SEASONALITY, WEATHER SHOCKS AND THE TIMING OF BIRTHS AND CHILD MORTALITY IN SENEGAL

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Abstract

This paper uses data from Senegal to examine two complementary explanations of seasonal fertility based upon the inability of households to smooth consumption and labor time over the crop seasons. First, if the value of time varies seasonally parents may wish to shift births to those months of the year when the shadow value of time, particularly women's time, is relatively low. Second, if parents care about the survival chances of their potential births, and, facing highly seasonal income streams, they are not able to smooth consumption, they may time conceptions so that births occur after harvests have been gathered and monthly income is high. In rural Senegal, births occur disproportionately in the dry season months which is consistent with both of these hypotheses. If the inability to smooth consumption and labor demand over the seasons is an important cause of the seasonal pattern of births, then unanticipated weather shocks are also likely to alter the timing of births. Estimation of a dynamic model of the joint determination of the month of birth and the probability of survival to age 24 months with a sample of rural Senegalese women from the 1986 Senegal Demographic and Health Survey reveals that fertility and mortality are indeed responsive to rainfall shocks. Positive rainfall shocks increase fertility, particularly rainfall shocks in the likely month of conception and in the prior rainy season. Simulations imply that births and deaths respond more to rainfall shocks in rural areas than they do in urban areas. Rainfall shocks result in a substantial permanent increase in surviving offspring among rural households but have essentially no effect on the number of surviving children of urban households. Since rainfall is likely to be more correlated with income shocks for rural populations than urban populations, these findings are consistent with the idea that variations in income flows, anticipated or not, are important determinants of fertility and subsequent mortality. The difference in the effect of rainfall shocks on the permanent quantity of surviving children is consistent with an insensitivity of urban incomes, as compared to rural incomes, to rainfall deviations, and the normality of the quantity of children.

1. Introduction

Persistent, seasonal fluctuations in fertility and mortality are observed in virtually every society, but these patterns are particularly pronounced in developing countries. Besides being extraordinarily stable over time, these seasonal cycles are quantitatively very large relative to other kinds of temporal trends (Lam and Miron 1991). Many researchers have examined these dramatic fluctuations, but most studies have relied on short sample periods and discuss general regularities. Surveying the literature on the seasonality of births, Lam and Miron (1991) conclude that no single explanation receives strong, consistent support from the data.

A separate stream of literature has demonstrated the importance of uncertainty and the seasonal variability of incomes faced by farmers in low income agriculture and its effect on behavior (for example, Binswanger and Rosenzweig (1993), Rosenzweig(1988), Rosenzweig and Wolpin (1993), Paxson (1993), Alderman and Paxson (1992)). In the absence of well functioning credit and insurance markets, households may be unable to smooth consumption across seasons or compensate for shortfalls in income arising from departures in rainfall from its seasonal pattern. Forward looking households in such an environment may engage in precautionary savings when information on future income is made available to them in the form of rainfall realizations, with consequent changes in current and future consumption. As with other goods, decisions on the quantity and quality of children and the timing of births may reflect the response of households to seasonal income variations and uncertainty in the absence of well functioning markets that would allow them to smooth consumption. Field work by Caldwell *et. al*. (1986) in India reinforces the view that a fundamental consideration of parents in making decisions on fertility and the education of children is to strengthen the household's ability to withstand periodic crises, the most important of which are related to weather shocks.

Seasonal variations in mortality are often explained biologically. The most frequently cited explanation is the seasonality of disease itself. Malaria and parasitic diseases are more of a threat during rainy seasons when it is damp and organisms can grow more quickly. But this is precisely the time when food is scarce and labor demand is at a peak. Intrahousehold allocations of resources and time might, therefore, explain at least part of the observed seasonality. Foster

(1995) examines the impact of severe floods on health investments in children in Bangladesh as measured by anthropometric indicators. He finds that children in the poorest households were especially vulnerable to the conditions created by flood but that children in better off households were able to experience less disinvestment in health human capital, in part, as a result of access to the credit market.

Observed seasonal patterns in fertility have been explained with both biological and bio-behavioral theories (Campbell and Wood 1994). Biologists have noted that sperm counts are lower in high temperatures. This is used to explain the almost universal drop in conceptions during the hottest months of the year (Lam and Miron 1996). Seiver's (1985) finding that seasonal variations in fertility diminished with the widespread use of air conditioning in the southern United States gives some credence to this hypothesis. Seasonal changes in exposure to sunlight are also purported to have rather large hormonal effects which might alter the likelihood of a conception (Ehrenkranz 1983). These purely biological arguments, however, fail to explain the well documented, virtually universal variation in seasonal fertility by social class (for example, Pasamick, Dintz and Knobloch (1960), James (1971), Lyster (1971), Zelnick (1979), Kestenbaum (1987), and Caldwell (1990)) . Simulation models developed by Lam, Miron, and Riley (1994) suggest that temperature changes have a smaller and more inconclusive impact on fertility than had been previously hypothesized.

There are a number of epidemiologically and nutritionally based explanations for observed seasonal fertility cycles and for why the seasonal effects found in the developing countries are more pronounced (for example, Bantje (1988), Warren, Gwinn, and Rubin (1986), and Sahn (1989)). During the wettest seasons of the year, spontaneous abortions due to infection and disease are more likely, and these miscarriages are often unknown to women or are unreported to interviewers. In seasons where food is scarce, and physical demands high, it is more likely that a woman will be malnourished or ill and, therefore, unable to conceive. Since the rainy season is also the planting and preharvest season, it is a time when food stores are most depleted. This is not, however, a purely biological argument. Because households choose how to distribute food among their members, and since the provision of food is also something that varies by season (Behrman 1988), the observed seasonal fertility cycles may be, at least in part, explained by the way in which food is allocated to women at different times of the year. The returns to nutritional well-being by age and sex groups may vary over the seasons and as a result of weather shocks and may result in time-varying relative allocations of food as in Pitt *et. al.* (1989). Prices, including the price of time, vary with the seasons and with weather shocks. The shadow cost of a child may be less when the birth occurs during the early part of the dry season when the demand on women's time in agricultural field production is lower. Similarly, the cost of continued nursing of a child will reflect both the seasonally varying opportunity cost of mother's time and the seasonally varying cost of substitute sources of nutrition.

Figure 1 presents a monthly distribution of births in rural Senegal based on the 1986 Demographic and Health Survey (DHS). About 47 percent of all reported births in rural Senegal occur in the four months of the year -- February through May, which is 14 percent more than implied by a uniform distribution. These months are at the beginning of the dry season, which places conceptions between May and August. While this timing is consistent with the lower value of time associated with dry season births, it is likely to be consistent with competing behavioral and biological theories of seasonality in fertility, although it is not consistent with food scarcity and high seasonal demands for agricultural labor reducing fecundity.[1] Some other evidence can be brought to bear that suggests that there is an important behavioral component to this seasonal pattern. Figure 2 present the distribution of births for urban households in the same DHS dataset. In urban Senegal, less than 39 percent of births occur in the four months February through May, which is only 6 percent more than implied by a uniform distribution. The seasonal variation in births is markedly less among urban households, who, unlike those in the American South, are unlikely to benefit from widespread air conditioning which may biologically influence reproduction. It also unlikely that urban incomes have as strong a seasonal component as rural income, or are as sensitive to weather shocks. The implication is that the greater seasonality of rural households may reflect the larger seasonal variation in income that they face.

If rates of child mortality are highly seasonal and child survival is valued by parents, parents may try to time births in those months in which (biologically determined) survival

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[1] Nor is it consistent with reduced fertility of men during hotter months of the year. These months of peak conception are hotter than the yearly average at Dakar, Senegal.

probabilities are high. Furthermore, the period of greatest risk for child death is the first 24 months of life, the first 12 months in particular. In the Senegal DHS sample, 36 percent of deaths prior to 24 months occurred in the first month of life and 89 percent took place prior to the 13th month of life. Positive income shocks, perhaps induced by advantageous rainfall shocks, may enhance the probability of child survival during the dangerous first months of life. As a result, after experiencing positive rain shocks that suggest a bountiful rainy season harvest and higher consumption, parents may seek a pregnancy timed to take advantage of the reduced mortality associated with that higher consumption. Recent work by Pitt (1997) using DHS data for 14 Sub-Saharan African nations, and by Lee *et. al*. (1997) using data from India, Bangladesh and the Philippines, demonstrates that fertility decisions and mortality and health outcomes are correlated. Parents are apparently attentive to the health and mortality outcomes of the child they might bear when making fertility decisions. If they perceive these outcomes to vary seasonally, they may try to alter the timing of births accordingly.

Figure 3 presents the seasonal distribution of mortality rates prior to 24 months of age by month of birth predicted by an econometric model (discussed in detail below) that controls for cohort, time trend and region effects among other things, and predicts the seasonal pattern of deaths with a set of month dummy variables. Notice that these predicted death rates display a marked seasonal pattern. Overlaid on this figure is the seasonal distribution of mean rainfall over a 37 year period in the southern region of Senegal, the same region for which deaths are predicted.[2] It clear that there is a positive correlation between mean monthly rainfall and the rate of child mortality by month of birth ($\rho=0.81$). No such correlation exists for birth rates adjusted in the same fashion and mean rainfall ($\rho=0.03$).[3]

In this paper, we investigate the effects of seasonality and weather shocks on the joint determination of fertility and child survival using monthly retrospective data from the 1986 Demographic and Health Survey of Senegal merged with monthly rainfall data from the high-quality database assembled by the National Center for Climatic Data of the U.S. National

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[2] Details on these data are presented below.

[3] Adding quadratic terms in a regression of birth rates and death rates on mean rain by month did not significantly improve the fit of the regression.

Oceanographic and Atmospheric Administration (NOAA). We estimate both reduced form and structural state dependence models using a bivariate random effects probit model. In the next section, we set out reduced form and dynamic probit models of the joint determination of fertility by month and the survival of children born by month of birth. These models, by controlling for historical mean rainfall or month fixed effects, examine the role of seasonality, as well as rainfall shocks, in influencing the timing of births and the likelihood of child survival to age 24 months. Section 3 of the paper describes the Senegalese setting as well as the data used in the analysis. Section 4 interprets the parameter estimates from the set of models estimated and demonstrates the importance of rainfall shocks on fertility and survival by simulating the effect of a dry season and a rainy season shock on a single cohort of women. A comparison of parameter and simulation estimates for rural and urban women suggests that behavioral hypotheses, such as the inability to smooth consumption, are consistent with the empirical results. Section 5 summarizes our results.

2. A Dynamic Econometric Model of Fertility and Child Survival

a. Reduced form models

To examine the effects of seasonality and rainfall shocks on the timing and frequency of births and child mortalities, we begin with linear reduced-form demand equations for latent fertility and mortality:

$$F_{it}^{*} = X_{fit}\beta_{f} + \mu_{fi} + v_{fit} \tag{1}$$

$$D_{it}^{*} = X_{hit}\beta_{h} + \mu_{hi} + v_{hit} \tag{2}$$

where F^{*}_{it} is latent fertility of woman i in time t, D^{*}_{it} is latent mortality of the child of woman i born in time t, X_{fit} and X_{h} are vectors of exogenous regressors, the compound error in each equation ($\epsilon_{fit} = \mu_{fi} + v_{fit}$ and $\epsilon_{hit} = \mu_{hi} + v_{hit}$) contain a heterogeneous component of health known to parents but unmeasured in the data μ_{fi} and μ_{hi} (inherent healthiness), as well as nonsystematic shocks v_{fit} and v_{hit}, and the β's are parameters to be estimated representing parental responses to exogenous variables. Latent fertility F^{*}_{it} represents the unobserved intensity of reproductive effort including fecundity. If this intensity exceeds some threshold, then a birth results, otherwise it does not.[4]

If the error terms have zero means, and the nonsystematic errors v_{fit} and v_{hit} are uncorrelated, then the covariance between the compound errors ϵ_{fit} and ϵ_{hit} is

$$cov(\epsilon_{fit}, \epsilon_{hit}) = cov(\mu_{fi}, \mu_{hi}) \tag{3}$$

The compound errors of the fertility and health equations are correlated. Selection bias results from estimating equation (2) from samples of children if unmeasured health heterogeneity actually exists in the sampled population and if parents take unobserved health heterogeneity into account when making fertility decisions, that is, if μ_{fi} consists of, in part, the effect of innate survival probabilities on fertility behavior.

Jointly estimating the determinants of fertility and the survival of those born is complicated by the difficulty in disentangling the parameters of the reduced-form determinants of fertility from the parameters of the reduced-form determinants of child mortality. If parents care about the health and survival outcomes of potential births, then any exogenous variable that affects health and survival also affects the fertility decision. Even if there were uncertainty about inherent healthiness and decisions were sequential and myopic, because the birth decision precedes the health behaviors resulting from that decision, there cannot be fewer observed or known exogenous variables influencing health and survival than influencing the fertility decision. Essentially, the problem is very similar to the identification problem of instrumental variable estimation such as two-stage least squares. We want to estimate the "demand" for survival of each child conditional on an endogenous right-hand-side regressor -- whether or not it was born.

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[4] These are fertility and health demand equations derived, in principle, from the standard framework of a household maximizing a utility function that includes the number and health “quality” of children, where quality is produced by the household. These “solved out” (reduced-form) demand equations are functions of only the exogenous variables of the household’s optimization problem, ignoring, for now, dynamic considerations such as replacement effects. If, for example, fertility responded to the number of children born in past periods and the number of those that survived, then the reduced-form would have to include all past exogenous determinants, not just contemporaneous determinants. Alternatively, these kinds of effects are captured directly by the model of structural state dependence set out and estimated below. The specification presented here is meant to motivate the ensuing discussion and is representative of the fertility and health demand reduced form equations most often estimated in the literature.

Conditioning on birth is required, in the case of the mortality reduced form, if the children whose births were averted have differing inherent survival probabilities than those whose births are not averted. This might be the case, for example, if low fertility women tend to have children with higher survival probabilities than higher fertility women (negative birth selection). The sequential nature of the decision process means that there is not likely to be an exclusion restriction of the usual sort -- a variable or variables that influences the endogenous regressor, birth, that does not otherwise influence child health <u>conditional</u> on this regressor. The discrete nature of mortality makes identification based exclusively on the choice of an error distribution problematic. The identification problem arises because all the regressors contained in X_f are also contained in X_h.[5]

The restrictions on the error terms attached to the fertility and health reduced forms (equations (1) and (2) above) are sufficient for identification as long as fertility and the mortality outcomes of resulting births are observed for more than one time period in the life of each woman in the sample. Under the assumptions that $E(v_{fit},v_{hit})=0$, $E(v_{fit},v_{fit'})=0$ and $E(v_{hit},v_{hit'})=0$, we can write the joint likelihood of births and deaths for T periods as [6]

$$Prob\ (F_{i1},F_{i2},\ldots,F_{iT},D_{i1},D_{i2},\ldots,D_{iT}) = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty}[\prod_{t=1}^{T}\Phi[(\frac{X_{fit}\beta_f}{\sigma_{v_f}} + (\frac{\rho_f^2}{(1-\rho_f^2)})^{1/2}\tilde{\mu}_{fi})I_{fit}]$$

$$x\ \prod_{t=1}^{T}\Phi[(\frac{X_{hit}\beta_h}{\sigma_{v_h}} + (\frac{\rho_h^2}{(1-\rho_h^2)})^{1/2}\tilde{\mu}_{hi})I_{hit}]^{F_{it}}\ x\ \phi_2(\tilde{\mu}_{fi},\tilde{\mu}_{hi},\rho)^{F_{it}}\ x\ \phi_1(\tilde{\mu}_{fi})^{1-F_{it}}]\ d\tilde{\mu}_{fi}d\tilde{\mu}_{hi} \qquad \textbf{(4)}$$

where $\tilde{\mu}_{hi} = \mu_{hi}/\sigma_{\mu h}$, $\tilde{\mu}_{fi} = \mu_{fi}/\sigma_{\mu f}$, $I_{fit}=1$ if $F_{it}=1$, $I_{fit}=-1$ if $F_{it}=0$, $I_{hit}=1$ if $D_{it}=1$, $I_{hit}=-1$ if $D_{it}=0$, and where

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[5] The set of regressors X_h can also includes variables that affect health outcomes but are not known to parents until after the fertility decision is made. Among them are the sex of the child, whether the pregnancy resulted in multiple births (twins), and rainfall outcomes realized subsequent to conception or birth.

[6] The t subscript should be taken as the date of the child's birth when attached to mortality, so that D_{it} is a binary indicator of the whether a the child of woman i born in period t is still alive at some fixed time since birth.

$$\rho_f = \left(\frac{\sigma^2_{\mu_f}}{\sigma^2_{\mu_f} + \sigma^2_{v_f}} \right)^{1/2} \quad and \quad \rho_h = \left(\frac{\sigma^2_{\mu_h}}{\sigma^2_{\mu_h} + \sigma^2_{v_h}} \right)^{1/2} .$$

The simplification of the 2T-variate probability to the form on the right-hand side of (4) results from integrating out the women-specific effects μ_{fi} and μ_{hi}, the only sources of correlation between the sequence of birth and death/survival events. Numerically evaluating the integrals in (4) is accomplished with fast and highly accurate Gauss-Hermite integration.[7]

The likelihood (4) is referred to as the random effects bivariate probit model. The random effects probit model was introduced into the economics literature by Heckman (1980) and the use of Gauss-Hermite quadrature to evaluate the likelihood was popularized by Butler and Moffitt (1982).

Associating all correlation with a single factor (μ) is sufficient to yield an error correlation matrix with equicorrelation, a special case of the exchangeability property. In the case of a single set of random variables $F_{i1},F_{i2},...,F_{iT}$, equicorrelation restricts the correlation between any pair of the sequence to be equal. The sequence can be shuffled or *exchanged* in any way and the TxT correlation matrix will consist of ones on the diagonal and ρ_f in the off-diagonal. If F_{it} is fertility in time t, μ_{fi} represents unobserved fecundity, the woman's innate health, the inherent survival probabilities of her offspring, and other factors that are specific to the ith woman and time invariant. Life-cycle changes in fecundity (and other factors) are captured by introducing age effects. In the case of the sequences of two random variables $F_{i1},F_{i2},...,F_{iT}$, and $D_{i1},D_{i2},...,D_{iT}$, the model imposes exchangeability within each sequence and, since the shocks v_{fit} and v_{hit} are assumed to be uncorrelated, the only source of correlation between the sequences arises from the constant correlation ρ between the fertility factor μ_{fi} and the mortality factor μ_{hi}. Here, there are three free parameters describing the correlation structure of the two sequences of events -- ρ_f (the

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[7] The assumption of normality assumed for the woman-specific effects μ in the random effects probit model (4) is not necessary for identification. Identification can be achieved with a nonparametric distribution. Moreover, the distribution of the errors v and μ need not be the same. In the estimation reported below, the μ error terms are assumed to be normally distributed and the v error terms are assumed to take the logistic distribution.

intertemporal correlation among fertility outcomes), ρ_h (the interchild correlation among survival events of a woman's offspring), and ρ_{fh} (the cross-correlation between fertility and survival events).

What restrictions on error correlations are imposed by this model and how realistic are they? Note that this is the <u>same</u> correlation structure among errors that is assumed in the fixed and random effects models commonly estimated in the social sciences -- all the error correlation across observations for a single individual (or household) in a panel dataset derives from a time invariant component of individual heterogeneity. This equicorrelated model is substantially over-identified in that there are 2T(2T-1)/2 - 3 restrictions imposed, leaving open the possibility of less restrictive specifications.[8] Essentially, much of the literature on child survival and health has assumed an even more restrictive form of equicorrelation, that of zero correlation between the unobserved heterogeneity associated with fertility and child mortality. If there is correlated heterogeneity, then models that impose zero correlation will confound the effects of regressors determining one of these behaviors with their effect on the other behaviors.

b. Models with structural state dependence

So far the discussion has assumed that fertility and survival are correlated across time as a result of correlated random effects associated with each woman μ_{fi} and μ_{hi}. There is another important mechanism through which fertility and survival may effect each other over time -- structural state dependence. State dependence is the term given to behaviors in which the probabilities of future choice's are altered in response to previous choices (states). To make this more explicit consider the simple model of fertility alone:

$$F_{it}^{*} = X_{fit}\beta_f + \gamma \sum_{\tau=0}^{\tau=t-1} F_{i\tau} + \mu_{fi} + v_{fit} \qquad \textbf{(5)}$$

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[8] A variety of less restrictive models that still possess much of the relative computational ease of this model are proposed and estimated with DHS data from 14 Sub-Saharan African countries in Pitt (1997).

The sum of the realizations of past fertility events (number of births) effects the determination of latent fertility in (5). If $\gamma>0$, having a birth in the initial period generates a higher probability of a birth in subsequent periods. Obviously, if $\gamma<0$, the opposite is true. A more general model would allow for a vector of parameters γ associated with all prior fertility events to vary with the length of the lag, as in

$$F_{it}^{*} = X_{fit}\beta_{f} + \sum_{\tau=1}^{\tau=\ell} \gamma_{\tau} F_{it-\tau} + \mu_{fi} + v_{fit} \tag{6}$$

A general model of fertility and child mortality incorporating both state dependence and random effects takes the following form

$$F_{it}^{*} = X_{fit}\beta_{f} + \sum_{\tau=1}^{\tau=\ell} \gamma_{f\tau} F_{it-\tau} + \sum_{\tau=1}^{\tau=L} \delta_{f\tau} D_{it-\tau} + \mu_{fi} + v_{fit} \tag{7}$$

$$D_{it}^{*} = X_{hit}\beta_{h} + \sum_{\tau=1}^{\tau=\ell} \gamma_{h\tau} F_{it-\tau} + \sum_{\tau=1}^{\tau=L} \delta_{h\tau} D_{it-\tau} + \mu_{hi} + v_{hit} \tag{8}$$

in which the probability of current fertility and mortality events depend on past fertility and mortality experience with lags of length ℓ for past fertility and L for past mortality, as well as possibly correlated woman-specific effects μ_{fi} and μ_{hi}. This is the form of the model estimated below. The exchangeability property no longer holds in the model with structural state dependence since now the ordering of time periods is unique, although the model is no more complicated to estimate than the random effects model without state dependence.

The model of state dependence with serial correlated heterogeneity given by (7) and (8) makes a strong demand on the nature of the stochastic process that generates the sequence of fertility and mortality outcomes. It requires that the initial conditions of the process are nonstochastic (Heckman 1980). This means that estimation that uses a panel of data that is sampled midstream will result in inconsistent estimates. In our case, we can avoid a midstream start of the process by making the initial (stochastic) observation the first time period for which a woman is at risk for pregnancy. Fortunately, the Demographic and Health Survey data provide the entire life history of reproduction and the survival history of any live birth. Consistency not only requires that we begin at the beginning, but also that the initial conditions are nonstochastic -- not generated by the same process that generates the panel data. Heckman (1980) considers this assumption about initial conditions to be “neither innocuous nor especially plausible (p. 143)" in most cases and suggests various solutions. However, the fertility case seems to conform to the assumption of nonstochastic initial assumptions better than most processes. The time at which a young woman is first at risk for pregnancy is the time of menarche, an event which seems to be determined by a very different process than becoming pregnant. What we require is that the timing of menarche be the result of an essentially biological process over which a young woman has little control, an assumption which does not seem unreasonable to us. To be certain that the start of the process is nonstochastic, we assume the risk of pregnancy begins at a girl’s 13th birthday.[9] So, while the start of the process is likely to be nonstochastic, there may be a small (relative to a woman’s entire reproductive life) number of midstream observations in the data for girls who are at risk prior to this age. Although assuming an earlier date for the onset of the first risk of pregnancy will avoid this problem, it will also add observations to the stochastic model for which the probability of pregnancy is actually deterministically zero.

Note that aside from the requirement that the time series begin with nonstochastic initial conditions, adding lagged values of the dependent variables raises no other econometric issues (Heckman, 1980). Because we integrate out the woman-specific effects, the sole source of the correlation in behaviors across time, merging models of heterogeneity (given by (1), (2) and likelihood (4)) with a model that allows for state dependence (equations (7) and (8)) yields the same error variance structure required by the reduced form likelihood (4).

3. The Setting and the Data

Senegal is a West African country which lies predominantly in the Sahel region and borders the North Atlantic between Guinea-Bassau and Mauritania and is subject to damaging periodic droughts. In 1994, total fertility was approximately 6.09 births per woman. At 75.7 per

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[9] The DHS survey does ask for the date of menarche, however, there are many missing values.

1,000 live births, Senegal’s infant mortality rate is actually low compared to the rest of sub-Saharan Africa, but childhood mortality is extremely high relative to that of infants (Goldberg and M'Bodji 1988) Serious, infectious diseases like measles, pertussis, and neonatal tetanus, continue to thrive despite the fact that vaccines are available to prevent them (Cantrelle 1980). The majority of Senegal's population (about 77%) is dependent upon rainfed, small-scale cultivation. The major cash crop is peanuts which accounts for about 2/5 of all cultivated land.   Other important agricultural outputs include millet, corn, sorghum, and rice, but these are grown predominantly for home consumption.   Despite the large numbers of people engaged in farming, agricultural output comprises only about 20% of the national product.

The climate in Senegal is hot and humid with a single rainy season which lasts from mid-July until mid-October. Harvests tend to occur between September and November. During these months, labor demand is at a peak and almost every adult is busy working in the fields. Some researchers have suggested that seasonal peaks in labor demand may be somewhat detrimental to the health and well-being of children (Chen, Chowdry, and Huffman 1979). For instance, in Senegal it has been shown that young children are more likely to be weaned during the rainy season (Carloni 1984). This means that young children are often deprived of the antibodies in their mother’s milk at a time when exposure to endemic malaria is a particular threat (Cantrelle and Leridon 1971). Infants frequently become the responsibility of older sisters who themselves have less time available to collect fuel and water for the household (Schofield 1974). Often meals are only cooked once a day during the rainy season, and nutrient rich pulses are much less frequently consumed because they require too much cooking time (Carloni 1984). Given that the value of a woman's time varies with seasonal labor demands, the season in which a child is born may be an important indicator of its ultimate survival.

The data used in the estimation come from the 1986 Senegal Demographic and Health Survey (DHS) dataset. We separate rural and urban households into two distinct subsamples. The estimation below emphasizes the effect of seasonality and weather shocks on rural households since it is likely that their income streams are more seasonal and influenced by weather shock because of the agrarian nature of the rural economy. We also present estimates using the urban subsample in order to draw some inferences about the underlying sources of fertility and mortality response to weather shocks and seasonality.

Despite the fact that Africa appears to be a particularly good candidate for studies of seasonality, there are many data problems which might confound an analysis of fertility and, to a lesser extent, mortality (Arnold 1991). In many African datasets, fertility and mortality histories are plagued by problems of incompleteness and displacement. People may forget or neglect to report the birth of a child that has died (Arnold (1990) and Curtis (1995)). A child's birth date is not always clearly recalled, and thus, ages tend to be heaped at numbers which end in zero or five (Arnold 1991). Reported age of death is frequently heaped at 12 months (Sullivan, Bicego, and Rutstein 1990), and in some datasets, like the DHS, ages are sometimes purposely misreported by interviewers who do not want to gather the extra information required for all children under five (Arnold 1991) . These issues are always troublesome to researchers, but they pose an even greater problem when events are disaggregated to a monthly or seasonal level. Senegal is one of the few African countries for which the DHS is reported to have reasonably accurate birth dating (Arnold 1991), and since the mortality measure that we utilize is death within 24 months, a 12 month mortality heap does necessarily imply a measurement error problem.

The rainfall data was assembled by the National Climatic Data Center (NCDC) of the U.S. National Oceanographic and Atmospheric Administration (NOAA) and obtained from their site on the World Wide Web. Mean and actual monthly rainfall measures taken at rain stations in Dakar, Diourbel, Ziguinchor, and Saint-Louis which are located in the west, central, south and northwest regions respectively. Appendix Figure 1, which displays monthly means over the 1947-86 period graphically illustrates the seasonal pattern of rainfall at these four locations. Our measure of actual and lagged rainfall is the natural logarithm of monthly millimeters of precipitation plus one, which is a convenient way to deal with the prevalence of zero rainfall observations in dry season months. Women are matched to the rain station closest to their region of residence as reported in the DHS at the time of the survey. The NCDC database has 33 different rain stations for Senegal, but they vary tremendously in terms of years covered and data completeness. Only one third of the stations had data available for the time period of our study, and of those, only about half were free from large numbers of missing values and quality control failures. The stations that we use are in the generally defined DHS regions, and their data is some of the most accurate available for Senegal. They have no missing values and only one or zero failures of the serial and spatial checks.[10]

The fertility and mortality observations for each woman consist of whether or not she had a birth in each month beginning with her 13th birthday, and if there was a birth, whether or not the child survived to its 24th month. This is the finest time disaggregation of fertility that the DHS data permit. For a woman who has just turned 40 in the sample, the likelihood (4) computes the joint probability of a sequence of 336 monthly fertility events and the mortality outcomes of all births. Recognizing that a woman cannot ordinarily have a birth in the 8 months subsequent to a birth, we constrain the probability of a birth in those months to be deterministically zero. There is a reasonably large number of women in the sample who reported a birth nine months after a birth and so we allowed for this event.

The use of such a fine time disaggregation affected the ease with which we could maximize the likelihood (4) and our choice of an error distribution for the v_{fit} and v_{hit} error terms. Even in high fertility Senegal, the probability of a birth in any one month (conditional on the woman-specific fertility effect μ_{fi}) is quite low. These probabilities are often so low that even state-of-the-art approximations to the standard normal cumulative distribution function (cdf) performed poorly at these extreme tails of the distribution.[11] Since normality of the nonsystematic component of the errors provides no computational or theoretical advantage in this model, we

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[10] Outliers from the monthly time series for each station are determined by a multiple of the interquartile range for each dataset. A rainfall observation that exceeds this multiple fails the time series check. Spatial tests rely on comparisons with the ten nearest neighbors. for which difference series are computed. Up to four stations are chosen with the highest R^2 (minimum R^2 is .35). If none of the 10 closest neighbors are chosen the check automatically fails. Then using 6 other methods the station and its four closest neighbors are compared. If the station in question is too different from it's closest neighbors, it fails. Further details on the quality checks applied to these data are available from the National Climatic Data Center home page at http://www.ncdc.noaa.gov.

[11] Evidence for this was obtained by computing gradients for the log-likelihood both analytically and numerically. The derivative of the normal cdf is the normal pdf which has a simple closed-form analytic expression. Nonetheless, maximizing the likelihood could not drive the analytic gradients close enough to zero for our admittedly strict tastes. On the other hand, two-sided numerical derivatives could be driven closer to zero by standard algorithms, the Berndt-Hall-Hall-Hausman (BHHH) algorithm and the Broyden-Fletcher-Goldfarb-Shanno (BFGS) variant of the DFP algorithm. All estimation was carried out in double-precision Fortran on a Sun workstation equipped with dual 64-bit UltraSparc cpu’s.

assumed that these errors follow the logistic distribution. This distribution has the attractive property of having a closed-form analytic expression for both the cdf and the probability density function (pdf) so that the probability of unlikely events, and their derivatives, can be computed with great accuracy.[12]

Table 1 presents summary statistics for the sample of births used in the empirical analysis. It provides numbers of children, variable definitions, means and standard deviations for the children born to the women in the sample. These data are used in the child mortality portion of the various likelihoods. The likelihoods also use "woman-months" in which there is no birth as data in computing the probability of a birth in every month subsequent to each woman's thirteenth birthday. The number of women, woman-months, and births used in the estimation is also presented in Table 1. Table 2 provides means and standard deviations for the monthly rainfall data.

4. Results

a. Reduced form models

We begin by estimating reduced form equations for fertility and child mortality prior to age 24 months of the type described by equations (1) and (2), allowing for rainfall shocks to effect fertility and child mortality outcomes for a period of 16 months prior to conception. As computation of this model is not trivial, especially with monthly data, we conducted only limited experimentation with various rain lag specifications.[13] The specification presented seems to capture most of the effects of rainfall surprises. We examine two approaches to isolating the effects of rainfall shocks from the expected seasonal patterns of weather. In the first, we include

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[12] In the logistic case, the analytic gradients were driven to very close to zero by the BHHH algorithm, usually without much difficulty, and they were very close in magnitude to two-sided numerical gradients.

[13] Various procedures have been suggested for determining the appropriate lag length, such as Akaike's (1973) information criterion (AIC). These methods require successive estimation of models with increasing lag lengths, rewarding goodness of fit but penalizing the loss of degrees of freedom. Computation of these criterion functions was beyond the computational scope of this research.

dummy variables for each month and region. In the absence of month/region interactions[14], these dummy variables fully capture month-specific variation in fertility and child mortality outcomes from all sources including rain, temperature, prices, and biology. In the second approach, we see how much information is foregone by treating rainfall as the only driving force in the seasonal pattern of fertility and mortality. We do this by dropping the month and region dummy variables, replacing them with regional measures of historical mean rainfall for the same months for which we include measures of actual rainfall.

Measures of actual rainfall in these models represent unanticipated rainfall shocks. The mean (expected) monthly rainfall is captured either by the month and region dummies in the one model, and by measured monthly historical means for the region in which the woman resides in the other model. We allow actual rainfall 8 through 11 months prior to a potential birth to have separate, free parameters in both the fertility and mortality equations. To save on parameters, we restrict the effects of actual rainfall 12 through 23 months prior to a potential birth to have the same effect, by month, on birth and mortality probabilities by using an equally weighted linear combination of these (log) monthly rainfalls -- their mean[15].

In addition to month and region dummies (or historical rainfall means) and actual monthly rainfall, the other included regressors in both the fertility and mortality reduced form equations include each woman's age (in years) and its square, her schooling (in years), and calendar time (in months since January 1900, known as "cmc" months in the DHS). In the mortality equation we include two regressors that are revealed to mothers only after a birth occurs -- the sex of the

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[14] We also estimated a single reduced form model with month/region interactions. This model contains 119 free parameters and was cumbersome to estimate. A likelihood ratio test rejects the null hypothesis that the set of month-by-region interactions are jointly zero. Nonetheless, we were constrained to use the more parsimonious specification of separate month and region effects to keep computation tractable.

[15] In the model with historical mean monthly rainfall, we must include historical means as regressors for every month we include actual rainfall in order to interpret the associated parameters as response to rainfall shocks. Since actual rainfall for the months 12 to 23 months prior to a potential birth is included as a mean, and since these encompass 12 months of rainfall means, the historical mean of this set of rainfall lags does vary from month-to-month and hence is not separately identified from the intercept.

child, and whether it is a multiple birth.[16]

In Table 3, the model with month and region dummy variables (columns (1) and (2)) provides a better fit with these data than the model with four historical rainfall means (columns (3) and (4)) in the sense that the likelihood improved significantly relative to the loss of degrees of freedom. The model with dummy variable adds 20 additional parameters and improves the log-likelihood by 13.23 points, which implies a χ^2 test statistic of 26.46 with 20 degrees of freedom. This statistic has a p-value of 0.15 . It is thus somewhat surprising that the dummy variables, which "perfectly" capture observed and unobserved month-specific factors improve the fit as little as they do. It would seem that historical rainfall patterns go a long way to explaining the seasonal pattern of fertility and mortality outcomes.

In both models, we find that woman-specific effects (μ_{fi} and μ_{hi}) are statistically significant parts of the errors, that is, ρ_f and ρ_h are both quite different from zero and statistically significant. More importantly, the fertility and mortality woman-specific effects are positively correlated (ρ=.508, t=4.93 in the dummy variable model), suggesting negative birth selection -- high fertility women give birth to high mortality children.[17] Independent estimates of the determinants of child mortality from a sample of births will, therefore, result in selection biased parameter estimates.

Rainfall shocks are statistically important determinants of fertility. Rainfall 8 months prior to the month of a potential birth has a large positive and significant (t=14.70) effect on fertility in the model with dummy variables.[18] The other individual month actual rainfall parameters are not

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[16] Rainfall subsequent to conception is also "news" to women that might affect mortality probabilities but not fertility choices. We undertook some limited experiments adding such rainfall measures and found they were decidedly insignificant statistically in the mortality equation.

Lack of data prohibits us from studying pregnancies that do not result in live births. Miscarriage and induced abortion are conceivably outcomes that are both selective and influenced by seasons and rainfall shocks.

[17] See Pitt (1997) for elaboration on the interpretation of birth selection.

[18] Subtracting eight from the (cmc) months of a birth is typically somewhat early as a date of conception, although it may be accurate for many births that occured late in the month given the distribution of gestational ages. Mean gestational age is commonly considered to be 38 weeks, one week short of 9 months, and there is signficant variation around the mean. In any case, there is no reason why rainfall *leads*, as opposed to lags, might not be significant in this econometric specification. Weather is well known to follow an autoregressive process so that realized rainfall in any month reflects rainfall in

significantly different from zero, but rain lagged 12 to 23 months is statistically significant and positive. In this model, only rainfall 11 months prior to birth has an effect on mortality. We defer discussion on the magnitude of rainfall shocks effects until after we present estimates of the models with structural state dependence.

b. Models of structural state dependence

Table 4 presents estimates of models of structural state dependence once again specifying seasonal effects as month dummy variables in one model, and as historical means of monthly rainfall in the other. As with rainfall lags, there is no theoretical guidance on the time length of the state dependence terms -- the lagged values of birth and mortality outcomes. We have chosen to add a single lag measuring the number of births in the prior 24 months to both the fertility and mortality equation, and a lag measuring the number of child deaths in the prior 24 months to the fertility equation. Statistically identifying the effect of lagged child deaths is not possible in the mortality equation, and thus its exclusion is innocuous. Identification requires that there be some women who experienced the death of a child born in month t who also experienced the death of at least one child born in months t-24 through t-9.[19] This did not happen in these data.

The relative size and significance of the share of the error variance attributable to the woman-specific effects (ρ_f and ρ_h) are quite similar qualitatively compared to the reduced form models. However, the correlation between the fertility and the mortality random effects is negative and statistically significant (ρ=-.577, t=-7.17 in the dummy variable model) implying that high fertility women are <u>less</u> likely to have high mortality children <u>conditional</u> on past fertility and mortality realizations, reverse the sign of the reduced form models.

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prior months and information on other lagged weather variables unmeasured in our data. A regression of our Senegalese monthly rainfall series on month dummy variables and 12 months of lagged monthly rainfall indicates that lagged monthly rainfall, the prior month's rainfall in particular, are statistically important predictors of current rainfall.

[19] There is no chance of a birth in t-9 to t-1 since the woman is pregnant with the child she gives birth to in month t.

State dependence seems to matter in these models.[20] Lagged births and death are significant determinants of fertility and of the expected signs (columns (1) and (2)). Recent fertility reduces the probability of a subsequent birth[21] and increases the probability that subsequent births will not survive to 24 months of age (*crowding out*.) The death of a child born in the prior 24 months increases the probability of a birth by a slightly greater magnitude (the *replacement* effect) than does a prior birth.

Most importantly for this study, rainfall shocks continue to be statistically significant determinants of fertility and mortality. As in the reduced form models, the structural state dependence model with dummy variables demonstrates a strong positive effect of rainfall 8 months prior to birth, no large effect in months 9 through 11 prior to birth, but significant effects for the 12 months before that. Those 12 months capture, necessarily, the prior rainy season, which is crucial to household income. In short, if the rainfall is better than average in the month of conception and in the prior rainy season, woman are more likely to have a birth. In contrast, only the last individual rain lag, eleven months prior to birth, and average rainfall in the 12 months before that, are reasonably significant determinants of mortality. In short, it seems that better than

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[20] Models of state dependence generate a result very much like the random effects models -- past fertility experience and future fertility experience are correlated. Spurious random effects will be generated when there is a real effect of past experience that is omitted from the estimated model. Likewise, spurious state dependence can be generated if unobserved time-persistent heterogeneity is ignored. Heckman (1980) suggests the use of test statistics based on "runs" to discriminate between models of state dependence and random effects. As in Heckman, consider outcomes in three time periods, where the first element in the ordered time-series of outcomes, such as (1,0,0), refers to the first period (true), the second element to the next period (false) and the last element to the third period (false). Among observationally equivalent women, the fertility series (1,1,0), (0,1,1) and (1,0,1) all have equal probability in the basic random effects model. As a consequence of the intertemporal exchangeability property, the probability of a birth in any period is the same in each period, conditional on the observed regressors. The ordering of time periods does not matter. Exchangeability does not hold if there is state dependence because of the nonstationary process induced by including the outcomes of past periods. If, for example, past births reduce the probability of future births ($\gamma_f<0$), a later period without a birth is more likely than an earlier period without a birth. That is, Prob(0,1,1) < Prob(1,0,1) < Prob(1,1,0). We allow for both state dependence and random effects in our model and thus these tests are not relevant. If there is both state dependence and random effects, all the probabilities will differ but will be unordered.

[21] Since we treat the probability of a birth in the 8 months subsequent to a birth as deterministically zero, this lagged fertility parameter is not capturing those purely biologically determined effects but rather any effects on fertility beyond that date in time.

average rain some months prior to conception, including the previous rainy season, but not the months of conception, increase the probability of child survival, conditional on the prior fertility state.

c. Simulation of the effects of rainfall shocks on fertility and mortality

In order to illustrate the magnitude of the effect of weather shocks on fertility and mortality over the reproductive lives of women in rural Senegal in the context of a dynamic probabilistic model of behavior with correlated heterogeneity, we simulate the effects of the seasons and rainfall shocks for a representative cohort of women.

We simulate the reproductive lives of 50,000 rural women all of whom turn thirteen years old in January 1960, have mean education and reside in the Southern region of Senegal. We draw from a bivariate normal distribution having the estimated correlation coefficient ρ to obtain each woman's fertility and mortality random effects and weight them with the estimated value of ρ_f accordingly. In each month of each year we calculate the probability of a birth for each women based upon the regressors and the drawn value of the fertility random effect and then draw randomly to see if a birth results. If there is a birth, we draw randomly to determine the sex of the child and whether it is a multiple birth, calculate the logit probability of mortality and then draw to see if a mortality occurs. The deterministic zero probability of birth in the months after conception and before a birth, the state dependence on lagged births and deaths, and all the other features of the model are accounted for. We then average over the 50,000 simulated life histories to get monthly birth rates per woman and death rates per child. We simulate two rainfall shocks. We fix the rainfall in the early dry season months of January and February 1965, when women are 60 and 61 months beyond their 13th birthday, at one-half the maximum of the log rainfall reported in those months in the post-war years of data we possess. Actual rain in those months was zero. The other rainfall shock adds one standard deviation of the log of rain to the log rain in each month of the rainy season, June through October 1965, when these simulated women were 66 through 70 months past their 13th birthday.[22]

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[22] The estimated model does not allow the effect of rainfall shocks to vary by calendar month. As a result, a proportional change to actual rainfall in any month has the same effect on the linear probit index

Figure 4 tracks the effects of the simulated January/February 1965 shock on the birth rate per woman per year relative to the values predicted with actual rainfall. It begins 10 months prior to the rainfall shock with the 50th month after reaching 13 years of age, and continues until 180 months after reaching 13 years of age. Figure 5 tracks the effect of the same shock on death rates per child, again relative to the values predicted with actual rainfall. Figures 6 and 7 depict the effects of the rainy season (months 66-70) shock in an analogous fashion. Remember that time in both figures represent the birth month of the child in terms of the mothers age, not the age of the child or the month of the child's death if indeed there was a death. The start of the shock is indicated with a vertical line on each figure, and zero deviation in fertility or death rates are indicated by a horizontal line at zero. There are some obvious features of both figures. First, the area of the curve above the zero deviation line (representing no change in fertility) clearly is greater than the area under the zero line. That is, these single positive rain shocks increase fertility over the reproductive lives of women. In the case of the January/February 1965 shock, we predict an increase of 8612 births to the 50,000 women until their 38th year (300 months past their 13th birthday). Furthermore, this Jan/Feb 1965 rain shock reduces child deaths by 2755 through the 300th month. This nets out to an additional 11,385 surviving births or 0.227 additional surviving births per woman from a single two-month rain shock. The rainy season rainfall shock (months 66-70) has even larger effects. Births increase by 8948, deaths decline by 2788, yielding a net increase of 11,736 surviving births or 0.235 additional surviving births per woman from this single rain shock. These effects are strikingly large and are consistent with the quantity of children being a normal good.

The second obvious feature is that the effects of these shocks are felt for many months beyond their date, they oscillate around zero, and they dampen with time. For the shock in months 66-70, the largest single month effect on birth rates is in month 82, 12 months after the end of the shock, and the largest single month effect on the death rate is in month 93, fully 23 months after the end of the shock. The oscillation around zero results from the feedback of fertility to mortality and vice-versa -- reduced death rates due to the direct effects of the positive

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as in any other month. The rationale for simulating both a dry season and rainy season shock in this case is that we are relating the size of the shock to the dispersion of rainfall in these seasons, which does vary.

rain shock are offset by increased death rates resulting from higher fertility resulting from the shock. Higher death rates in turn increase fertility, an so on.

d. Behavior or biology?: inference from a comparison of rural and urban samples

The results presented thus far suggest that rainfall shocks have a large and permanent effect on the number of surviving children born to rural women. A much richer dataset than the Senegal DHS coupled with a more structural model of fertility and survival might be used to test hypothesis about the sources of this behavior. However, lacking richer data, some further inference concerning the underlying sources of response to rainfall can be gleaned by comparing the results for rural household with results obtained by estimating the same model for urban households in the same dataset. Rural and urban households are facing the same policy regime, almost the same rainfall and temperature, and are likely quite similar racially and ethnically. One obvious way in which they are likely to differ is in the seasonality of income. Although we do not have monthly data on household income or consumption, urban Senegal is predominately nonagricultural and is unlikely to be characterized by income streams as affected by the seasons and rainfall shocks as rural income streams.

The relative seasonal insensitivity of the fertility and child survival outcomes of urban households is clearly demonstrated in Figures 8 and 9. Figure 8 plots urban and rural birth rates against calendar month based upon the monthly means of 50,000 simulated women using actual rainfall data. Urban birth rates mimic rural (except for October) but with much smaller month-to-month variation. Similarly, in Figure 9, which plots urban and rural child mortality rates again the calendar month of birth from the simulated reproductive histories, urban death rates do not show the large June-August peak, and are markedly less seasonal overall than rural mortality rates.

Figure 10 plots the simulated effects of the rainy shock (months 66-70), as described earlier, on annualized per woman birth rates relative to actual rainfall in those months (June-October 1965) separately for urban and rural women.[23] Figure 11 does the same plots the simulated effects on per child death rates plotted against the month of birth. The parameter

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[23] This figure, as well as Figure 11, examine a smaller number of months after the shock than does the earlier figures depicting the effects of rainfall shocks in order to improve readability.

estimates for the structural state dependence bivariate random effects probit model underlying the urban simulations are presented in columns (1) and (2) of Appendix Table 1, which, for completeness, also presents urban estimates for a model using historical mean rainfall instead of month and region dummy variables. Figures 10 and 11 clearly demonstrate that the fertility and child survival outcomes of urban households are less sensitive to rainfall shocks than are rural households. Moreover, the permanent effects of this rainfall shock on urban households are practically zero. Simulating through month 300 generates only one less child death and only 30 more births for 50,00 women, versus the 2788 fewer child deaths and 8948 more births experienced by rural women. Urban women net 0.0006 additional surviving children per woman as a result of the shock compared with 0.235 for rural women, a ratio of almost 400 to one.

The insensitivity of urban fertility and child mortality to seasons and weather shocks as compared with rural fertility and child mortality is more suggestive of a behavioral explanation given the similar (but not identical) biological circumstances of these households and our prior beliefs concerning the seasonality of income streams. The difference in the effect of rainfall shocks on the permanent quantity of surviving children is consistent with an insensitivity of urban incomes, as compared to rural incomes, to rainfall deviations, and the normality of the quantity of children. Whatever the source of this difference in outcomes, our quantification of the permanent effects of positive rain shocks on fertility, mortality and surviving offspring is important evidence that the effects of rainfall shocks to rural household have substantial permanent effects, and do not cause a primarily transitory change in the timing of vital events.

5. Summary

In this paper we use data from Senegal to examine two complementary explanations of seasonal fertility based upon the inability of households to smooth consumption and labor time over the crop seasons. First, if the value of time varies seasonally, rising during the rainy season months of greatest agricultural activity, parents may wish to shift births to those months of the year when the shadow value of time, particularly women’s time, is relatively low. Second, if parents care about the survival chances of their potential births, and, facing highly seasonal income streams, they are not able to smooth consumption, they may time conceptions so that births occur after the rainy season harvests have been gathered and monthly income is likely to be high. In rural Senegal, births occur disproportionately in the dry season months of February through May (and peaking in February) which is consistent with both of these hypotheses. These hypotheses are further bolstered by the observation that urban incomes and labor demands are likely to be less seasonal than rural incomes and labor demands, and that urban births appear to be much less seasonal than rural births. Theories with biological underpinnings which posit food availability at the time of conception as a major determinant in fertility cycles, are not consistent with the Senegalese data since conceptions appear to be occurring precisely at those times of the year (May-August) when planting has begun, but harvesting has not. These are the times when physical demands are high and food supplies low, factors which should act to reduce fecundity in women.

If the inability to smooth consumption and labor demand over the seasons is an important cause of the seasonal pattern of births, then unanticipated weather shocks are also likely to alter the timing of births. Moreover, positive income shocks, perhaps induced by advantageous weather shocks, may enhance the probability of child survival during the dangerous first months of life. Parents, after experiencing positive rain shocks that point to a bountiful rainy season harvest and higher consumption, may seek to time births so as to take advantage of the reduced mortality associated with that higher consumption. Estimation of a dynamic model of the joint determination of the month of birth and the probability of survival to age 24 months with a sample of rural Senegalese women from the 1986 Senegal Demographic and Health Survey reveals that fertility and mortality are indeed responsive to rainfall shocks. Positive rainfall shocks increase fertility, particularly rainfall shocks in the likely month of conception and in the prior rainy season. Since rainfall is likely to be more correlated with income shocks for rural populations than urban populations, these findings are consistent with the idea that variations in income flows, anticipated or not, are important determinants of fertility and subsequent mortality. Moreover, simulations imply that births and deaths respond more to rainfall shocks in rural areas than they do in urban areas. In particular, rainfall shocks result in a substantial permanent increase in surviving offspring among rural households but have essentially no effect on the number of surviving children of urban households. This difference in the effect of rainfall shocks on the permanent quantity of surviving children is consistent with an insensitivity of urban incomes, as compared to rural incomes, to rainfall deviations, and the normality of the quantity of children. Common biological explanations do not explain either the observed seasonal pattern among rural women and the differences between rural and urban women.

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Table 1

Summary Statistics for the Rural and Urban Sample of Births

	rural sample (n=8186)		urban sample (n=4309)	
Variable	mean	st.d	mean	st.d
Died before 2 years	0.1757	0.3805	.1095	.3123
Mother's age	23.9665	6.4409	24.3302	6.004
Mother's age squared (/100)	6.1587	3.4016	6.2800	3.1825
Years of Education	.1531	.9823	2.2388	4.0866
Year of Birth	74.8831	6.7628	75.0290	6.7186
Male	.5170	.4997	.5066	.5000
Western region	.1523	.3594	.6853	.4644
Central region	.4882	.4999	.1388	.3458
Southern region	.1653	.3715	.0982	.2976
Multiple Birth	.0101	.1002	.0125	.1113
Number of Women	2597		1809	
Number of Women Months	426167		272112	

Source: Senegal DHS 1986 dataset

Table 2

Mean Log Monthly Millimeters of Rainfall by Region,1948-1987

	Dakar		Diourbel		Ziguinchor		Saint-Louis	
	mean	st.d	mean	st.d	mean	st.d	mean	st.d
Month								
January	0.2558	0.7788	0.2042	0.6697	0.0902	0.3467	0.3976	0.8278
February	0.2843	0.7117	0.2110	0.6792	0.1374	0.4241	0.4069	0.7593
March	0	0	0	0	0	0	0.1384	0.3975
April	0.0365	0.1569	0.0365	0.1569	0	0	0.0365	0.2249
May	0.2585	0.6777	0.4585	1.0464	1.1341	1.2878	0.1663	0.4724
June	1.6420	1.3156	2.9778	1.3619	4.5453	0.6449	1.1996	1.3023
July	3.8501	1.3094	4.5504	0.8370	5.7308	0.3451	3.3241	1.0844
August	5.0181	0.6696	5.2356	0.5599	6.0260	0.4171	4.4308	0.7382
September	4.8535	0.5878	5.0723	0.4887	5.7835	0.3000	4.3038	0.7824
October	2.8150	1.6737	3.000	1.5188	4.5623	0.7717	2.3332	1.6926
November	0.4522	1.0180	0.4571	1.1057	1.0632	1.3346	0.2021	0.6147
December	0.2675	0.8262	0.3426	0.8172	0.3559	0.8187	0.3551	0.8171

Source: National Climatic Data Center home page http://www.ncdc.noaa.gov

Table 3
Reduced Form Models of the Joint Determination
of Fertility and Child Mortality:
Rural Sample

	Month & Region Dummies		Regional Historical Mean Rainfall	
Variables	ML Bivariate Random Effects Probit		ML Bivariate Random Effects Probit	
	fertility (1)	mortality (2)	fertility (3)	mortality (4)
woman's age	.44472 (33.766)	-.05861 (-1.895)	.44415 (35.331)	-.05559 (-1.867)
woman's age squared/100	-.79042 (-31.305)	.08668 (1.451)	-.78902 (-33.165)	.08202 (1.432)
multiple birth	-	1.1932 (5.022)	-	1.1865 (5.202)
child is male	-	.10649 (1.881)	-	.10612 (1.916)
schooling (years)	-.01181 (-2.796)	-.09313 (-2.858)	-.01151 (-3.682)	-.08462 (-2.648)
calendar time (cmc months)	-.02258 (-10.024)	-.02535 (-4.993)	-.02426 (-12.199)	-.02339 (-4.717)
actual rainfall (-8)	.11658 (14.699)	-.02292 (-0.747)	.04375 (3.388)	-.04115 (-1.246)
actual rainfall (-9)	-.01218 (-1.235)	-.01509 (-0.479)	.03764 (2.861)	-.03283 (-1.012)
actual rainfall (-10)	.00033 (0.031)	-.02280 (-0.757)	.03823 (2.808)	-.004889 (-0.154)
actual rainfall (-11)	-.00740 (-0.818)	-.06776 (-2.255)	.01102 (0.734)	-.00776 (-0.238)
actual rainfall (-12 to -23), average	.12237 (3.400)	-.11953 (-1.335)	-.46762 (-1.688)	.08749 (1.360)
historical mean rain (-8)	-	-	.19512 (10.893)	-.06998 (-1.497)
historical mean rain (-9)	-	-	-.23842 (-9.012)	.06717 (1.060)
historical mean rain (-10)	-	-	.05506 (1.944)	.05215 (0.822)
historical mean rain (-11)	-	-	-.01237 (-0.566)	.06326 (1.310)
Dakar	-.04594 (-0.959)	-.10127 (-0.890)	-	-

Diourbel	-.13537 (-3.370)	.01125 (0.113)	-	-
Ziguinchor	-.29987 (-5.288)	.50136 (3.393)	-	-
January	.13909 (2.255)	-.29630 (-1.741)	-	-
February	.33046 (5.726)	-.22584 (-1.288)	-	-
March	-.00986 (-0.158)	-.29946 (-1.366)	-	-
April	-.06238 (-1.013)	-.14235 (-0.578)	-	-
May	-.01243 (-0.204)	.36681 (1.362)	-	-
June	.12993 (2.139)	.82895 (3.090)	-	-
July	.12312 (1.974)	1.1454 (4.494)	-	-
August	.07627 (1.221)	.81185 (3.694)	-	-
September	.07951 (1.291)	.40354 (2.082)	-	-
October	.16245 (2.662)	.16432 (0.971)	-	-
November	.00177 (0.028)	.10594 (0.591)	-	-
constant	-8.1735 (-31.320)	1.4426 (2.577)	-7.8400 (-35.316)	.90543 (1.736)
ρ	.50847 (4.930)		.47684 (4.911)	
ρ (fertility)	.30453 (15.758)	-	.31105 (32.922)	-
ρ (mortality)	-	.58021 (18.356)	-	.58081 (18.818)
log-likelihood	-33965.223		-33978.45	

Table 4
Structural State Dependence Models of the Joint Determination
of Fertility and Child Mortality:
Rural Sample

Variables	Month & Region Dummies		Regional Historical Mean Rainfall	
	ML Bivariate Random Effects Probit		ML Bivariate Random Effects Probit	
	fertility (1)	mortality (2)	fertility (3)	mortality (4)
woman’s age	.48525 (43.057)	-.10433 (-3.084)	.48502 (45.489)	-.05559 (-1.867)
woman’s age squared/100	-.85538 (-38.757)	.15642 (2.401)	-.85451 (-42.299)	.08202 (1.432)
multiple birth	-	1.2021 (5.123)	-	1.1865 (5.202)
child is male	-	.09709 (1.675)	-	.10612 (1.916)
schooling (years)	-.01311 (-2.898)	-.08935 (-2.659)	-.01281 (-4.020)	-.08462 (-2.648)
calendar time (cmc months)	-.02402 (-10.149)	-.02098 (-4.041)	-.02513 (-13.199)	-.02339 (-4.717)
actual rainfall (-8)	.11091 (14.737)	-.02181 (-0.690)	.04756 (3.911)	-.04115 (-1.246)
actual rainfall (-9)	-.01347 (-1.448)	-.01550 (-0.483)	.04068 (3.286)	-.03283 (-1.012)
actual rainfall (-10)	-.00104 (-0.104)	-.02890 (-0.935)	.03954 (3.079)	-.004889 (-0.154)
actual rainfall (-11)	-.00905 (-1.060)	-.07824 (-2.583)	.01221 (0.856)	-.00776 (-0.238)
actual rainfall (-12 to -23), average	.14241 (4.106)	-.17411 (-1.902)	.00353 (0.126)	.08749 (1.360)
historical mean rainfall (-8)	-	-	.18070 (10.782)	-.06998 (-1.497)
historical mean rainfall (-9)	-	-	-.23877 (-9.660)	.06717 (1.060)
historical mean rainfall (-10)	-	-	.05327 (2.011)	.05215 (0.822)
historical mean rainfall (-11)	-	-	-.01760 (-0.854)	.06326 (1.310)
number of births in last 24 months	-.85269 (-32.547)	.43579 (6.616)	-.85267 (-33.856)	.38912 (6.112)
number of children born in the past 24 months who died	.96946 (25.888)	-	.96214 (30.118)	-

Dakar	-.04485 (-0.842)	-.06987 (-0.630)	-	-
Diourbel	-.14655 (-3.376)	.04445 (0.446)	-	-
Ziguinchor	-.33349 (-5.568)	.55703 (3.721)	-	-
January	.13096 (2.241)	-.43556 (-2.470)	-	-
February	.30771 (5.620)	-.34084 (-1.898)	-	-
March	-.01193 (-0.203)	-.40355 (-1.794)	-	-
April	-.06141 (-1.055)	-.20331 (-0.801)	-	-
May	-.00668 (-0.117)	.36131 (1.303)	-	-
June	.13455 (2.375)	.86354 (3.123)	-	-
July	.13165 (2.295)	1.1950 (4.587)	-	-
August	.08211 (1.394)	.85590 (3.819)	-	-
September	.08319 (1.431)	.40419 (2.048)	-	-
October	.16498 (2.856)	.16655 (0.911)	-	-
November	.00979 (0.164)	.11641 (0.636)	-	-
constant	-8.2723 (-32.054)	1.9318 (3.231)	-8.0370 (-30.118)	.90543 (1.736)
ρ	-.57720 (-7.166)		-.55123 (-16.570)	
ρ (fertility)	.44944 (29.093)	-	.45720 (60.698)	-
ρ (mortality)	-	.54004 (13.721)	-	.54710 (16.649)
log-likelihood	-33339.050		-33352.524	

Appendix Table 1
Structural State Dependence Models of the Joint Determination
of Fertility and Child Mortality:
Urban Sample

Variables	Month & Region Dummies		Regional Historical Mean Rainfall	
	ML Bivariate Random Effects Probit		ML Bivariate Random Effects Probit	
	fertility (1)	mortality (2)	fertility (3)	mortality (4)
woman’s age	.60849 (37.025)	-.19453 (-3.021)	.60806 (37.444)	-.19054 (-2.979)
woman’s age squared/100	-1.0469 (-32.868)	.29792 (2.439)	-1.0457 (-33.250)	.28915 (2.386)
multiple birth	-	1.5665 (5.170)	-	1.5382 (5.192)
child is male	-	.08123 (0.770)	-	.08257 (0.809)
schooling (years)	-.03690 (-6.646)	-.05921 (-3.236)	-.03706 (-6.747)	-.06011 (-3.350)
calendar time (cmc months)	-.04537 (-13.242)	.00091 (0.100)	-.04399 (-12.957)	.00092 (0.105)
actual rainfall (-8)	.04702 (4.609)	-.00447 (-0.076)	.03950 (2.401)	.00977 (0.171)
actual rainfall (-9)	-.02205 (-1.769)	.00728 (0.133)	.02600 (1.597)	.00199 (0.036)
actual rainfall (-10)	-.00456 (-0.374)	-.01176 (-0.230)	.03330 (2.136)	-.01309 (-0.253)
actual rainfall (-11)	-.02130 (-2.008)	-.03220 (-0.603)	-.01226 (-0.750)	.04251 (0.781)
actual rainfall (-12 to -23), average	-.03527 (-0.817)	-.11075 (-0.682)	.05899 (2.301)	-.11901 (-0.972)
historical mean rainfall (-8)	-	-	-.11328 (-2.813)	.01209 (0.132)
historical mean rainfall (-9)	-	-	-.02236 (-0.562)	-.00707 (-0.052)
historical mean rainfall (-10)	-	-	.00917 (0.363)	-.00234 (-0.018)
historical mean rainfall (-11)	-	-	-.02050 (-0.524)	.05133 (0.606)
number of births in last 24 months	-.77778 (-23.846)	.28532 (2.396)	-.77940 (-24.458)	.28929 (2.601)
number of children born in the past 24 months who died	.65131 (9.419)	-	.65007 (9.882)	-

Dakar	-.15236 (-1.764)	.04224 (0.205)	-	-
Diourbel	-.19553 (-1.928)	.30849 (1.182)	-	-
Ziguinchor	-.06134 (-0.525)	-.05452 (-0.166)	-	-
January	.21672 (3.017)	-.06987 (-0.273)	-	-
February	.16834 (2.285)	-.12364 (-0.418)	-	-
March	.15800 (2.147)	.00221 (0.006)	-	-
April	.02613 (0.334)	-.02507 (-0.064)	-	-
May	.15180 (2.023)	.14884 (0.336)	-	-
June	.19642 (2.691)	-.00127 (-0.003)	-	-
July	.15770 (2.074)	.23174 (0.575)	-	-
August	.12020 (1.640)	.18718 (0.535)	-	-
September	.19738 (2.749)	.15675 (0.530)	-	-
October	.10421 (1.394)	-.27574 (-0.933)	-	-
November	.04850 (0.642)	-.08947 (-0.305)	-	-
constant	-7.8653 (-20.999)	.94898 (0.836)	-8.0121 (-22.098)	.88499 (0.814)
ρ	-.51795 (-4.735)		-.50516 (-5.060)	
ρ (fertility)	.55494 (29.112)	-	.55915 (29.635)	-
ρ (mortality)	-	.49964 (6.820)	-	.50378 (7.120)
log-likelihood	-17007.324		-17011.359	

File Contains Data for PostScript Printers Only

Appendix Figure 1

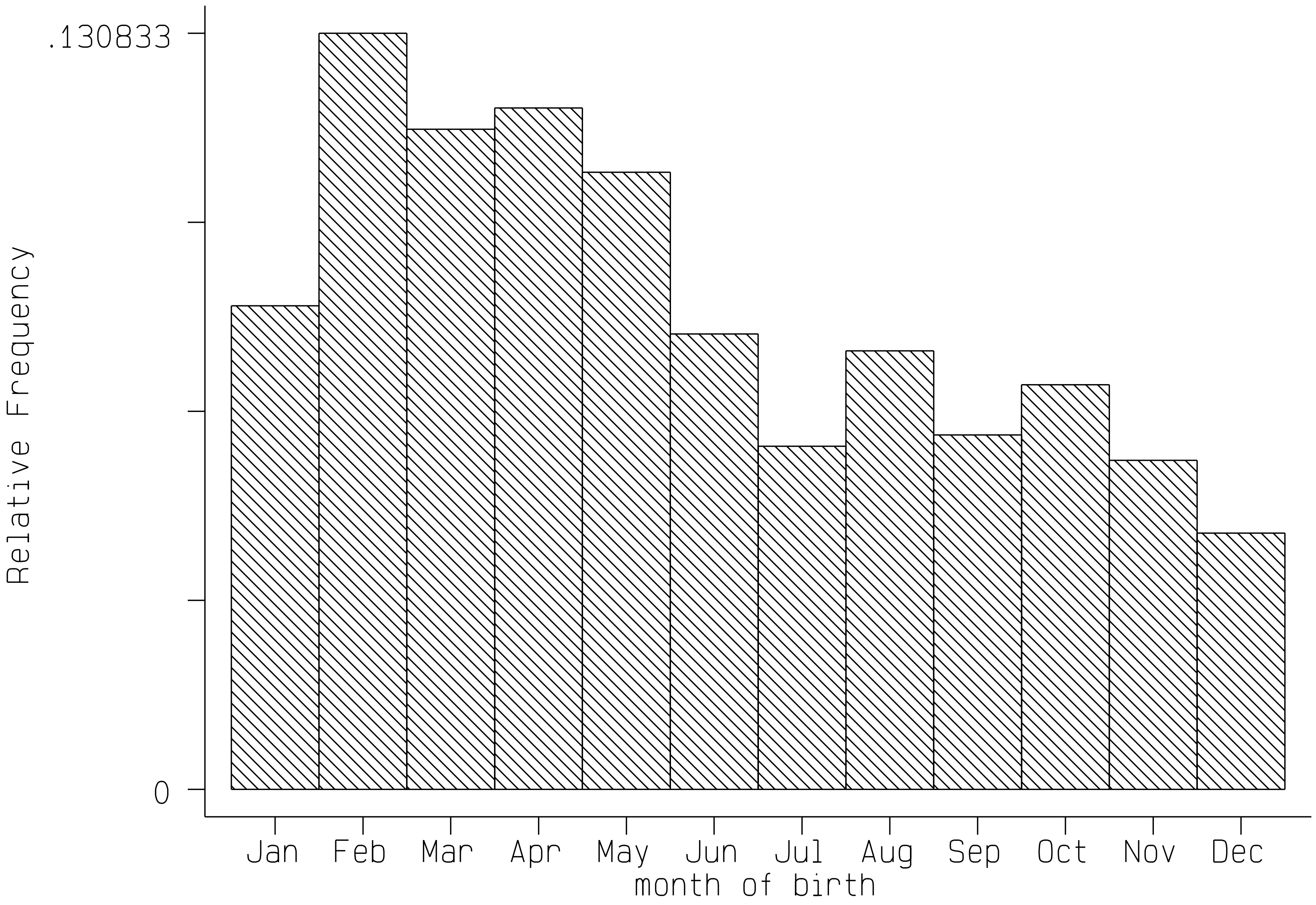


Figure 1. Frequency of Rural Births

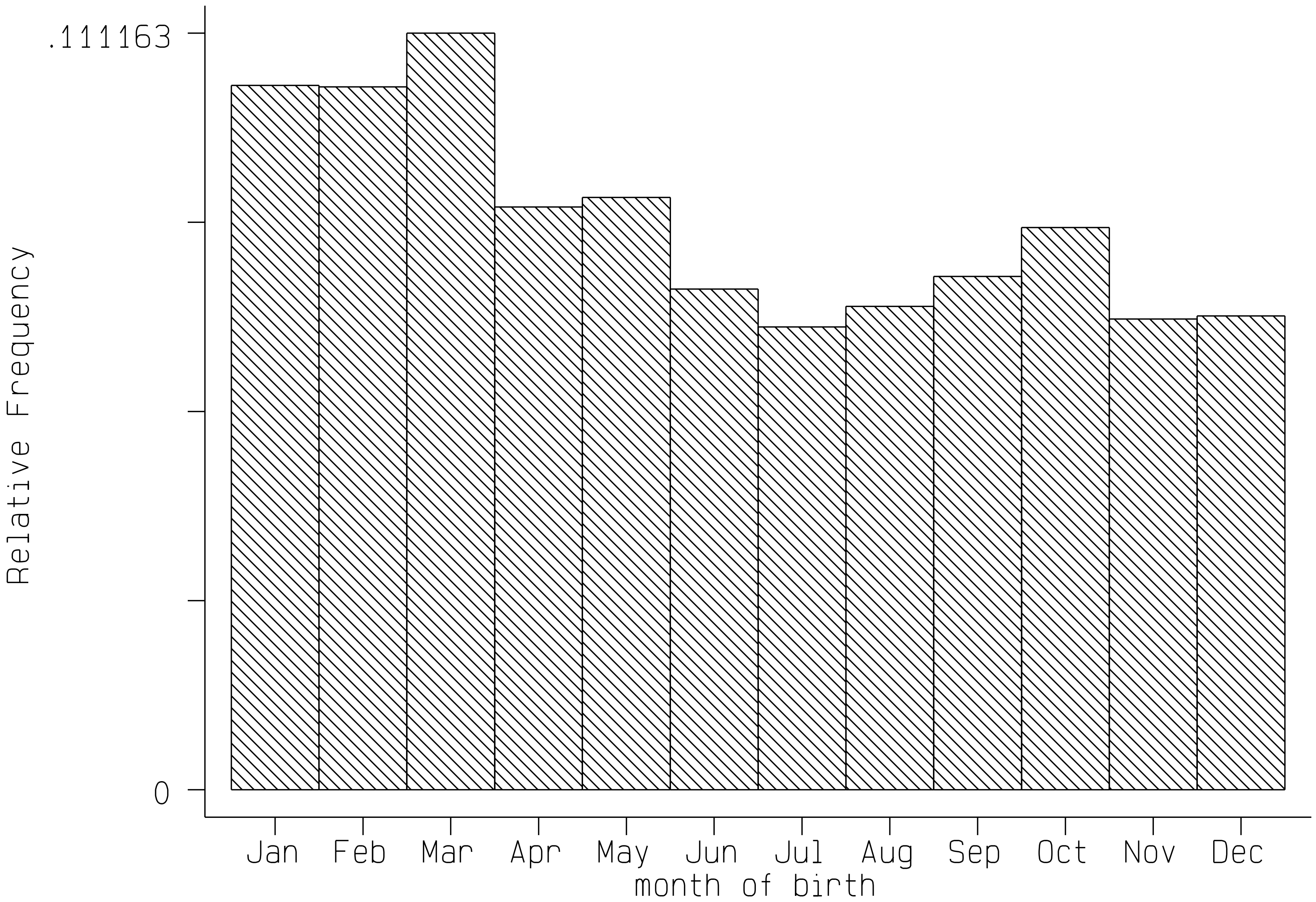


Figure 2. Frequency of Urban Births

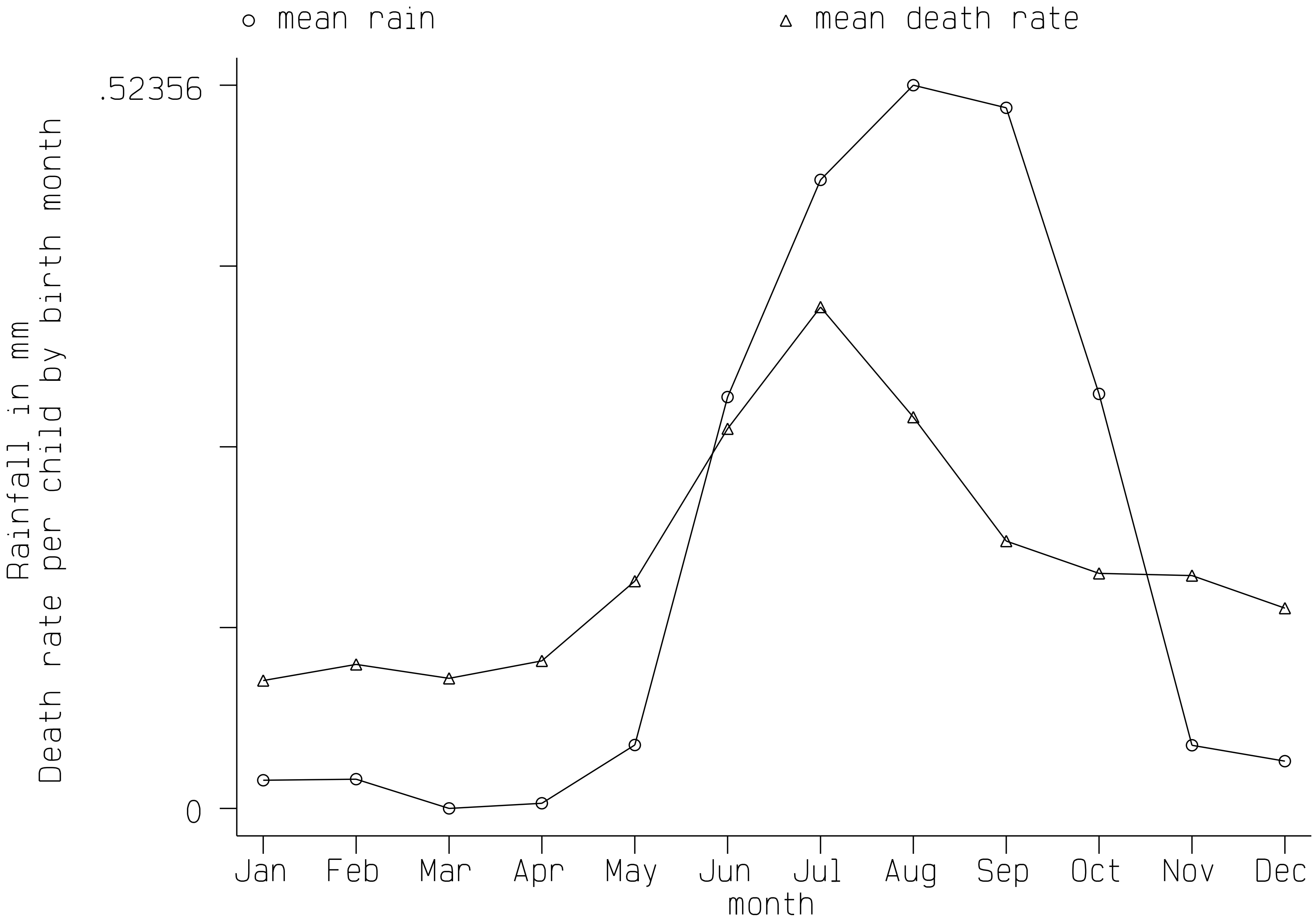


Figure 3 Seasonal Rain and Age/Cohort Adjusted Deaths

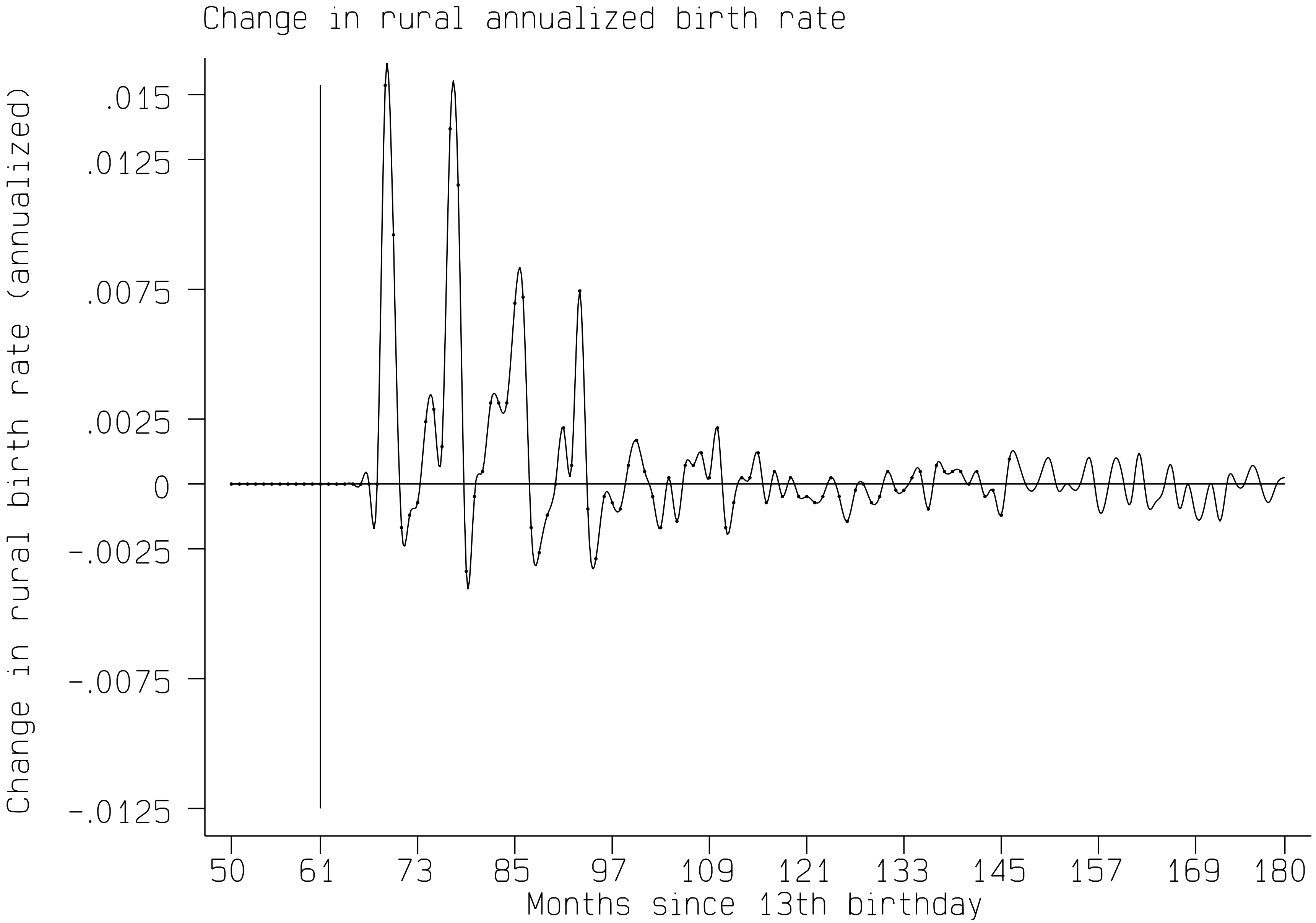


Figure 4: Effect of Rain Shock in Months 61-62

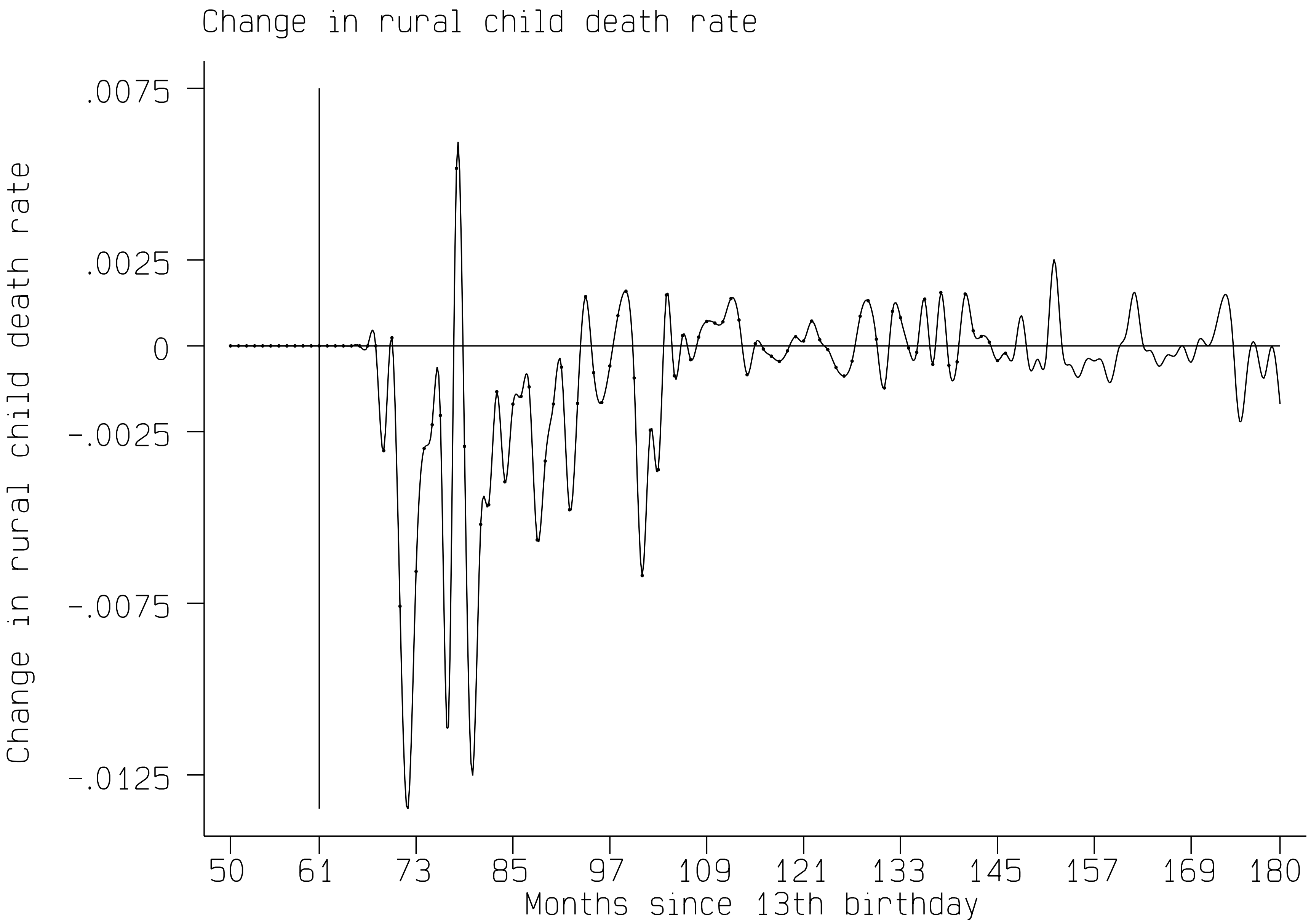


Figure 5: Effect of Rain Shock in Months 61-62

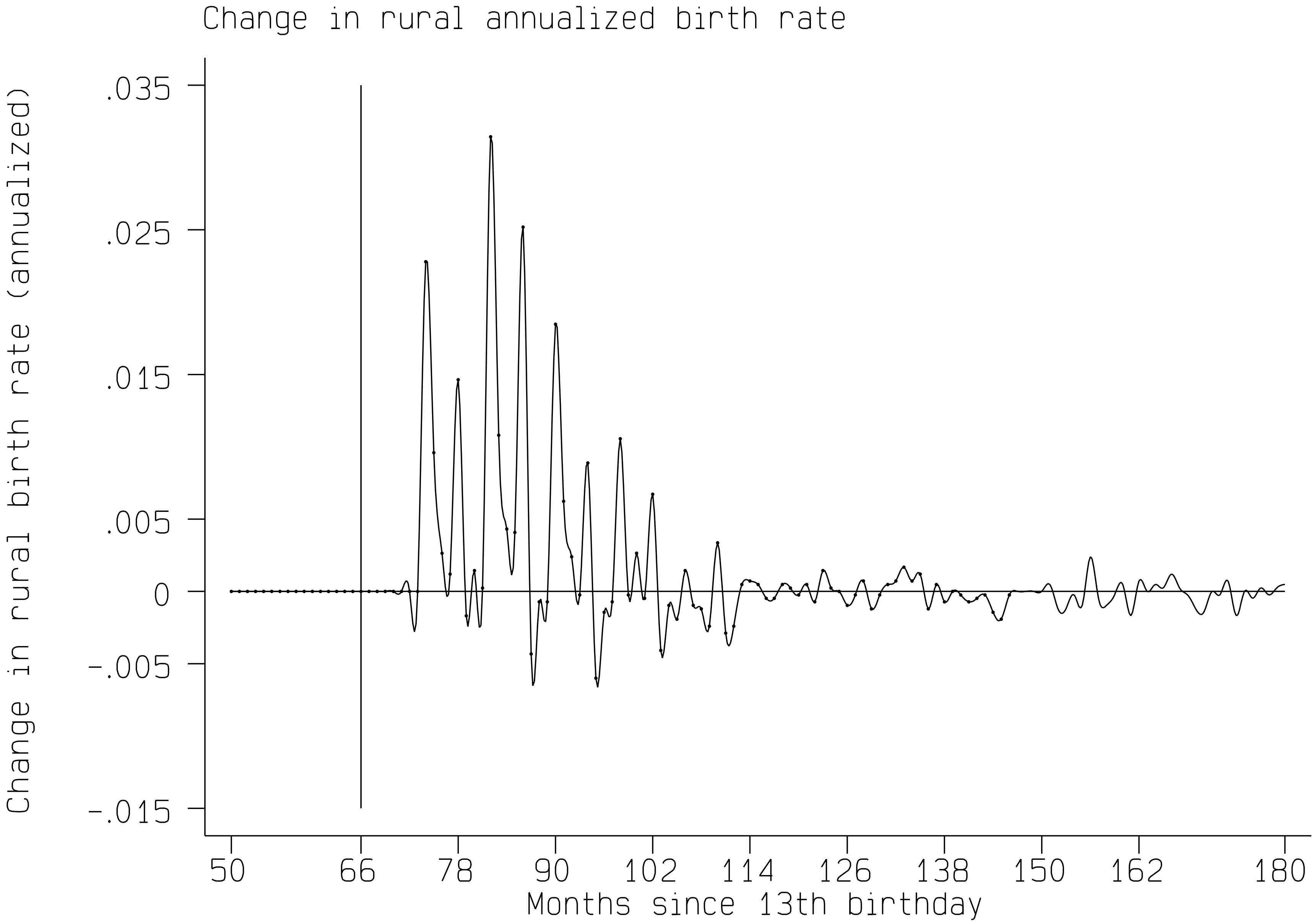


Figure 6: Effect of Rain Shock in Months 66-70

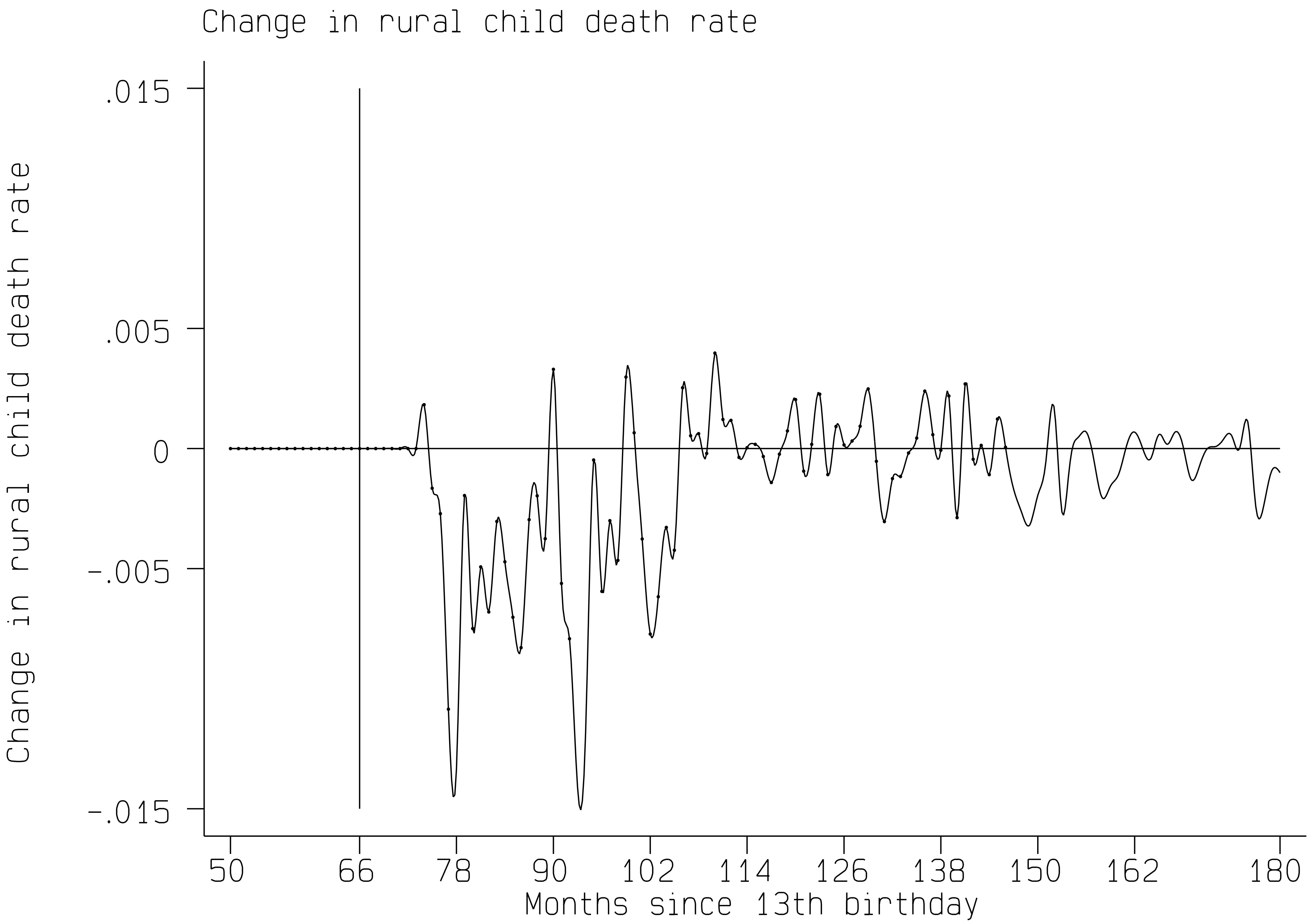
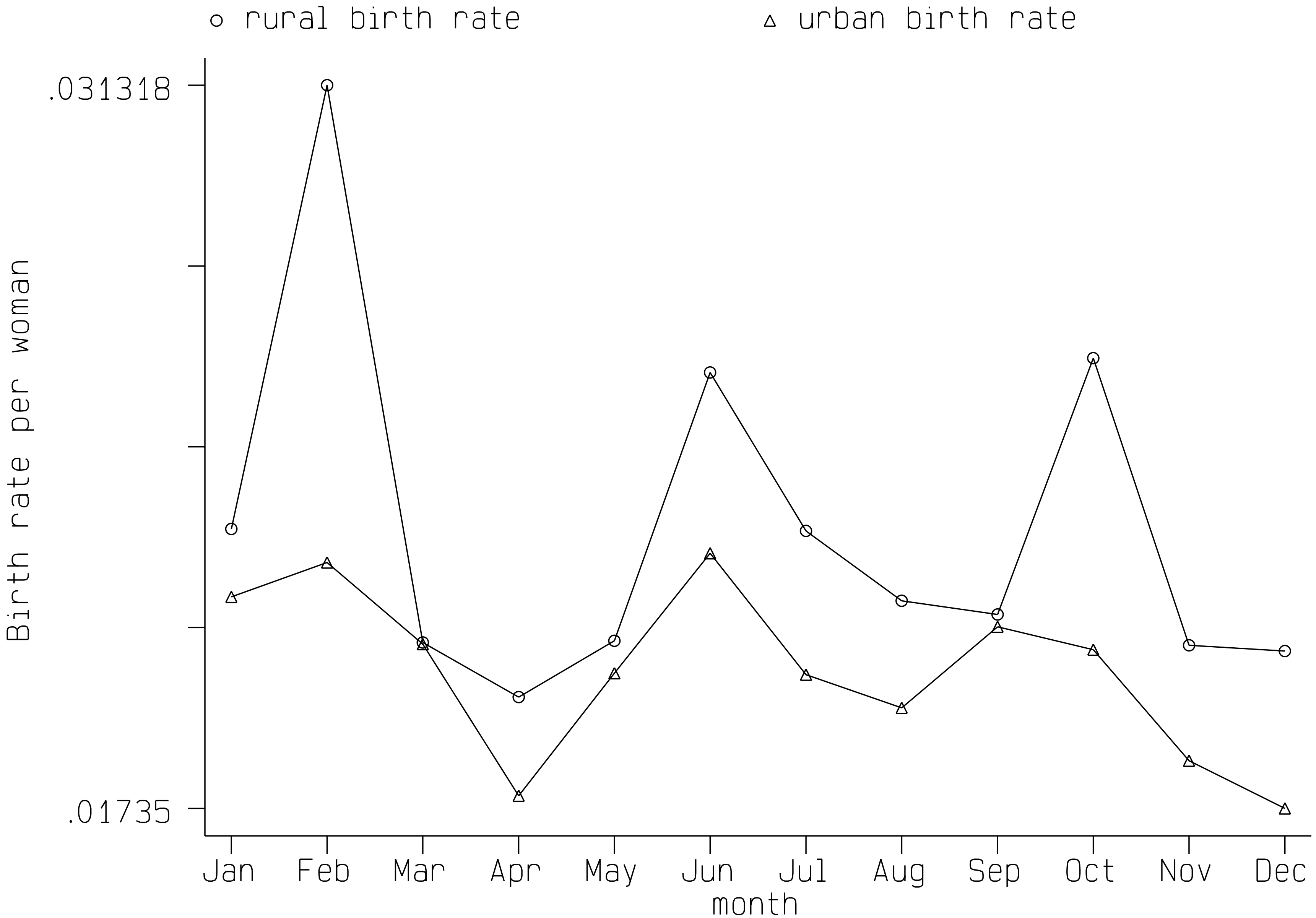


Figure 7: Effect of Rain Shock in Months 66-70



Firgure 8 Seasonal Pattern of Age/Cohort Adjusted Births

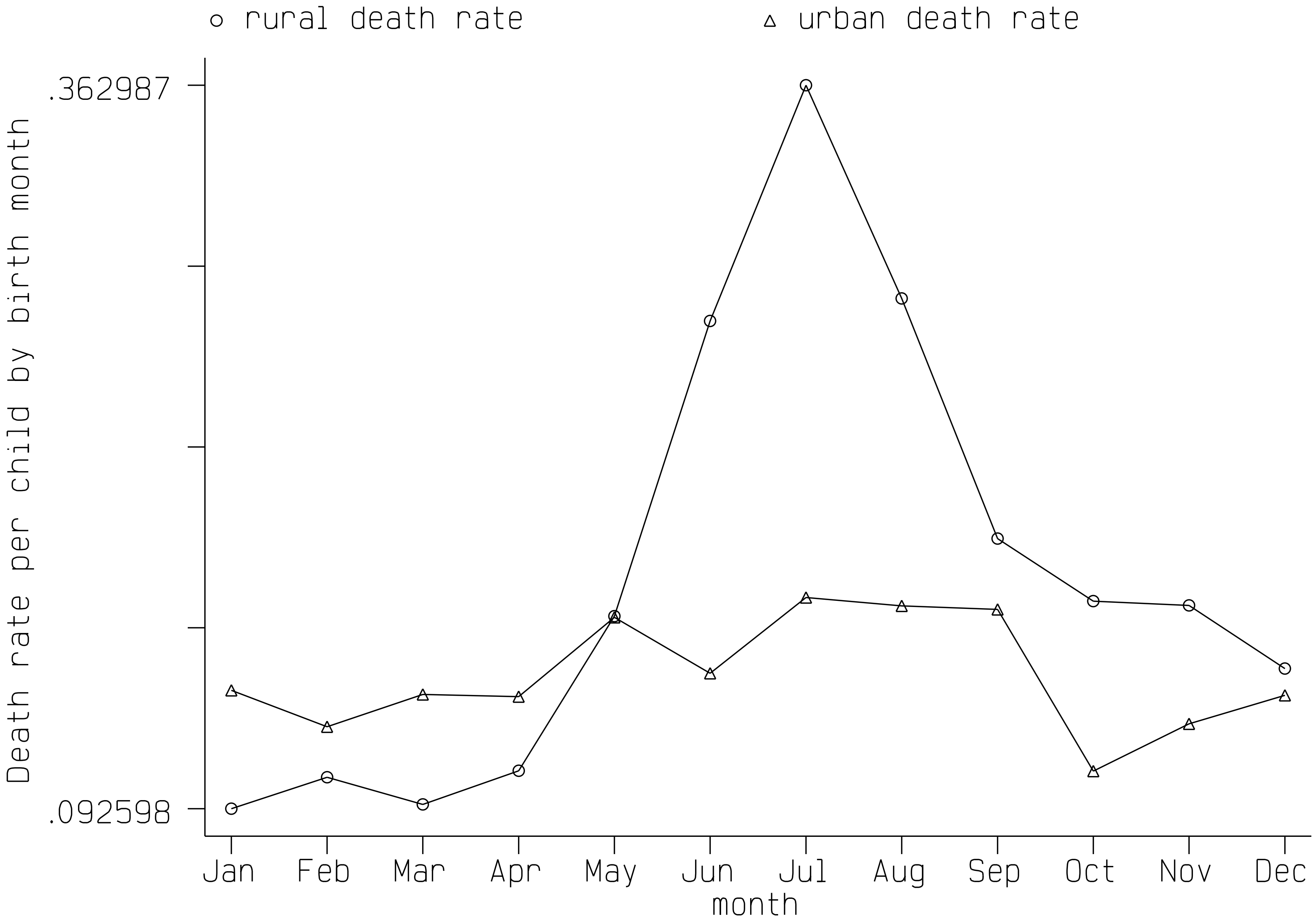


Figure 9 Seasonal Pattern of Age/Cohort Adjusted Deaths

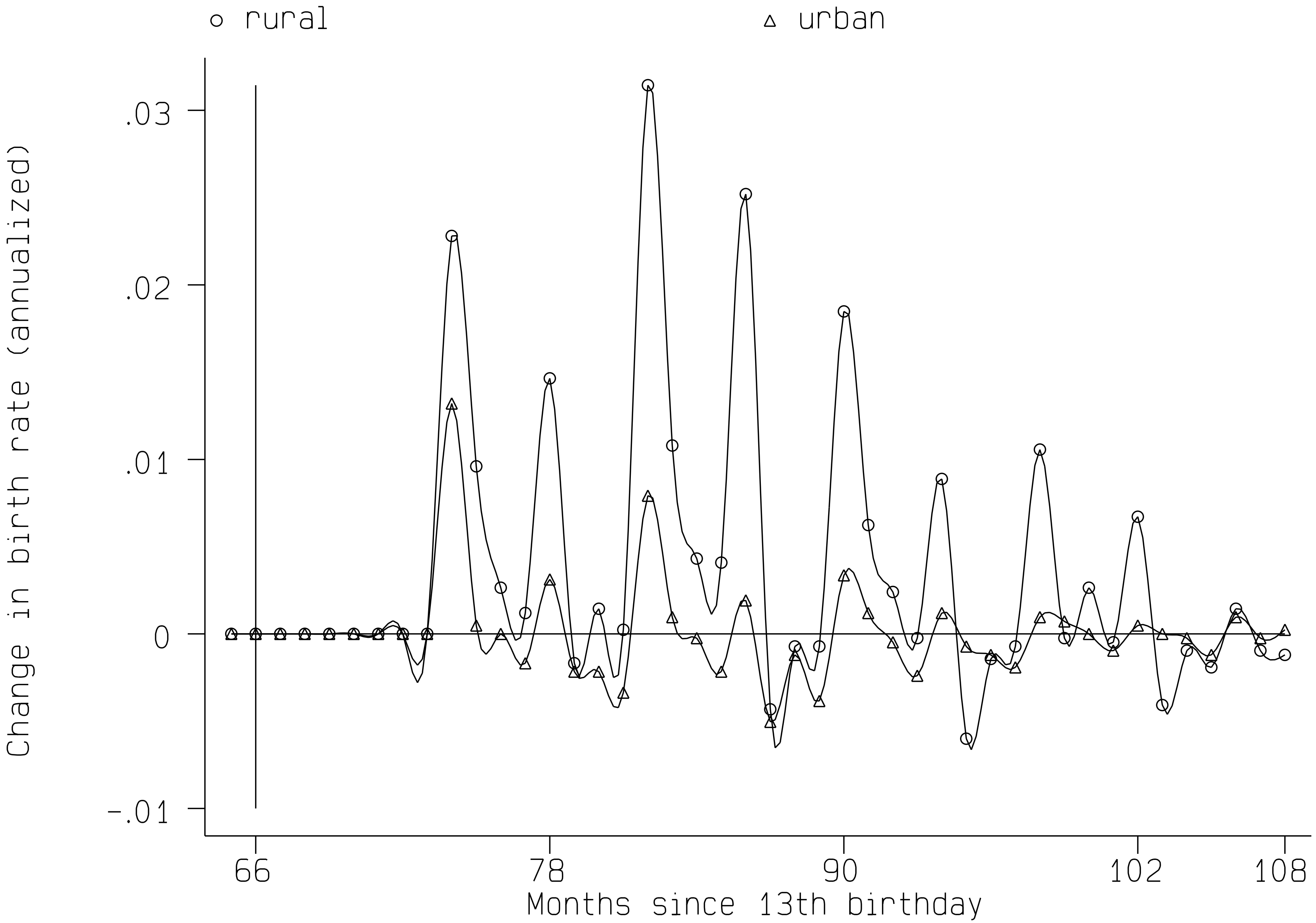


Figure 10: Rain Shock in Months 66-70: Rural and Urban

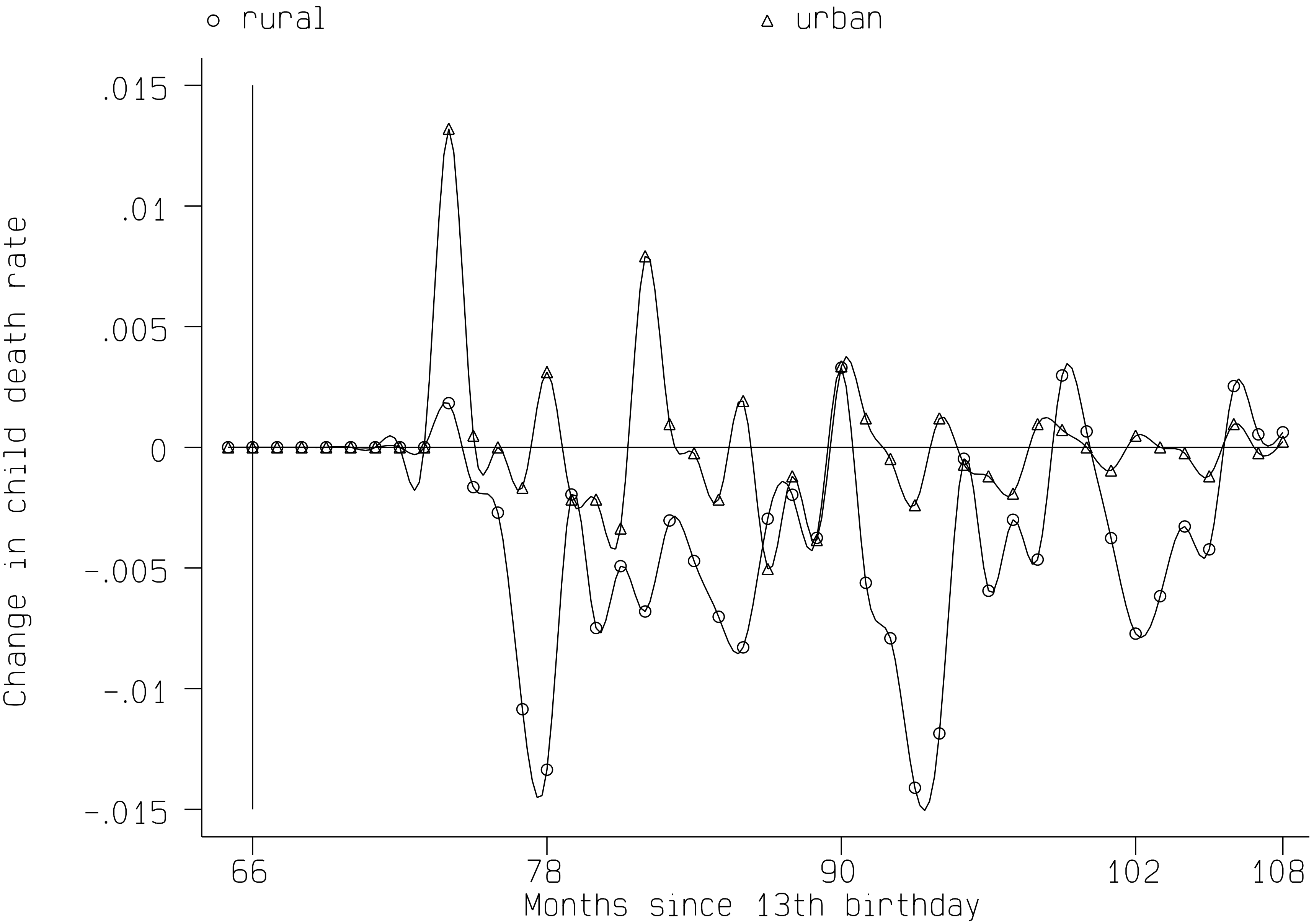


Figure 11: Rain Shock in Months 66-70: Rural and Urban