. Program	Private Insurance	Self Pay
Parametric Model - within 200g window				
Flexible linear	-0.0148	-0.0028	0.0266	-0.0241**
	(0.0254)	(0.0285)	(0.0259)	(0.0111)
Flexible quadratic	-0.0328	-0.0148	0.0533	-0.0387**
	(0.0437)	(0.0457)	(0.0332)	(0.0155)
Observations	5202	5202	5202	5202
Parametric Model - within 150g window				
Flexible linear	-0.0199	-0.0034	0.0297	-0.0276**
	(0.0313)	(0.0317)	(0.0286)	(0.0112)
Flexible quadratic				
	-0.0425	-0.0335	0.0775*	-0.0420***
	(0.0490)	(0.0457)	(0.0466)	(0.0148)
Observations	3847	3847	3847	3847
Nonparametric - local linear within CCFT window				
	-0.0200	-0.0083	0.0389	-0.0312**
	(0.0302)	(0.0295)	(0.0268)	(0.0125)
Observations	20672	20672	20672	20672
Eff obs left	3983	4149	4675	2765
Eff obs right	3629	3767	4155	2709
BW Local Poly	292	302	335	212

Notes: Data source is from HCUP-SID AZ 2006-2007, NC 2006-2010 and NY 2006-2012 databases. Other government programs include Medicare, and other state and local programs like Indian Services or programs for the indigent. All regressions limited to infants living in bottom 3 zip code income quartiles and gestational age <=32 weeks. Infants born at 32 weeks between 1200 and 1250 grams were dropped from the sample. Parametric regressions have bootstrapped and non-parametric regressions have robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 5: Length of Stay, HCUP-SID

Days in Hospital Including At Birth	(1) At Birth	(2) Neonatal Period	(3) 9 months	(4) 1 Year	(5) 2 Years
Parametric Model - within 200g window					
Flexible linear	-1.5846	0.3263	-1.4085	-1.0492	-1.0539
	(1.2131)	(0.3137)	(1.0729)	(1.2940)	(1.6053)
Flexible quadratic	-3.7015**	0.3941	-3.9908**	-3.5729**	-3.2367*
	(1.5705)	(0.4317)	(1.8832)	(1.6945)	(1.8904)
Observations	5202	5199	4664	4451	3545
Parametric Model - within 150g window					
Flexible linear	-2.4099*	0.2657	-2.4888*	-2.1390	-1.8961
	(1.3328)	(0.3129)	(1.4079)	(1.3112)	(1.7567)
Flexible quadratic	-4.4935*	0.6917	-4.4646*	-3.9266*	-3.6260
	(2.3067)	(0.4921)	(2.3731)	(2.3488)	(2.2262)
Observations	3847	3845	3441	3293	2626
Nonparametric - local linear within CCFT window					
	-3.7912*	0.5130	-3.8744**	-3.3260*	-3.0745
	(1.9653)	(0.4415)	(1.9758)	(2.0186)	(2.2243)
Observations	20669	20608	18346	17449	13607
Eff obs left	1724	1927	1507	1475	1265
Eff obs right	1760	1945	1542	1513	1259
BW Local Poly	139	154	135	139	145

Notes: Data source is from HCUP-SID AZ 2006-2007, NC 2006-2010 and NY 2006-2012 databases. Length of stay at birth includes length of stay in originating hospital plus any transfers. Columns 2 through 5 report cumulative days spent in the hospital within the given time period. This cumulative measure captures the total number of days spent in the hospital, summing the length of stay at birth as well as any hospital readmissions later in childhood. All regressions limited to infants with living in bottom 3 zip code income quartiles and gestational age <=32 weeks. Infants born at 32 weeks between 1200 and 1250 grams were dropped from the sample. Parametric regressions have bootstrapped and non-parametric regressions have robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 6: Hospital Readmissions, HCUP-SID

	(1)	(2)	(3)	(4)
Number of Hospital Readmissions	Neonatal Period	9 months	1 Year	2 Years
Parametric Model - within 200g window				
Flexible linear	0.0054	0.0045	0.0078	0.0114
	(0.0113)	(0.0400)	(0.0450)	(0.0602)
Flexible quadratic	0.0108	-0.0277	-0.0234	-0.0473
	(0.0184)	(0.0660)	(0.0545)	(0.0670)
Observations	5199	4664	4451	3545
Parametric Model - within 150g window				
Flexible linear	0.0056	-0.0033	-0.0030	-0.0105
	(0.0122)	(0.0385)	(0.0459)	(0.0551)
Flexible quadratic	0.0187	-0.0399	-0.0349	-0.0686
	(0.0261)	(0.0632)	(0.0709)	(0.1010)
Observations	3845	3441	3293	2626
Nonparametric - local linear within CCFT window				
	0.0075	-0.0078	-0.0031	-0.0218
	(0.0113)	(0.0417)	(0.0449)	(0.0677)
Observations	20612	18350	17453	13611
Eff obs left	4289	2878	2917	1982
Eff obs right	3889	2752	2765	1941
BW Local Poly	312	241	255	221

Notes: Data source is from HCUP-SID AZ 2006-2007, NC 2006-2010 and NY 2006-2012 databases. All regressions limited to infants living in bottom 3 zip code income quartiles with gestational age <=32 weeks. Infants born at 32 weeks gestation with birth weights between 1200 and 1250 grams were dropped from the sample. Parametric regressions have bootstrapped and non-parametric regressions have robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 7: Discharge Reason Birth Hospitalization, HCUP-SID

	(1)	(2)	(3)
Discharge Reason	Routine	Transfer	Death
Parametric Model - within 200g window			
Flexible linear	0.0380	-0.0132	-0.0258**
	(0.0290)	(0.0265)	(0.0115)
Flexible quadratic	-0.0083	0.0286	-0.0213
	(0.0463)	(0.0412)	(0.0213)
Observations	5202	5202	5202
Parametric Model - within 150g window			
Flexible linear	0.0132	0.0059	-0.0203
	(0.0272)	(0.0306)	(0.0147)
Flexible quadratic	0.0006	0.0276	-0.0287
	(0.0410)	(0.0587)	(0.0244)
Observations	3847	3847	3847
Nonparametric - local linear within CCFT window			
	0.0211	0.0137	-0.0241
	(0.0360)	(0.0363)	(0.0181)
Observations	20672	20672	20672
Eff obs left	2768	2521	1974
Eff obs right	2712	2414	1986
BW Local Poly	213	193	155

Notes: Data source is from HCUP-SID AZ 2006-2007, NC 2006-2010 and NY 2006-2012 databases. Discharge reason is discharge reason at originating birth hospitalization. All regressions limited to infants living in the bottom 3 zip code income quartiles with gestational age <=32 weeks. Infants born at 32 weeks gestation with birth weights between 1200 and 1250 grams were dropped from the sample. Parametric regressions have bootstrapped and non-parametric regressions have robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 8: Infant Mortality-VS-L 2001 Birth Cohort, All States

	(1) Infant Mortality	(2) Post Neonatal Mortality	(3) Neonatal Mortality
Parametric Model - within 200g window			
Flexible linear	-0.0036	-0.0011	-0.0020
	(0.0105)	(0.0068)	(0.0082)
Flexible quadratic	0.0054	0.0053	0.0019
	(0.0143)	(0.0074)	(0.0104)
Observations	9880	9880	9880
Parametric Model - within 150g window			
Flexible linear	0.0001	0.0003	0.0008
	(0.0118)	(0.0059)	(0.0085)
Flexible quadratic	0.0179	0.0142*	0.0058
	(0.0159)	(0.0085)	(0.0130)
Observations	7223	7223	7223
Nonparametric - local linear within CCFT window			
	0.0107	0.0034	0.0065
	(0.0140)	(0.0062)	(0.0118)
Observations	60460	60460	60460
Eff obs left	3484	7041	3392
Eff obs right	3629	7147	3545
BW Local Poly	146	275	139

Notes: Data from NCHS 2001 Linked Birth/infant Death Birth Cohort Data Set. All regressions limited to infants with mother with a high school degree or less and gestational age <=32 weeks. Infants at 32 weeks gestation with birth weights between 1200 and 1250 grams were dropped from the sample. Parametric regressions have bootstrapped and non-parametric regressions have robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 9: Child Development at 9-month wave, ECLS-B

	(1) Bayley Mental T-Score	(2) Bayley Motor T-Score	(3) Nursing Child Assessment Teaching Scale – Parent Score	(4) Nursing Child Assessment Teaching Scale – Child Score
<u>Parametric Model - within 200g window</u>				
Flexible linear	0.768	3.688	3.313**	0.762
	(3.343)	(3.092)	(1.676)	(0.829)
Flexible quadratic	2.305	8.402**	3.404	0.710
	(4.622)	(3.671)	(2.702)	(1.118)
Observations	250	250	200	200
<u>Parametric Model - within 150g window</u>				
Flexible linear	0.353	5.589*	3.270	0.629
	(3.633)	(3.244)	(2.300)	(0.854)
Flexible quadratic	5.961	6.806	3.942	1.415
	(4.921)	(4.270)	(2.629)	(1.263)
Observations	150	150	150	150
<u>Nonparametric - local linear within CCFT window</u>				
	1.656	6.381**	3.555*	0.861
	(4.159)	(3.070)	(1.973)	(0.971)
Observations	650	600	500	500
Eff obs left	150	100	150	100
Eff obs right	150	100	150	100
BW Local Poly	231.7	206.1	255.8	244.9

Notes: Data source is the ECLS-B, 9-month wave. All regressions limited to infants with mother with education of high school or less and gestational age <=32 weeks. Infants born at 32 weeks between 1200g and 1250g were dropped from the sample.

Parametric regressions have bootstrapped and non-parametric regressions have robust standard errors in parentheses. All sample sizes rounded to nearest 50 as per NCES confidentiality restrictions.

*** p<0.01, ** p<0.05, * p<0.1

Table 10: Maternal Labor Supply at 9 month wave, ECLS-B

VARIABLES	(1) Mother Employed	(2) Mother Works Full Time	(3) Mother Works Part Time	(4) Mother Not In Labor Force
Parametric Model - within 200g window				
Flexible linear	-0.028	-0.214*	0.187*	0.001
	(0.133)	(0.126)	(0.097)	(0.132)
Flexible quadratic	-0.050	-0.199	0.149	0.059
	(0.204)	(0.159)	(0.138)	(0.226)
Observations	250	250	250	250
Parametric Model - within 150g window				
Flexible linear	-0.150	-0.276**	0.126	0.082
	(0.163)	(0.123)	(0.085)	(0.151)
Flexible quadratic	0.220	-0.069	0.289*	-0.152
	(0.209)	(0.160)	(0.151)	(0.197)
Observations	150	150	150	150
Nonparametric - local linear within CCFT window				
	-0.054	-0.237*	0.181*	0.018
	(0.155)	(0.130)	(0.104)	(0.161)
Observations	650	650	650	650
Eff obs left	150	150	150	150
Eff obs right	150	100	150	150
BW Local Poly	242.6	207.9	257.2	244.4

Notes:

Data source is the ECLS-B, 9 month wave. All regressions limited to infants with mothers with education of high school or less and gestational age <=32 weeks. Infants born at 32 weeks between 1200g and 1250g were dropped from the sample. Parametric regressions have bootstrapped and non-parametric regressions have robust standard errors in parentheses. All sample sizes rounded to nearest 50 as per NCES confidentiality restrictions. *** p<0.01, ** p<0.05, * p<0.1

Appendix Table 1: SSA Birth weight Cutoffs by Gestational Age

Gestational Age (in weeks)	Birth weight (in grams)	Birth weight (in lbs. and oz.)
≥ 37-40	≤ 2000	4 lbs 6.50 oz
≥ 36	≤ 1875	4 lbs 2.14 oz
≥ 35	≤ 1700	3 lbs 11.97 oz
≥ 34	≤ 1500	3 lbs 4.91 oz
≥ 33	≤ 1325	2 lbs 14.74 oz
≥ 32	≤ 1250	2 lbs 12.09 oz
Any	< 1200	2 lbs 10.33 oz

Source: SSA Program Operations Manual System (POMS)

Appendix Table 2: Means of Key Variables by Heaping Type, ECLS-B

	Analysis sample	No oz heaps	No 100g heaps	No oz or 100g heaps
SSI/SSDI receipt	0.311	0.297	0.315	0.307
Any health insurance coverage	0.980	0.976	0.983	0.978
Private health insurance coverage	0.281	0.289	0.277	0.277
Public health insurance coverage	0.772	0.791	0.774	0.799
Child is male	0.503	0.463	0.506	0.465
Child is nonwhite	0.651	0.703	0.652	0.713
Mother not married	0.608	0.614	0.610	0.622
Apgar score	7.667	7.718	7.650	7.668
Mother works	0.356	0.292	0.359	0.294
Mother works full time	0.234	0.218	0.236	0.219
Mother works part time	0.121	0.074	0.123	0.075
Mother not in labor force	0.525	0.593	0.523	0.592
Bayley mental t-score	43.167	43.000	43.213	43.143
Bayley motor t-score	45.017	45.008	44.994	44.987
Nursing child assessment teaching scale - parent	33.010	33.047	33.040	33.156
Nursing child assessment teaching scale - child	14.729	14.766	14.727	14.729
Observations	650	250	650	250

Appendix Table 3a: Characteristics of Infants at 42oz and 43oz heaps, ECLS-B

	42 oz (1191g)	43 oz (1219 g)	difference	t-statistic
Child is male	0.455	0.385	-0.070	(-0.33)
Child is nonwhite	0.455	0.231	-0.224	(-1.14)
Mother not married	0.636	0.462	-0.175	(-0.83)
Apgar score	7.700	7.846	0.146	(0.36)
Number of Observations	Rounds to zero	Rounds to zero		

* p<0.10, **p<0.05, *** p<0.01
Number of Observations masked due to data NCES policy. See Notes to Table 3.

Appendix Table 3b: Characteristics of Infants at 42oz and 43oz heaps, VS-L

	42 oz (1191g)	43 oz (1219 g)	difference	t-statistic
Child is male	0.486	0.528	0.042	1.366
Child is nonwhite	0.390	0.345	-0.044	-1.510
Mother not married	0.422	0.429	0.008	0.251
Apgar score*	7.497	7.677	0.180	1.588
Number of Observations	508	576		

* p<0.10, **p<0.05, *** p<0.01
Data Source: Linked Birth and Infant Health Data, 2001
Sample limited to infants with mother with a high school degree or less and gestational age <=32 weeks. Infants born at 32 weeks between 1200g and 1250g were dropped from the sample.For Apgar, number of observations is: 376 (42 oz) and 465 (43 oz).

Appendix Table 4: Top Ten Hospital Revisit Primary Diagnoses, HCUP-SID

Three Digit ICD-9 Code	Diagnosis	Percent
466	Acute bronchitis and bronchiolitis	15.53
493	Asthma	7.59
486	Pneumonia, organism unspecified	5.83
765	Disorders relating to short gestation and low birth weight	5.11
770	Other respiratory conditions of fetus and newborn	4.87
530	Diseases of esophagus	4.01
550	Inguinal hernia	3.58
518	Other diseases of lung	2.52
769	Respiratory distress syndrome in newborn	2.44
276	Disorders of fluid electrolyte and acid-base balance	2.41
	Total	53.89

Notes: Data from the HCUP-SID AZ 2006-2007, NC 2006-2010 and NY 2006-2012 databases. The sample is limited to infants with living in bottom 3 zip code income quartiles and gestational age <=32 weeks. Infants born at 32 weeks between 1200 and 1250g were dropped from the sample.

Appendix Table 5: Infant Mortality-VS-L 2006 to 2010 Birth Cohorts, All States

	(1) Infant Mortality	(2) Post Neonatal Mortality	(3) Neonatal Mortality
<u>Parametric Model - within 200g window</u>			
Flexible linear	0.0022	0.0020	0.0005
	(0.0043)	(0.0024)	(0.0033)
Flexible quadratic	0.0035	0.0040	-0.0001
	(0.0070)	(0.0039)	(0.0063)
Observations	49605	49605	49605
<u>Parametric Model - within 150g window</u>			
Flexible linear	0.0030	0.0028	0.0009
	(0.0052)	(0.0035)	(0.0042)
Flexible quadratic	-0.0023	0.0046	-0.0070
	(0.0076)	(0.0040)	(0.0073)
Observations	36033	36033	36033
<u>Nonparametric - local linear within CCFT window</u>			
	-0.0010	0.0041	-0.0053
	(0.0074)	(0.0033)	(0.0065)
Observations	298687	298687	298687
Eff obs left	14596	21745	13714
Eff obs right	16567	23370	13913
BW Local Poly	130	182	113

Notes: Data from NCHS 2006 to 2010 Linked Birth/infant Death Birth Cohort Data Set. All regressions limited to infants with mother with a high school degree or less and gestational age <=32 weeks. Infants at 32 weeks gestation with birth weights between 1200 and 1250 grams were dropped from the sample. Parametric regressions have bootstrapped and non-parametric regressions have robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Appendix Table 6: Infant Mortality-VS-L 2001 Birth Cohort, AZ, NC and NY

	(1) Infant Mortality	(2) Post Neonatal Mortality	(3) Neonatal Mortality
<u>Parametric Model - within 200g window</u>			
Flexible linear	-0.0015	-0.0205	0.0190
	(0.0294)	(0.0169)	(0.0231)
Flexible quadratic	-0.0083	-0.0444	0.0361
	(0.0498)	(0.0303)	(0.0329)
Observations	883	883	883
<u>Parametric Model - within 150g window</u>			
Flexible linear	-0.0117	-0.0409	0.0293
	(0.0329)	(0.0268)	(0.0317)
Flexible quadratic	0.0688	-0.0014	0.0702*
	(0.0517)	(0.0408)	(0.0372)
Observations	632	632	632
<u>Nonparametric - local linear within CCFT window</u>			
	-0.0042	-0.0265	0.0348
	(0.0380)	(0.0214)	(0.0288)
Observations	5580	5580	5580
Eff obs left	422	564	365
Eff obs right	449	636	441
BW Local Poly	190	265	181

Notes: Data from NCHS 2001 Linked Birth/infant Death Birth Cohort Data Set from AZ, NC, and NY. All regressions limited to infants with mother with a high school degree or less and gestational age <=32 weeks. Infants at 32 weeks gestation with birth weights between 1200 and 1250 grams were dropped from the sample. Parametric regressions have bootstrapped and non-parametric regressions have robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10