The Dynamics of Health Behaviors, Pregnancies, and Birth Outcomes *

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November 3, 2021

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Abstract

Women who smoke, use marijuana, and binge drink during pregnancy are significantly more likely to experience poor birth outcomes than those who don't. However, little is known about how these behaviors prior to pregnancy impact birth outcomes. Using data that chronicles annual behaviors and pregnancies of women from adolescence through their fecund years, I jointly estimate a set of multiple dynamic equations to examine the impact of health behavior histories on birth outcomes. I use the estimated parameters to simulate counterfactual scenarios consisting of different histories of health behaviors to quantify resulting changes in pregnancy, live birth, gestation length, and birth weight. I find that a woman's history of smoking increases her likelihood of having a low birth weight child after accounting for multiple sources of endogeneity bias associated with selection, simultaneity, and habitual behavior. Conversely, I find no evidence of marijuana use or binge drinking histories impacting birth outcomes beyond the negative impacts of use during or immediately prior to pregnancy.

JEL classification: I10, I12, J13.

Keywords: Risky health behavior, pregnancy, birth outcomes, dynamic structural equation system.

1 Introduction

Poor birth outcomes often have short-term consequences in the form of high health care expenditure and low survival rates within one month of birth (Goldenberg and Culhane, 2007). A recent study using medical claims data found that median 6-month medical costs for infants with low

*I would like to thank my advisor Donna Gilleskie for her comments and guidance. I would also like to thank David Guilkey, Luca Maini, Andres Hincapie, Mark Holmes, Martin Braun, Sid Biswas, and participants of the UNC Applied Micro Workshop for their helpful feedback.

birth weight status (<2500g) were $48,906, while the comparable costs for normal birth weight infants were $3,826 (Beam et al., 2020). There is also well-documented evidence that birth outcomes, along with other indicators of early childhood development, impact later life outcomes (Behrman and Rosenzweig, 2004; Black et al., 2007; Currie and Almond, 2011). The potentially crippling immediate financial cost of a poor birth outcome coupled with the long lasting economic repercussions for both the child and caregivers raises a question about what can be done to avoid or reduce poor outcomes. The American Academy of Pediatrics (AAP) and the American College of Obstetricians and Gynecologists (ACOG) details, for physicians, best practice information about every potential situation during a pregnancy, during the birth, and after birth. For prospective mothers, the CDC outlines 10 recommendations to aid in producing positive birth outcomes. These sources of guidance uniformly endorse the cessation of smoking, drinking, and use of most substances (e.g., marijuana) during pregnancy. They also advise women to maintain a healthy weight leading into pregnancy, and recommend avoiding exposure to toxic chemicals in the environment while pregnant. Most of the focus is on what a woman can do to maximize her pregnancy outcome during or directly leading up to a pregnancy. If the returns to particular behavior cessation during pregnancy are high, then a focus on behavior while pregnant is warranted. Indeed, cessation of smoking, marijuana use, and binge drinking has been linked to dramatic improvements in birth outcome statistics (Hayatbakhsh et al., 2012; Mills, 1984; Zhang et al., 2017).

Yet, encouragement of behavior modification during or directly before a pregnancy is unsatisfying for many reasons. First, the ability to quit smoking for those who are already habitual smokers can be hard (Gilleskie and Strumpf, 2005; Jones, 1994). Additionally, there is growing evidence in the medical and biological literatures that particular health behaviors (like overeating) have long-lasting effects on the body even after cessation (Hahn et al., 2019; Jeffery et al., 2015). Within the context of maternal health, it is clear that women who recently quit smoking have worse heart health, and heart disease is a risk factor for poor birth outcomes. As prenatal care uptake continues to increase and the distribution of pregnancies in the U.S. shifts to a higher risk profile (driven predominantly by pregnancies occurring at older ages), public health officials are starting to look towards life-cycle health improvements to improve birth outcomes. For example, the last two renditions of Healthy People[1] have emphasized health behaviors before and in

[1]Healthy People provides 10-year measurable public health objectives and tools to measure them. The goals are

between pregnancies. However, there is little empirical evidence on the effects of *past* smoking, marijuana use, and binge drinking. This omission begs the question, what impact does a history of risky health behaviors have on birth outcomes? Put differently, conditional on current health behaviors, does past behavior matter for birth outcomes?

To answer the question, I jointly estimate a set of multiple maternal health behaviors, pregnancy and birth outcomes, and other behaviors[2] as women age to examine the impacts of pre-pregnancy health behaviors on birth outcomes. An important characteristic of my empirical model is the ability to disentangle direct effects of past health behaviors on birth outcomes from indirect effects through past health behaviors' influences on current and future health behaviors. For example, it may be the case that smoking five years before pregnancy has no impact on birth outcomes conditional on smoking behavior while pregnant, but that doesn't rule out that smoking five years ago may make smoking while pregnant more likely and lead to poor birth outcomes. Another model characteristic to highlight is the inclusion of (estimated) unobserved heterogeneity (UH) that is flexibly correlated across all behaviors and outcomes and across time. Failure to account for permanent and time-varying UH would produce biased results if unobserved factors affecting health behaviors, such as genetic endowments and endogenous selection (Bitler and Currie, 2005), also affect pregnancy and birth outcomes. My empirical specification also addresses potential selection and survivorship bias that is likely present when examining health and birth outcomes. For example, women who smoke are more likely to have an elective abortion, which would lead to no observed birth outcome (Windham et al., 1999).

I use panel data from the National Longitudinal Survey of Youth, 1997 Cohort (NLSY97) to estimate the dynamic empirical model. The NLSY97 questionnaires allow me to track birth outcomes, pregnancies, and health behaviors annually from a woman's teen years into her 30s. Currie (2020) discusses the importance of examining health outcomes and behaviors in the teen years because this "missing middle" may provide high returns from behavior changes on future outcomes. Additionally, the NLSY97 provides information on other characteristics that affect pregnancy like romantic relationships, employment, and educational attainment. Maternal health behaviors in my empirical model include cigarette smoking, marijuana use, and binge drinking. While annual

determined by the U.S. Office of Disease Prevention and Health Promotion.

[2]Including sexual activity, birth control usage, abortion behavior, marriage, employment, and education.

observations of other health behaviors such as nutrition, exercise, and preventative or curative medical care consumption are unavailable, I do control for maternal health outcomes characterized by body mass index (BMI) and self-reported health status (SRHS). Pregnancy behaviors include frequency of sex and birth control use. Finally, I use information on women's pregnancy, abortion, live birth, and birth weight to describe birth outcomes.[3]

Using the estimated model, I evaluate the impacts of past smoking, marijuana use, and binge drinking by simulating cessation of these behaviors at each age between ages 16 and 30. I find increasing direct returns to smoking cessation on the probability of a low birth weight. That is, the reduction in low birth weight probability is greater the greater the duration of smoking cessation. For example, women who give birth at age 30 and quit smoking at age 18 are 50.1% less likely to have a low birth weight infant than women who quit smoking at age 25. The impacts vary by age of the mother at the birth as well as the age of smoking cessation.[4] Conversely, I find no evidence that a history of marijuana use has an impact on birth outcomes.[5]

2 Background and Motivation

As recently as 1960, half of women reported smoking while pregnant (Aizer et al., 2009). It was around this time that it became widely known that a woman's health behaviors while pregnant, or *in utero*, can have a large impact on birth outcomes and infant health. Some attribute this realization to a highly publicized thalidomide incident where thalidomide was prescribed for pregnant women with morning sickness and caused a large number of severe birth defects (Almond and Currie, 2011). Since then, behaviors like smoking, marijuana use, and binge drinking during pregnancy have been flagged as risky behaviors that cause poor birth outcomes (Gunn et al., 2016; Iyasu et al., 2002; Lightwood et al., 1999). Perhaps as a result of this knowledge, the incidence of some behaviors during pregnancy has fallen dramatically. Less than 8% of women who had live births in 2018 reported smoking during their pregnancy (Drake et al., 2018). However, the inci-

[3] Although NLSY97 has a question that allows me to back out a gestational age at birth, the information is restricted to only women who were surveyed during their pregnancy. I utilize this information when possible, and discuss it in more depth later on.

[4] A 30 year old woman who quits at 20 is 44.8% less likely to have a low birth weight birth than a woman who quits at age 27.

[5] While I find that poor health behaviors during or immediately leading up to pregnancy negatively impact birth outcomes, the focus of my work is on the impact of histories of poor health behaviors. A more detailed discussion is provided in Section 7.1.

dence of marijuana use during pregnancy has increased in recent years as marijuana laws have been relaxed (Gnofam et al., 2021). Additionally, prenatal care has increased substantially in recent years to the point where it is almost universal.[6]

Despite increases in prenatal care uptake and the reduction of some risky health behaviors during pregnancy, there has been an observed *increase* in poor birth outcomes in the last 30 years or so (Goldenberg et al., 2008). While medical technology has improved over time allowing potential miscarriages and stillbirths to result in live births, that explanation alone can not account for the well-established differences in birth outcomes between the United States and other developed countries (Chen et al., 2016). Additionally, substantial differences in birth outcomes exist within the US. For example, the low birth weight incidence among Black women is twice that for White women. Lu and Halfon (2003) posit that much of this disparity is due to differences in behaviors that affect health over the life-cycle.

A life-cycle approach to evaluating health outcomes is not new to the economics literature. Starting with Grossman (1972), the evolution of health as a form of capital has been studied extensively in economics. The concept of health capital evolution extends naturally to birth outcomes as an initial condition. This idea of early health capital in tandem with the myriad of links between birth outcomes and later life outcomes[7] make the study of birth outcomes economically relevant. This work also suggests that unequal outcomes manifest early and grow over time.

Understanding the dynamic relationship between maternal health and birth outcomes is important for several reasons. First, one of the two potential levers through which policy can influence birth outcomes is in maternal health behavior, the other being medical innovation. Second, while the birth outcome (by itself) is economically relevant, all aspects of pregnancy (the event, planning, and interactions with decisions on marriage, employment, and education) contribute to the economic relevancy of continued study. Finally, pregnancy directly affects two generations of a population, and so the returns to any improvements through policy are long-lasting.

By isolating the impact of past behaviors on later life outcomes, my paper is similar in spirit to Grönqvist et al. (2020). By accounting for direct and indirect mechanisms through which behaviors can have future impacts it is similar to recent papers by Gilleskie et al. (2017) and Darden

[6] A 2016 NCHS report finds 93.8% of all pregnant women started receiving prenatal care during the first or second trimester.

[7] See Almond and Mazumder (2011); Costa (1998); Currie and Hyson (1999) for a few examples.

et al. (2021). By expanding the horizon through which one evaluates health and birth outcomes, my paper is similar to Yan (2015) where they evaluate the impact of BMI entering pregnancy on birth outcomes. A few other papers have looked at the impact of "preconception" health on birth outcomes with mixed results. Strutz et al. (2014) find that chronic stressors when young have an impact on the probability of having a low birth weight birth, but acute stressors do not exhibit a similar effect. Witt et al. (2012) find that women who have poor self-reported mental health in the "preconception" period are more likely to experience adverse birth outcomes.

The conclusions of this paper have direct policy relevance to the importance of targeted interventions at specific points in the life cycle. A body of literature on the impacts of early-childhood interventions on later life health, education, and employment outcomes already exists. The results of my paper suggest, similarly, that policy aimed at reducing key health behaviors prior to pregnancy improves birth outcomes. Additionally, the results inform best practices of OB-GYNs. For example, pregnant women presenting at the doctor's office may report having good folic intake today, indicate no smoking behavior today, and be normal weight today. Is current health and health behavior information sufficient for a physician to provide appropriate care to maximize the probability of a healthy pregnancy and birth? Could the birth outcomes be better if the doctor had additional information on the woman's pre-pregnancy health behaviors? While it may be standard practice for a woman to relay health history when she presents pregnant, education about the negative effects of pre-pregnancy health behaviors needs to be communicated before conception.

3 Descriptive Evidence from NLSY97

The National Longitudinal Survey of Youth 1997 (NLSY97) provides life-cycle information on health behaviors, health outcomes, and pregnancy outcomes. The survey was initially administered to 8,984 individuals (4,385 females) ages 12-18 in 1997, who have been followed in 18 rounds of annual/biennial interviews. I augment the individual-level data with market-level data at the state, metropolitan statistical area (MSA), and county level. These supplemental data are used to characterize the environment in which women make their decisions and to aid in identification. Additional details about the data are available in Table 8 of the Appendix. Other data sources also provide information on health behaviors and birth outcomes, but not as consistently as the NLSY97 data. For example, the National Longitudinal Study of Adolescent and Adult Health (Add Health) provides detailed information on a woman's pregnancy outcomes as well as some information on other behaviors throughout her life, but the survey is only administered five times over a 24-year period.

In order to estimate the dynamic model described in the next section, I restrict the estimation sample to women who contribute observations for at least the first two survey waves. Additionally, the sample is restricted to women who have never reported being pregnant entering the survey. Finally, a woman attrits from the estimation sample upon the year of her first non-response to a survey or the first year in which she has missing information on health behaviors or health outcomes. After these exclusions, the estimation sample contains 3,675 women (84% of initial sample) who contribute 40,797 consecutive person-years. I analyze the first 15 survey waves because I am able to observe behaviors and outcomes annually; after 2011, the NLSY97 survey is only administered biennially. I utilize a key feature of the pregnancy survey questions that ask women to recall at every survey wave if they had any past pregnancies. Even if a woman does not report information on pregnancy outcomes in one survey, it is likely that the information is obtained in future waves.

Summary statistics for the modeled behaviors and outcomes (Table 1) illustrate the differences across age groups. This age variation in health behaviors, and health outcomes stresses the importance of modeling the dynamics associated with habitual or addictive behavior. Table 1 also provides summary statistics for pregnancy and birth outcomes. Conditional on giving birth, women of ages 13 to 17 are much more likely to experience a low birth weight birth than older women. Unsurprisingly, women in the age 23 to 32 bracket are most likely to get pregnant, while women from age 18 to 22 are the most likely to terminate a pregnancy through an abortion. The NLSY97 survey also oversamples some individuals among whom pregnancies and abortions occur at higher rates statistically. A more detailed discussion of comparisons between the estimation sample and the full NLSY97 sample are provided in Table 9 in the Appendix. Additionally, it is well known that abortion is often underreported in survey data (Lindberg et al., 2020). Forsstrom (2021) uses population rates of abortion stratified by age, race, and year as a bias correction in the likelihood function. From a policy perspective, there is value in utilizing responses to the survey question to

Table 1: Variable means by different age groups

Category	Estimation Sample	Age 13-17	Age 18-22	Age 23-32
Health/Pregnancy Behaviors				
Cigarette smoking last 30 days	30.6%	25.7%	33.3%	30.5%
Marijuana use last 30 days	13.6%	12.7%	15.9%	11.8%
Binge drinking last 30 days	25.3%	15.4%	27.7%	27.9%
Any sex	68.3%	30.8%	71.2%	84.4%
Any birth control use | sex	82.3%	92.8%	88.5%	75.2%
Health Outcomes				
BMI	26.0	23.3	25.4	28.1
SRHS: Excellent	27.9%	34.8%	29.3%	23.0%
SRHS: Very Good	36.9%	35.1%	36.3%	38.5%
SRHS: Good	28.2%	26.0%	27.9%	29.7%
SRHS: Fair or Poor	7.9%	6.0%	7.6%	9.4%
Pregnancy/Birth Outcomes				
Pregnant	10.1%	4.3%	11.1%	12.1%
Abortion | Pregnant	8.7%	7.9%	10.0%	7.7%
Live birth | Pregnant + no abortion	89.2%	88.6%	87.7%	90.5%
Gestational age at birth (weeks)	38.7	38.0	38.7	38.7
Low birth weight incidence	9.1%	14.9%	9.8%	8.0%

Notes: Table presents endogenous variable summary means for the 3,675 individuals and 40,797 person-years included in the estimation sample. Binge drinking is defined as having had at least five alcoholic beverages in one day within last 30 days. BMI refers to body mass index, which is calculated taking a person's mass in kilograms and dividing it by the square of their height measured in meters. Low birth weight refers to births that are less than 2500 grams (or 88 ounces). Some categorical variables don't add to zero due to rounding.

interpret observed abortions as those occurring to women who are willing to report an abortion in a survey.

While the observed data suggest that abortion rates are lower than those reported by medical providers, there is no evidence that pregnancy and live birth are underreported (Lindberg et al., 2020). I use four main features of the survey to construct the variables that provide a full description of a woman's pregnancy history: (1) a question about whether a woman is currently pregnant,[8] (2) a question about whether a woman has been pregnant since the last survey,[9] (3) biological children's birth dates, and (4) biological children's birth weights.[10] The dynamic model of the impacts of health behaviors on birth outcomes requires getting the timing as precise as pos-

[8] A yes response is followed up with questions about the current duration of the pregnancy.

[9] A yes response is followed up with questions asking when the pregnancy ended, and how it ended.

[10] This question was introduced in 2008, so birth weight information if a woman attrits before 2008 is unavailable. However, for women not attriting before 2008 birth weight information on all births is likely available because the question asks women to recall all births. For additional discussion discussion of the implications of birth weight variable construction see the Appendix.

sible from a survey administered annually. It is also important to have a long panel of uniformly asked questions. To my knowledge, the NLSY97 comes closest to facilitating the data requirements. By utilizing the entire history of information I can evaluate the impacts of behaviors up to 15 years in the past on pregnancy and birth outcomes.

To characterize the correlations between past health behaviors and birth outcomes I separately estimate a series of cross-sectional regressions of a low birth weight indicator on cigarette smoking, marijuana use, and binge drinking.[11] A woman is flagged as a time t smoker if she had smoked at least one day in the 30 days leading up to the interview, she is flagged as a marijuana user if she has answered yes to using marijuana since last interviewed, and she is flagged as a binge drinker if she drank at least five alcoholic drinks on at least one occasion in the 30 days leading up to the interview.[12] The CDC defines a binge drinking event for a woman as four drinks, but the survey only asks for occasions of five or more drinks. To determine whether there is any correlation between past health behaviors and low birth weight incidence I estimate the probability of low birth weight (LBW_t) conditional on pregnancy (P_t) and live birth (L_t):

$$ln\left(\frac{P(LBW_t=1|P_t,L_t)}{P(LBW_t=0|P_t,L_t)}\right) = \beta_0^j + \beta_1^j \mathbb{1}[j_t = 1] + \beta_2^j \mathbb{1}[\textstyle\sum^t (j_t = 1) \geq 1] + \beta_3(\textstyle\sum^t \mathbb{1}[j_t = 0| \textstyle\sum^{t-1} j_{t-1} \geq 1]) + X_t\gamma + \epsilon_t^j \qquad (1)$$

for each behavior j at time t. β_1^j is the effect of doing the behavior in t, β_2^j is the effect of having ever done the behavior up to time t, and β_3^j is the effect of years of cessation. I estimate each model with a logit specification and then add in a progressively larger set of covariates. Marginal effects of current behavior, ever doing the behavior, and years of cessation from the behavior are provided in Table 2 for smoking, binge drinking, and marijuana use.

Table 2 shows the positive correlation between smoking during pregnancy and low birth weight. Specifically, column 1 suggests that women who smoke while pregnant are 3.7 percentage points more likely to give birth to a low birth weight child.[13] Inclusion of the other two mea-

[11] The estimated models treat person-years as independent, but standard errors are clustered at the individual level. I use a logit specification, and the low birth weight outcome is conditional on being pregnant and having had a live birth during time period t.

[12] Life-cycle behaviors are described by an indicator of current behavior ($\mathbb{1}[j_t = 1]$), an indicator of ever having participated in the behavior ($\mathbb{1}[\sum^t (j_t = 1) \geq 1]$), and the years since cessation of the behavior if ever participated ($\sum^t \mathbb{1}[j_t = 0| \sum^{t-1} j_{t-1} \geq 1]$).

[13] This number is lower than the existing literature (e.g., Almond et al. (2005)), yet still suggests a relatively pronounced effect. Because my data are not as precise in the timing of behaviors near pregnancy, a muted effect is expected.

Table 2: Association of health behaviors with low birth weight probability

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Smoked entering t	0.037***	0.036**	0.013	0.016	0.015	0.011	-0.0022	-0.0035
	(0.014)	(0.015)	(0.019)	(0.019)	(0.24)	(0.018)	(0.019)	(0.018)
Ever smoked		0.0015	0.025	0.034*	0.048**	0.037**	0.042**	0.042**
		(0.017)	(0.021)	(0.021)	(0.24)	(0.019)	(0.020)	(0.020)
Smoking cessation (years)			-0.0064*	-0.0061*	-0.0086**	-0.0066**	-0.0075**	-0.0074**
			(0.0034)	(0.0034)	(0.043)	(0.0033)	(0.0035)	(0.0035)
Used marijuana entering t	0.041**	0.031	0.038	0.043*	0.055*	0.040*	0.033	0.032
	(0.018)	(0.020)	(0.024)	(0.024)	(0.031)	(0.024)	(0.024)	(0.024)
Ever used marijuana		0.016	0.0099	0.0035	0.0056	0.0076	-0.0049	-0.00071
		(0.015)	(0.020)	(0.020)	(0.025)	(0.019)	(0.020)	(0.020)
Marijuana cessation (years)			0.0015	0.0045	0.0048	0.0032	0.0035	0.0032
			(0.0029)	(0.0030)	(0.0040)	(0.0032)	(0.0032)	(0.0031)
Binge drank entering t	0.018	0.032*	0.042*	0.041*	0.047	0.039*	0.027	0.024
	(0.017)	(0.019)	(0.022)	(0.022)	(0.029)	(0.023)	(0.023)	(0.023)
Ever binge drank		-0.024*	-0.035*	-0.018	-0.014	-0.0088	-0.031	-0.030
		(0.014)	(0.019)	(0.019)	(0.025)	(0.019)	(0.020)	(0.019)
Binge drink cessation (years)			0.0035	0.0051	0.0065	0.0049	0.0060	0.0056
			(0.0044)	(0.0044)	(0.0061)	(0.0048)	(0.0047)	(0.0047)
Demographics				1	1	1	1	1
Preg. History					1	1	1	1
Local Market Conditions						1	1	1
Other Health Characteristics							1	1
Education, Schooling, Employment								1

Notes: Cluster robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The estimates shown are marginal effects. The results shown are for 2,660 live births that have birth weight information. The average sample low birth weight incidence is 9.4%. Each partitioned section represents its own set of logit models, with the pattern of other variables added in.

sures of smoking history suggests the important roles of lagged behaviors. The model with the most controls (column 8) shows that each additional year of smoking cessation reduces by 0.7 percentage points the likelihood of a live birth resulting in a low birth weight birth. Despite some evidence of an impact of current marijuana use and binge drinking on the probability of low birth weight in sparse specifications, models with controls for the history of those behaviors suggests no significant correlations. Moving from columns (1) - (8) highlights the importance of controlling for observable characteristics. For example, the effect of smoking on birth weight is almost entirely concentrated to the history of smoking after controlling for observable characteristics.

4 Dynamic Empirical Framework

In this section I first motivate the empirical model that allows me to capture the complicated relationship between health behaviors and birth outcomes and introduce notation. Then, I describe the set of equations that are jointly estimated in detail. Important theoretical and empirical considerations I take into account are (i) past health behaviors influence demand for current health behaviors, (ii) selection into observed birth outcomes, (iii) health capital evolution is a dynamic process, and (iv) correlations in health behaviors may exist across and within time periods.

The goal of this research is to answer whether or not health behaviors in the past have any impact on birth outcomes. Specifically, I want to answer whether or not there are any detrimental effects of a past history of risky health behaviors even if one does not engage in those behaviors while pregnant.

4.1 Model Summary

Let a woman's fecund years be defined over time periods $t = 1, ..., T$ and smoking, marijuana use, and binge drinking be captured by $[b_t^1, b_t^2, b_t^3] = b_t$. Additionally, let the probability of LBW entering $t+1$ (O_{t+1}^1) be defined by behaviors during and prior to pregnancy:

$$Pr(O_{t+1}^1 = o^1 | P_t, L_{t+1}) = f^{O^1}(b_t, B_t, X_t, u_{it}^{O^1}) \quad \forall t, \quad o^1 = 0, 1 \tag{2}$$

where B_t captures the history of behavior up to period t for all behaviors, X_t captures all other observed characteristics, and $u_t^{O^1}$ captures the component of birth weight production that is unobserved to the econometrician. With this specification, I can examine the marginal effect of B_t and answer my question of interest. However, in order to get a consistent estimate of this marginal effect, several issues need to be addressed.

First, health behaviors (b_t) are almost certainly endogenous in a birth weight production function. Explicitly, there are likely unobserved characteristics that determine both a woman's demand for smoking, marijuana, and binge drinking and the likelihood of having a low birth weight birth. For example, a time-varying stressor, like the illness of a family member or relationship problems, is likely going to be related to a woman's smoking behavior and influence her birth outcome.

One solution to address the problem is to jointly estimate the smoking, marijuana use, and binge drinking demand equations with the probability of a low birth weight and to allow for correlation across each equation. Jointly estimating each behavior also addresses concerns relating to possible correlations in health behaviors that exist across time periods. The health behavior equations are discussed in more detail in Section 4.3. Additionally, current health behaviors may depend on past health behaviors. For example, smoking may be addictive or past behaviors may act as a gateway to other behaviors. Hence, I model demand for smoking behavior as dynamic (i.e., dependent on past behavior).

By definition, I only observe birth weight and gestational age at birth for babies who are born alive. Additionally, a woman can't choose whether to get pregnant or not, she merely chooses behaviors that influence her probability of getting pregnant (i.e., sex frequency and contraception). Pregnant women may also choose to abort a pregnancy. It is important to account for these types of *selection* because observed and unobserved factors may affect pregnancy, live birth, and birth outcomes. Moreover, women with lower levels of health capital may be more likely to terminate a pregnancy. Thus, pregnancy related outcomes are jointly estimated with pre-pregnancy health behaviors and health outcomes since observed and unobserved variables that influence health behaviors and outcomes may also influence pregnancy outcomes. For example, women may select out of pregnancy-inducing behaviors if they have health behaviors that threaten subsequent birth outcomes. Not accounting for these selection and endogeneity issues would lead to biased estimates of past health behaviors on birth outcomes. The equations for sexual activity, pregnancy, and birth outcomes are discussed in more detail in Section 4.4.

Finally, I also model other life-cycle behaviors that may be confounding factors in health behaviors and birth outcomes. Specifically, along with everything previously discussed, I jointly estimate relationship status, school enrollment, and employment. Accounting for endogeneity, selection, dynamics, and confounding allows me to identify a consistent causal impact of lagged health behaviors on birth outcomes.

4.2 *Period t Timing*

Accuracy in timing of the model's behaviors and outcomes and how the data maps to each variable is vital for correctly specifying the model in light of multiple levels of selection and for motivating exclusion restrictions to aid in identification of the model. Figure 1 depicts the timing of behaviors and outcomes.

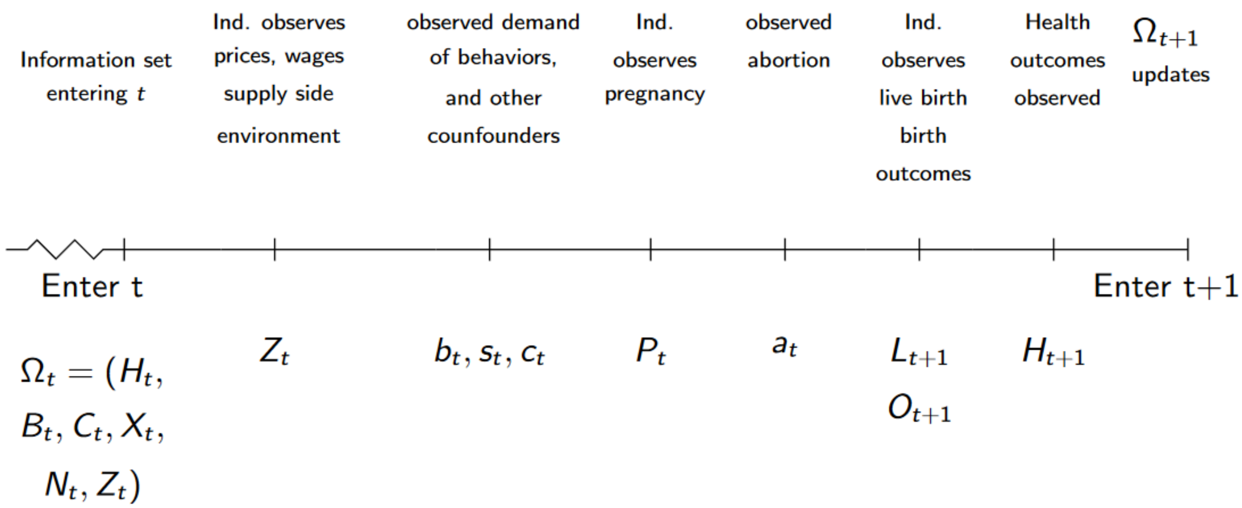

Figure 1: Period t timing

A woman enters each period t with information set, Ω_t, which includes her history of health behaviors (B_t), health capital (H_t), her history of pregnancies and birth outcomes (N_t), confounding behaviors from last period (C_t), exogenous characteristics (X_t), and her exogenous location-specific and supply side information (Z_t). She makes decisions about her period t health behaviors (b_t), sexual activity (s_t), and other behaviors (c_t). Her pregnancy status (P_t) is then observed, and she decides whether or not to terminate the pregnancy (a_t). Conditional on being pregnant and not terminating the pregnancy, a live birth (L_{t+1}) and birth outcomes (O_{t+1}) are observed. Then, her health outcomes (H_{t+1}) evolve and she enters period $t+1$.

4.3 Health Behaviors

The optimal health behavior portfolio requires solving an individual's forward-looking stochastic lifetime utility maximization problem.[14] In theory, the optimization problem can be solved to obtain a decision rule for health behaviors (b_t) and sexual activity (s_t), leading to demand equations of the form:

$$Pr(b_t^j = b) = f^B(B_t, H_t, N_t, C_t, X_t, Z_t^B, Z_t^P, Z_t^A, Z_t^O, u_t^N), \quad \forall t, j = 1,2,3, \quad b = 0,1 \tag{3}$$

$$Pr(s_t^k = s) = f^S(B_t, H_t, N_t, C_t, X_t, Z_t^B, Z_t^P, Z_t^A, Z_t^O, u_t^S), \quad \forall t, k = 1,2, \quad s = 0,1 \tag{4}$$

where $s_t = [s_t^1, s_t^2]$ is a vector of a woman's sexual activity and birth control usage. These demand equations are functions of the information known up to period t. It includes the history of health behaviors (B_t), health capital entering period t (H_t), histories of pregnancy and birth outcomes (N_t), endogenous confounding variables (C_t), exogenous individual characteristics (X_t), and exogenous price and supply side variables (Z_t). Because the woman is forward looking, her time t behavior decision depends on exogenous variables that also impact pregnancy, abortion, and birth outcomes. Specifically, $Z_t = [Z_t^B, Z_t^P, Z_t^A, Z_t^O]$ where each element of Z_t represents exogenous location-specific period t prices and supply-side information related to health behaviors, pregnancy, abortion, and birth outcomes, respectively.[15] Assumptions about the error terms in each demand equation are discussed in Section 4.8.

4.4 Pregnancy, abortion, live birth, and birth outcomes

I characterize pregnancy (P_t), live birth (L_{t+1}), and birth outcomes (O_{t+1}) by a set of conditional production functions that depend on health and pregnancy behaviors at time period t as well as the history of health behaviors up to time period t.

$$Pr(P_t = p) = f^P(b_t, s_t, c_t, B_t, H_t, N_t, X_t, Z_t^P, Z_t^A, Z_t^O, u_t^P) \quad p = 0,1 \; \forall \; t \tag{5}$$

[14] See Appendix Section 7.2.

[15] See Appendix Section 7.1 for a more detailed discussion of exclusion restrictions.

$$Pr(a_t = a|P_t = 1) = f^A(b_t, s_t, c_t, B_t, H_t, N_t, X_t, Z_t^A, Z_t^O, u_t^A), \quad a = 0, 1 \forall\, t \tag{6}$$

$$Pr(L_{t+1} = l|P_t = 1, a_t = 0) = f^L(b_t, s_t, c_t, B_t, H_t, N_t, X_t, Z_t^O, u_t^L) \quad l = 0, 1\ \forall\, t \tag{7}$$

$$Pr(O_{t+1}^1 = o^1|L_{t+1} = l) = f^{O^1}(b_t, s_t, c_t, B_t, H_t, N_t, X_t, Z_t^O, u_t^{O^1}) \quad o^1 = 0, 1,\ \forall\, t \tag{8}$$

$$O_{t+1}^2|L_{t+1} = l = f^{O^2}(b_t, s_t, c_t, B_t, H_t, N_t, X_t, Z_t^O, u_t^{O^2}) \quad \forall\, t \tag{9}$$

The vector of birth outcomes (O_{t+1}) includes an indicator of the probability of low birth weight (O_{t+1}^1) and gestational age at birth (O_{t+1}^2). Note that a woman's current and past health behaviors (b_t, B_t) may influence her demand for an abortion as well as the sequential production functions for pregnancy, live birth, and birth outcomes. This inclusion captures the possibility that a woman may terminate a pregnancy if she believes that her health behaviors might influence birth outcomes. Observed pregnancy may depend on supply side variables that impact pregnancy, abortion, live birth, and birth outcomes. Conditional on being pregnant, exogenous variables related to pregnancy do not impact abortion demand, but the exogenous characteristics that affect abortion and live birth outcomes are still relevant. Similarly, conditional on not terminating the pregnancy, supply side abortion characteristics do not affect live birth or birth outcomes. The correlation between error terms in this section and those in Section 4.3 are discussed in Section 4.8.

4.5 Health Outcomes

Since many health behaviors may influence birth outcomes, I include additional measures of health capital (H_t) (that depend on unobserved health behaviors) that may also influence birth outcomes. Health capital evolution (i.e., H_{t+1}), a dynamic stochastic process, is represented by a health production function:

$$Pr(H_{t+1} = h) = f^H(H_t, b_t, s_t, c_t, B_t, N_{t+1}, X_t, u_t^H), \quad h = 0, 1\ \forall t \tag{10}$$

Empirically, the two measures of health capital that I include are self reported health status and BMI. Health capital entering period $t+1$ is a function of health capital entering period t, current health behaviors (b_t), the history of health behaviors (B_t), other current behaviors, (s_t, c_t), the history of birth outcomes including any changes () that happened in t (N_{t+1}), and exogenous characteristics.

To summarize, equations 2-10 are a set of structural demand and production equations that are identified and estimable. Specific sources of identification based on theoretically justified exclusions+ are discussed in Section 4.8.

4.6 *Other Confounding Factors*

I seek to estimate the impact of the history of health behaviors on birth outcomes. A woman's demand for health behaviors depends on endogenous socioeconomic characteristics that may also influence sexual activities, pregnancy, and abortion. The vector of confounding variables (C_t) include a woman's romantic unions (r_t), school enrollment (se_t), and employment (e_t) in period t. Theoretically, these life decisions are made jointly with the health behaviors and sexual activity behaviors. Hence, the demand equations are functions of the same variables. The demand for relationships, schooling, and employment are represented by:

$$Pr(r_t = r) = f^R(B_t, H_t, N_t, C_t, X_t, Z_t^B, Z_t^P, Z_t^A, Z_t^O, u_t^R), \quad r = 0,1,2 \; \forall \; t \tag{11}$$

$$Pr(se_t = se) = f^{SE}(B_t, H_t, N_t, C_t, X_t, Z_t^B, Z_t^P, Z_t^A, Z_t^O, u_t^{SE}), \quad se = 0,1 \; \forall \; t \tag{12}$$

$$Pr(e_t = e) = f^E(B_t, H_t, N_t, C_t, X_t, Z_t^B, Z_t^P, Z_t^A, Z_t^O, u_t^E), \quad e = 0,...,4 \; \forall \; t \tag{13}$$

I refer to the lags of these behaviors collectively as (C_t), and the vector of the current behaviors as (c_t). Romantic unions (r_t) are characterized by being single, cohabitating, or married. Employment (e_t) is characterized by being unemployed or out of the labor force, employed part-time for part of the year, employed part-time for the full year, employed full-time for part of the year, and employed full-time for the full year.

4.7 *Initial Conditions*

The dynamic specification of period t behaviors requires period $t-1$ variables. When survey respondents are first observed (i.e., $t = 1$), lagged variables are unobserved. Hence, I estimate the initially observed ($t = 1$) variables of interest as non-dynamic equations, or initial conditions, and allow their error terms to be correlated with subsequent ($t > 1$) outcomes. The data include some women who enter the survey with non-zero values of these endogenous variables.[16] I explicitly model a woman's initial health behaviors (b_1),[17] sexual activity and birth control use (s_1), enrollment (se_1), and health outcomes (H_1).[18] These initial condition equations are:

$$b_1^j = b^j(X_1, Z_1, Z_1^{Par}, u_1^B) \quad j = 1, 2, 3 \tag{14}$$

$$s_1 = s(X_1, Z_1, Z_1^{Par}, u_1^S) \tag{15}$$

$$se_1 = se(X_1, Z_1, Z_1^{Par}, u_1^{SE}) \tag{16}$$

$$H_1^k = H^k(X_1, Z_1, Z_1^{Par}, u_1^H) \quad k = 1, 2 \tag{17}$$

These equations include price and supply side variables Z_1 during the first survey wave, and several parental characteristics (Z_1^{Par}) since women are ages 14 through 18 when first observed. The time variation in the Z_t variables identifies the inital conditions. I include the parental variables (Z_1^{Par}) such that the equations are over-identified.

4.8 *Individual Unobserved Heterogeneity and Identification*

I have suggested that individual unobserved heterogeneity (UH) impacts the demand for all the behaviors, health outcomes, and pregnancy outcomes described by equations 3-17. It remains to specify how this UH is related across equations and over time. Genetic endowments are an example of a characteristic unobserved to the econometrician that may affect smoking behavior and birth outcomes (hence forth, referred to as permanent UH). An example of common, time-varying

[16]Some of the variation in initial conditions is eliminated through sample construction. For example, I limit my sample to women who enter having reported never being pregnant.

[17]The three equations capture initial smoking behavior, marijuana use, and ever having drank alcohol. The alcohol measure differs from the measure I use in subsequent time periods because information on drinking intensity is not available prior to when the survey started.

[18]The two equations capture initial BMI and self-reported health status.

UH might be stressful health-related events that are unobserved but affect the demand for particular health behaviors and the production of health capital and birth outcomes (hence forth, referred to as time-varying UH). In addition to correlation through observable variables, it is important - for several reasons - to allow for correlation through unobservables across each of these demand equations. First, it may be the case that common UH impacts health behaviors, health, and also selection into pregnancy. Second, since the behaviors and outcomes are modeled as functions of endogenous explanatory variables, the error terms in the outcome equations may be correlated with the explanatory variables; not accounting for this correlation between explanatory variables and the error term would bias the estimates. Finally, the modeled UH may capture measurement error in dependent variables thus reducing measurement bias in any marginal effects of interest.

I model these likely sources of UH by decomposing the individual unobserved component in each equation j, u_t^j, into three addititively separable parts: a permanent unobserved component, μ^j, a time-varying unobserved component, ν_t^j, and an idiosyncratic shock, ϵ_t^j. The permanent component allows for time-invariant correlation across health behaviors, health outcomes, and pregnancy and birth outcomes within a period and across time. The time-varying component allows for correlation in behaviors and outcomes within a time period. I do not impose a distributional assumption on the permanent (μ) or time-varying (ν_t) components of UH. Rather, I estimate the mass points and weights of a discrete distribution, where each discrete mass point (e.g., a vector of equation specific UH parameters) and their weights are jointly estimated with the other model parameters. This method, termed the discrete factor method, has been shown to have minimal loss of efficiency and bias when the true distribution is normal, and performs much better than a normality assumption if the true distribution of the UH parameters is not normal (Mroz, 1999; Mroz and Guilkey, 1992). The idiosyncratic component is assumed to be Extreme Value or normally distributed depending on the functional form of the likelihood contribution for each equation and is uncorrelated across equations.

The identification of the model technically relies on the semi-parametric distributional assumptions made for each equation discussed (Lewbel, 2019). However, Mroz (1999) and Guilkey and Lance (2014) show that exclusion restrictions aid identification in practice. Therefore, the sources of identification for the jointly estimated system of equations are economically-relevant exclusion restrictions,[19] time-varying exogenous variables,[20] functional form, and normalizations on the non-linear UH error structure. These dynamic equations explain health behavior demand, health production, pregnancy behaviors and outcomes, and birth outcomes for all t, where t denotes a one-year period between survey waves in the data.

4.9 *History of Endogenous Behaviors B_t and Pregnancy Outcomes N_t*

Before I discuss the estimation strategy, it is useful to describe what is included in the vectors that represent the history of endogenous behaviors B_t and the history of pregnancy and birth outcomes N_t. While I observe health behaviors at every age, it would be impossible to include an indicator of smoking states at each age in estimation. Instead, I summarize the history of each behavior, say smoking, by an indicator of whether the woman ever smoked up to period t, smoking status in $t-1$, and years of cessation entering period t. I construct these variables for each behavior. I similarly include one's history of BMI. I also include an interaction for each lagged health behavior and age. This interaction allows me to account for possible changes in the penalty to smoking over the life-cycle. Additionally, I include the prior period's behaviors for sexual activity, birth control, relationship status, enrollment, and employment status. N_t is described by the accumulated number of pregnancies and live births a woman has had entering period t, whether or not she has had any low birth weight births up to t, and whether or not she has had any abortions up to t.

4.10 *Estimation Strategy*

For reference, Table 3 summarizes the set of equations previously discussed. I estimate the parameters of the multiple equation dynamic empirical model via full information maximum likelihood (FIML). In total, 23 probabilities or densities form the likelihood function.[21] The contribution of individual i to the likelihood function is found in Appendix Section 7.3. After obtaining the parameter estimates I quantify the marginal effects of interest through simulation.

By estimating the model using FIML with discrete factor random effects that allow for both

[19] Components of the vector Z_t of economically-relevant supply side variables and prices enter some equations and are theoretically excluded from others conditional on inclusion of the observed endogenous variables.

[20] See, for example, Arellano and Bond (1991).

[21] This set of likelihood components includes 15 behaviors and outcomes, 7 initial conditions, and 1 attrition equation.

Table 3: Specification Summary for Jointly Estimated Equations

Outcome	Explanatory Variables			
	Estimator	Endogenous	Exogenous	Unobserved
Health Behaviors (b_t)				
Any smoking in t	logit	B_t, H_t, C_t, N_t	$X_t, Z_t^B, Z_t^P, Z_t^A, Z_t^O$	$\mu^{b_1}, \nu_t^{b_1}, \epsilon_t^{b_1}$
Any marijuana use in t	logit	B_t, H_t, C_t, N_t	$X_t, Z_t^B, Z_t^P, Z_t^A, Z_t^O$	$\mu^{b_2}, \nu_t^{b_2}, \epsilon_t^{b_2}$
Any alcohol consumption in t	logit	B_t, H_t, C_t, N_t	$X_t, Z_t^B, Z_t^P, Z_t^A, Z_t^O$	$\mu^{b_3}, \nu_t^{b_3}, \epsilon_t^{b_3}$
Other Behaviors (c_t)				
Relationship status in t	mlogit	B_t, H_t, C_t, N_t	$X_t, Z_t^B, Z_t^P, Z_t^A, Z_t^O$	$\mu^r, \nu_t^r, \epsilon_t^r$
Not enrolled in school in t	logit	B_t, H_t, C_t, N_t	$X_t, Z_t^B, Z_t^P, Z_t^A, Z_t^O$	$\mu^{se}, \nu_t^{se}, \epsilon_t^{se}$
Employment status in t	mlogit	B_t, H_t, C_t, N_t	$X_t, Z_t^B, Z_t^P, Z_t^A, Z_t^O$	$\mu^e, \nu_t^e, \epsilon_t^e$
Sexual activities (s_t)				
Any sex in t	logit	B_t, H_t, C_t, N_t	$X_t, Z_t^B, Z_t^P, Z_t^A, Z_t^O$	$\mu^{s_1}, \nu_t^{s_1}, \epsilon_t^{s_1}$
Any birth control conditional on sex in t	logit	B_t, H_t, C_t, N_t	$X_t, Z_t^B, Z_t^P, Z_t^A, Z_t^O$	$\mu^{s_2}, \nu_t^{s_2}, \epsilon_t^{s_2}$
Pregnancy and Birth Outcomes ($P_t, a_t, L_{t+1}, O_{t+1}$)				
Pregnant in t (P_t)	logit	$B_t, H_t, N_t, b_t, s_t, c_t$	X_t, Z_t^P, Z_t^A, Z_t^O	$\mu^P, \nu_t^P, \epsilon_t^P$
Abortion in t conditional on preg. in t (a_t)	logit	$B_t, H_t, N_t, b_t, s_t, c_t$	X_t, Z_t^A, Z_t^O	μ, ν_t, ϵ_t^a
Live birth at end of t conditional on $P_t = 1, a_t = 0$ (L_{t+1})	logit	$B_t, H_t, N_t, b_t, s_t, c_t$	X_t, Z_t^O	$\mu^L, \nu_t^L, \epsilon_t^L$
Gestational age at birth conditional on $L_{t+1} = 1$ (O_{t+1}^1)	OLS	$B_t, H_t, N_t, b_t, s_t, c_t$	X_t, Z_t^O	$\mu^{O^1}, \nu_t^{O^1}, \epsilon_t^{O^1}$
Low birth weight conditional on $L_{t+1} = 1$ (O_{t+1}^2)	logit	$B_t, H_t, N_t, b_t, s_t, c_t$	X_t, Z_t^O	$\mu^{O^2}, \nu_t^{O^2}, \epsilon_t^{O^2}$
Health Outcomes (H_{t+1})				
BMI at end of t	OLS	$B_t, H_t, N_{t+1}, b_t, s_t, c_t$	X_t	$\mu^{H_1}, \nu_t^{H_1}, \epsilon_t^{H_1}$
Self-reported health status at end of t	mlogit	$B_t, H_t, N_{t+1}, b_t, s_t, c_t$	X_t	$\mu^{H_2}, \nu_t^{H_2}, \epsilon_t^{H_2}$

Note: B_t includes histories for b_t, s_t, r_t, se_t, e_t. The set of estimated equations also includes attrition at the end of t and initial conditions ($t = 1$) outlined in equations 14-17.

permanent and time-varying unobserved heterogeneity, I account for potential bias due to selection, endogeneity, and simultaneity. Additionally, I am able to simulate dynamic effects that consider how past behaviors influence other behaviors and outcomes over time.

5 Results

Parameter estimates for variables that explain low birth weight and health behaviors are in Tables 4 - 5.[22] Due to the complex dynamics of the model, the parameter estimates themselves are hard to interpret. It is likely the case, for example, that marijuana and smoking both directly affect the probability of having a low birth weight child, but it might also be the case that the histories of marijuana and smoking have an impact on the probability of getting pregnant or having a live birth. Marginal effects are further complicated by the presence of polynomials and interactions. For these reasons, I conduct several simulations that alter behaviors and outcomes systematically over time to evaluate the effects of past health and health behaviors on the probability of having a low birth weight child as well as selection into pregnancy, abortion, and a live birth.

Table 6 displays the estimated unobserved heterogeneity parameters for all equations. Allowing for correlation across equations allows for specific "types" to emerge of the data. For example, relative to the μ_1 type, a draw of the μ_2 type indicates an individual is more likely to smoke, more likely to engage in sexual activity and not use birth control, and more likely to get pregnant. Additionally, relative to the $\nu_{1,t}$ type, a draw of the $\nu_{2,t}$ type in period t indicates an individual is more likely to smoke, use marijuana, and binge drink in that period. Weights of each discrete mass point vector are also provided in the table.

5.1 Model Fit

To better understand if past health behaviors have any effect on current birth outcomes I use the estimated model and exogenous variables to simulate endogenous health behaviors and outcomes in a particular period t. Then, all endogenous explanatory variables are updated. I use those sim-

[22] I find that four mass points best characterize the distribution of permanent unobserved heterogeneity reflected by the parameters μ_2, μ_3, μ_4 and three mass points that characterize the distribution of time-varying unobserved heterogeneity reflected by the estimated parameter vectors $\nu_{t,2}, \nu_{t,3}$. Mass points μ_1^j and $\nu_{t,1}^j$ are normalized to zero for all equations. The vector $\lambda = [\lambda_1, \lambda_2, \lambda_3, \lambda_4]$ describes the probability weights of μ, and the vector $\phi = [\phi_1, \phi_2, \phi_3]$ describes the probability weights of ν_t.

ulated values to update the endogenous variables and move into year $t+1$. For example, if a woman's simulated number of children entering t is zero, and she has a live birth in t, then entering $t+1$ her number of children is updated to one. In Figure 2, I show that my estimated model captures the profile of health behaviors and BMI over time. To show fit, I use only those women observed to not attrit from the data to demonstrate that my estimated model and exogenous variables can create the same patterns of endogenous variables. For example, in the observed data binge drinking increases until the early twenties with a spike at age 21, and then starts to slowly fall. My model captures the rise, the spike, and the fall.

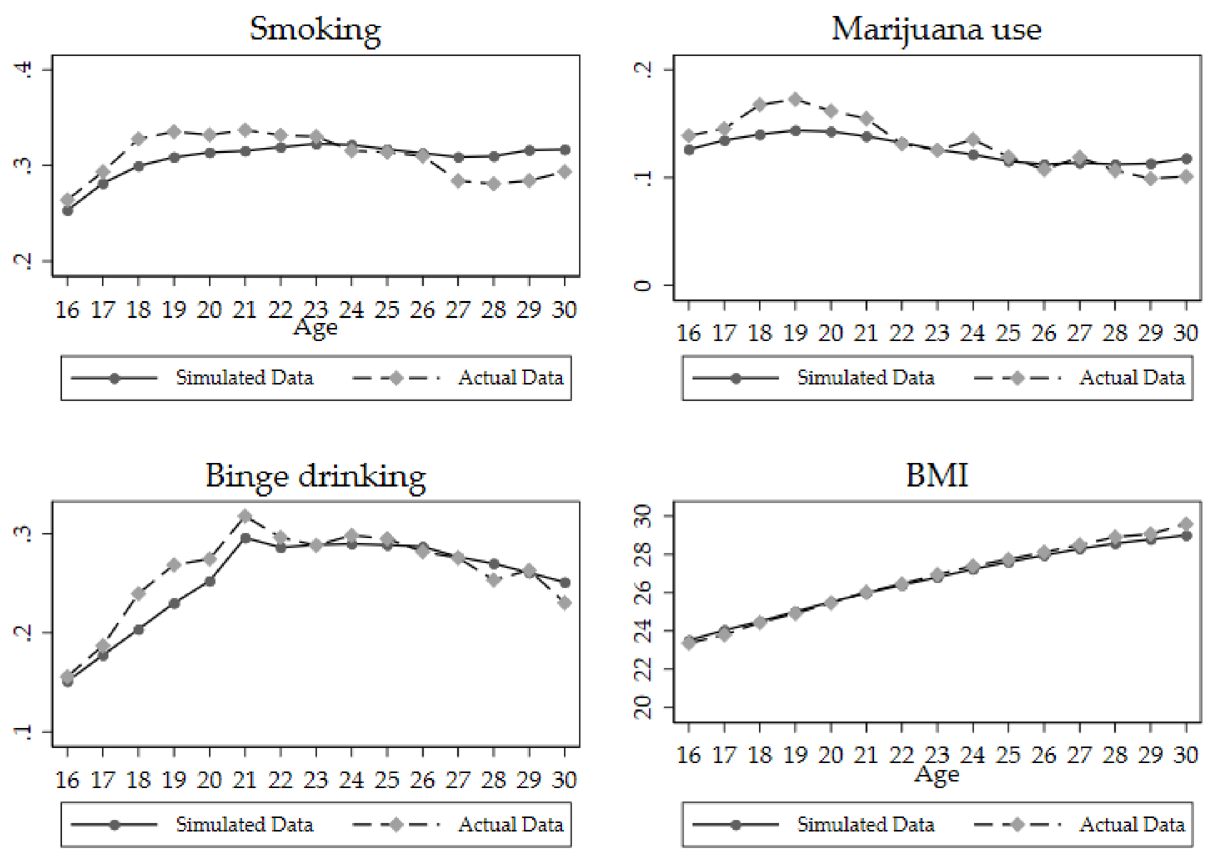

Figure 2: Model fit for key health behaviors and outcomes

Figure 3 demonstrates my estimated model's ability to capture the profile of pregnancies, abortions, live birth rates, and low birth weight rates over time. The ability of my estimated model to capture these variables jointly with health behaviors and health outcomes is important for moving forward to examine the impact of health behaviors and health outcomes on birth outcomes.

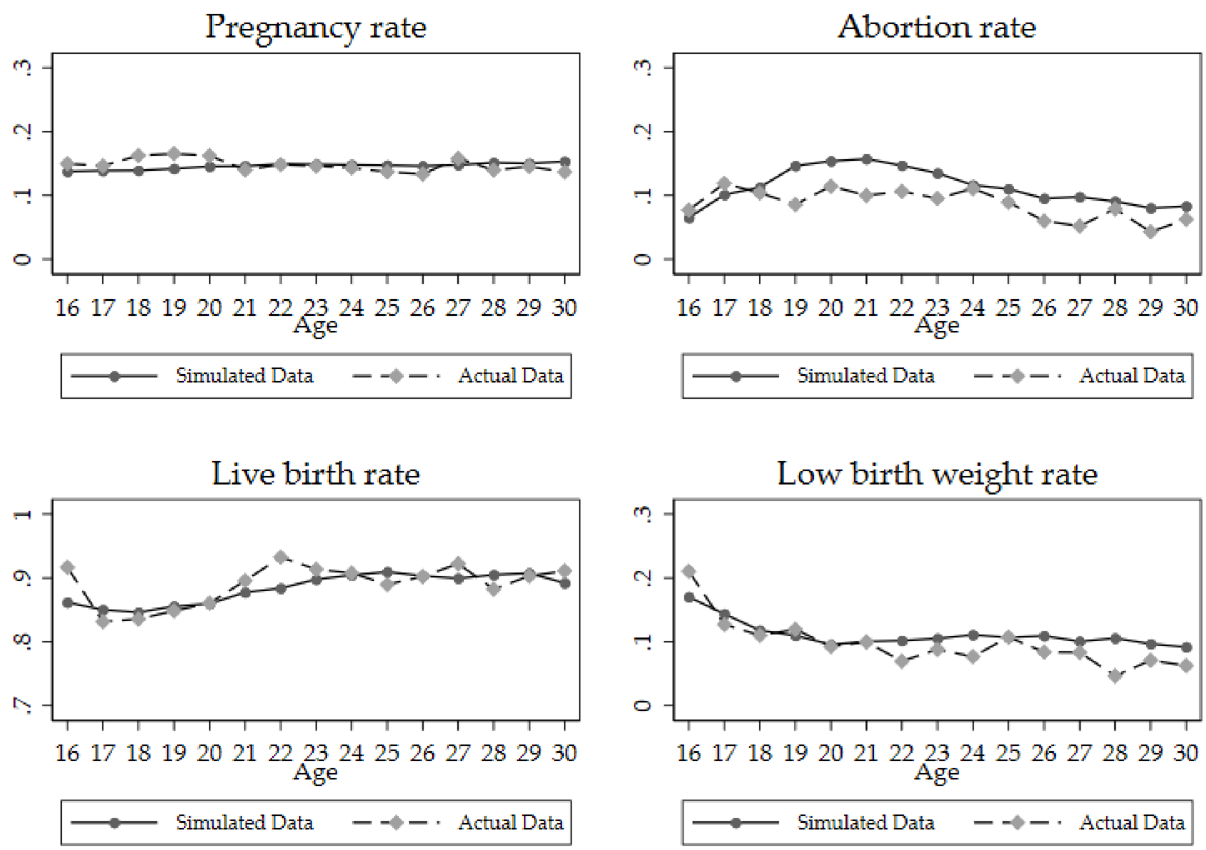

Figure 3: Model fit for pregnancy, abortion, and birth outcomes

To answer whether health behaviors and health outcomes have an impact on birth outcomes, I fix patterns of health behaviors or health outcomes and simulate all other endogenous behaviors and outcomes. To be clear, I simulate just as I do for Figures 2-3, but now I do it for women at every age holding fixed particular behaviors at particular ages. In the body of the paper I focus on cigarette smoking and marijuana use, but results for binge drinking are available in the Appendix.

5.2 *Impact of past smoking behavior on birth outcomes*

First, I compare the probability of having a low birth weight child when women are simulated to always smoke, quit at age 25, quit at age 18, and never smoke. The results of these simulations are in Figure 4. Not surprisingly, I observe a noticeable drop in low birth weight incidence af-

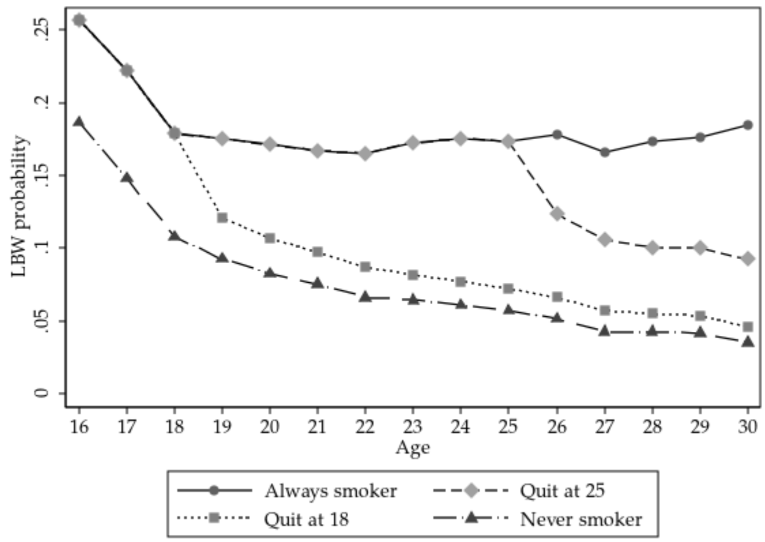

Figure 4: Low birth weight outcomes for different smoking cessation patterns

ter a woman quits smoking. After this initial drop, the gap between smokers and women who stopped smoking at 18 increases steadily. A similar pattern exists for women who stop smoking at age 25. Possibly the most interesting observation, however, is that the rates of LBW do not fully converge for women who stop smoking at age 18 and those who stop smoking at age 25. This finding implies that there are some lingering effects of longer histories of smoking on birth outcomes. If all that mattered was not smoking during pregnancy, there would be no difference in low birth weight probabilities for women who stop at 25, those who stop at 18, or those who never smoke. Smoking behavior is fixed in this simulation exercise. In other words, it is not the case that smoking behavior in one period can influence smoking behavior in the next, and thereby influence birth outcomes indirectly. Hence, Figure 4 shows the *direct* impact of smoking cessation at different periods of time on birth outcomes. The policy implications of these results are important as well. Getting women to stop smoking at 18 as opposed to 25 decreases the likelihood of having a low birth weight child by 46% by the time she reaches 30.

Next, I evaluate whether stopping smoking at each age between 16 and 27 has any differential impact on the probability of having a low birth weight child at age 27. I focus here on the age of 27 because that is the average age at which women have a first birth, but the general pattern holds for all births to adult women. First, I simulate women as smoking until age 16 and then never smoking again and I evaluate what the birth outcomes are for women who have a simulated birth

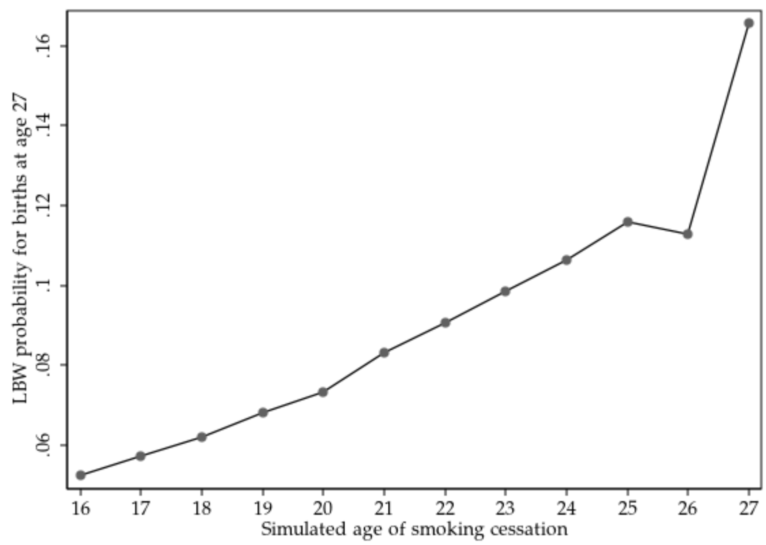

Figure 5: Impact of age of smoking cessation on low birth weight incidence for women giving birth at age 27 and started smoking at age 15

at 27. Then I do this for all ages up to age 27. Figure 5 shows the results of these simulations. As the descriptive evidence indicates , women who stop smoking further away from giving birth are less likely to have a low birth weight child. For example, the difference in probability between quitting at age 20 and age 25 is almost as large as quitting only while pregnant.

While the birth outcome of low birth weight is important, there are other outcomes of interest that could be related to smoking behavior. I also examine the impact that smoking behavior has on the probability of pregnancy, abortion behavior, and the probability of live birth. Parameter estimates from the model for pregnancy, abortion, and live birth are in Table 10 of the Appendix. Additionally, statistics from the simulations that hold the history of smoking fixed are shown in Table 5.2. The first pattern to note is that a long history of smoking lowers the amount of pregnancies that take place. When women are simulated to never quit smoking, the average number of pregnancies is 12.6% lower than when women never smoke, and 20% lower than when women quit smoking at age 18. We see a similar pattern in the live birth rate. Women who always smoke are 14.4% less likely to have a live birth conditional on getting pregnant and not having an abortion than when women never smoke.

5.3 Discussion of mechanisms

In the estimated model, smoking and the history of smoking are allowed to influence birth outcomes directly in the equation estimating the probability of a low birth weight birth, but also indirectly through all other behaviors and outcomes. For example, smoking could have an impact on a woman's demand for sexual activity, which in turn affects her likelihood of getting pregnant and having poor birth outcomes. To examine possible mechanisms through which smoking might affect birth weight I fix the history of smoking and simulate the birth weight outcome for women who actually had pregnancies at the age of 27. This "direct" effect accounts for roughly 60% of the effect the history of smoking has on the probability of a low birth weight birth. However, allowing smoking behavior to have an effect on selection into pregnancy and live birth almost fully explains the differences between the total effect and the direct effect. The results of these simulations are displayed in Figure 6.

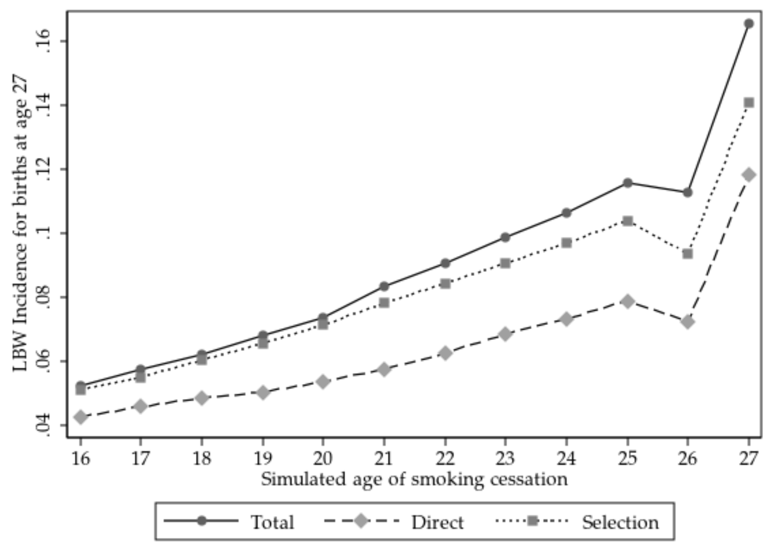

Figure 6: Mechanisms though which the history of smoking affects the probability of low birth weight for women giving birth at age 27

These findings are suggestive as to one of the important mechanisms through which a history of smoking has an effect on the probability of low birth weight. Allowing smoking behavior to influence pregnancy behaviors, the probability of pregnancy, abortion behavior, and the probability of a live birth captures most of the additional impact that smoking has on birth weight throughout the life-cycle. Not accounting for the influence that smoking behavior has on these important aspects of pregnancy and birth may lead to an underestimate of the impact of smoking on birth outcomes.

5.4 *Comparing the impact of marijuana use and smoking on birth weight*

Next, I explore how the history of marijuana use and smoking differ in their impact on birth outcomes. Figure 7 compares the impacts of smoking cessation and marijuana use cessation, again for births at age 27. Unlike smoking, the negative impact of marijuana use is concentrated only in the period during the pregnancy. The difference in pattern between smoking and marijuana use histories is stark. There is a large effect of using marijuana on the probability of low birth weight, but conditional on behavior while pregnant, there is no statistically significant impact of marijuana use behavior on the probability of low birth weight.

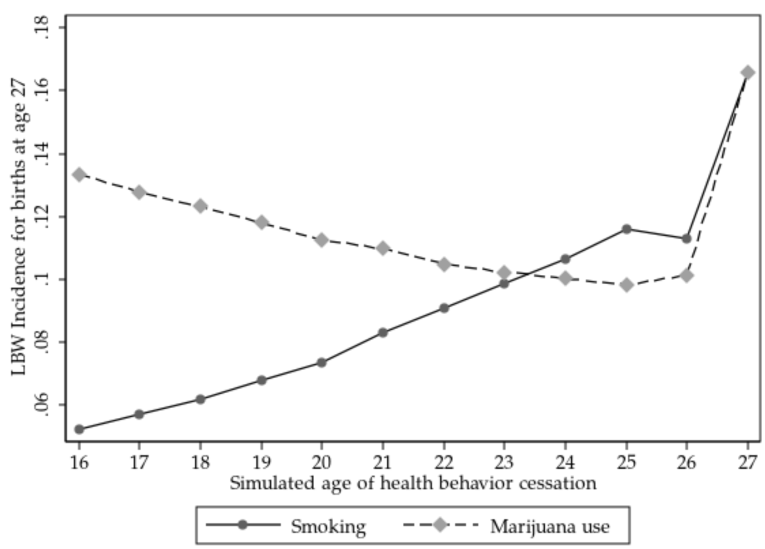

Figure 7: Impact of age of health behavior cessation on low birth weight incidence for women giving birth at age 27 and started the behavior at age 15

6 Conclusion

In this paper I estimate a dynamic system of equations that models health behaviors, health outcomes, behaviors that influence pregnancy, pregnancy itself, abortion, and birth outcomes to evaluate the impact of past health behaviors and outcomes on birth outcomes. In doing so, I am able to isolate a consistent estimate of the effect of past health behaviors conditional on behaviors leading up to and during pregnancy. Additionally, I allow the unobserved components of each estimated equation to be flexibly correlated across equations.

I find that smoking cessation further away from a pregnancy is beneficial in the form of a lower likelihood of giving birth to a low birth weight baby. Specifically, women who give birth at age 30 and quit smoking at age 18 are 50.1% less likely to have a low birth weight birth than women who quit smoking at age 25. That decrease takes into account selection into pregnancy, the abortion decision, and is conditional on a live birth. This result has direct policy repercussions in that it may be worthwhile to target younger populations for behavior changes in hopes of seeing the effect manifest in later life outcomes. This finding supports the ideas laid out in Currie (2020) that the time understudied time that bridges childhood and adulthood is important from a health capital standpoint. I also find that continuing to smoke up to age 30 leads to women getting pregnant less, having more abortions conditional on being pregnant, and a lower likelihood of live birth conditional on being pregnant and not getting an abortion. While my simulated results show that the return is higher as a woman gets closer to pregnancy, there is a noticeable impact of smoking history on birth outcomes. When I apply the same analysis to marijuana use, I find that the negative effects of marijuana use only manifest when the behavior is observed during the pregnancy. This finding suggests that the optimal policy to reduce the incidence of poor birth outcomes may be behavior specific.

Finally, while the underlying structure of the empirical results highlight the impact of risky health behaviors like smoking on the production of birth weight, this paper speaks to the more general importance of thinking about the dynamic formation of behaviors and outcomes over time. For smoking in particular, there is a clear direct and indirect effect of history of use.

Table 4: Probability of low birth weight equation parameters

Variable	Coefficient	Std. Error	Sig.
Smoked cigarettes (t)	0.645	0.241	***
Smoked cigarettes (t-1)	-0.497	1.012	
Ever smoke	0.495	0.285	*
Smoked cigarettes (t-1) x age	0.011	0.046	
Years smoking cessation	-0.096	0.047	**
Used marijuana (t)	0.767	0.336	**
Used marijuana (t-1)	1.101	1.099	
Ever use marijuana	-0.145	0.286	
Used marijuana (t-1) x age	-0.038	0.053	
Years marijuana cessation	0.063	0.044	
Binge drank (t)	0.780	0.297	***
Binge drank (t-1)	-0.014	1.102	
Ever binge drank	-0.570	0.277	**
Binge drank (t-1) x age	0.016	0.051	
Years binge drink cessation	0.087	0.063	
Any sex (t)	0.031	0.350	
Birth control use (t)	0.142	0.185	
BMI (t-1)	-0.003	0.075	
BMI squared uared (t-1)	-0.000	0.001	
Ever poor BMI	-0.000	0.210	
Years healthy BMI	0.057	0.039	
SRHS - Very Good (t-1)	0.166	0.244	
SRHS - Good (t-1)	0.438	0.255	*
SRHS - Fair or Poor (t-1)	0.264	0.364	
Number of Pregnancies	-0.285	0.448	
Number o Live Births	-0.073	0.459	
Ever had LBW birth	2.469	0.273	***
Ever had abortion	-0.088	0.648	
Relationship- Single	0.379	0.209	
Relationship- Cohabitating	-0.476	0.238	*
Not enrolled in school	-0.103	0.275	
Years Education	-0.001	0.050	
Employment- FT PY	-0.287	0.290	**
Employment- PT FY	-0.235	0.311	
Employment- PT PY	-0.062	0.260	
Employment- Not working	-0.079	0.249	
Age	-0.983	0.262	***
Age squared	0.024	0.006	***
Race/Ethnicity Black	0.887	0.213	***
Race/Ethnicity Hispanic	0.479	0.227	**
PCPs per 100,000	2.993	1.142	***
Hospital beds per 100,000	-0.492	0.268	*
Time trend	-0.522	0.354	
Time trend squared	0.102	0.044	**
Time trend cubed	-0.005	0.002	**
Constant	8.661	2.636	***

Table 5: Health behavior equation parameters

	Smoking		Marijuana use		Binge drinking	
	Coef.	SE	Coef.	SE	Coef.	SE
Smoked cigarettes (t-1)	1.776	0.061	0.139	0.071	0.233	0.052
Ever smoke	2.776	0.077	0.697	0.081	0.508	0.055
Years smoking cessation	-0.457	0.016	-0.041	0.014	-0.013	0.009
Used marijuana (t-1)	0.019	0.070	1.302	0.075	0.074	0.057
Ever use marijuana	0.605	0.065	2.341	0.088	0.579	0.055
Years marijuana cessation	-0.027	0.011	-0.389	0.020	-0.048	0.009
Binge drank (t-1)	-0.152	0.067	-0.068	0.076	0.731	0.055
Ever binge drank	0.318	0.070	0.561	0.084	1.731	0.065
Years binge drink cessation	-0.011	0.017	-0.076	0.022	-0.275	0.016
BMI (t-1)	0.037	0.015	-0.001	0.017	0.047	0.014
BMI squared (t-1)	-0.000	0.000	0.000	0.000	-0.001	0.000
Ever poor BMI	0.072	0.047	0.096	0.054	-0.094	0.040
Years healthy BMI	-0.014	0.009	-0.004	0.010	0.019	0.008
SRHS - Very Good (t-1)	0.039	0.051	0.094	0.060	0.040	0.043
SRHS - Good (t-1)	0.038	0.059	0.083	0.068	0.036	0.052
SRHS - Fair or Poor (t-1)	0.030	0.084	-0.036	0.097	-0.166	0.076
Any sex (t-1)	0.012	0.077	0.336	0.091	0.200	0.067
Birth control use (t-1)	0.045	0.063	-0.096	0.074	0.071	0.054
Number Pregnancies	0.439	0.082	0.097	0.085	0.141	0.063
Number Live Births	-0.341	0.086	-0.161	0.091	-0.219	0.067
Ever had LBW birth	0.157	0.124	-0.343	0.164	0.056	0.117
Ever had abortion	-0.484	0.130	0.175	0.137	-0.203	0.104
Pregnant (t-1)	-0.812	0.104	-0.620	0.114	-0.859	0.087
Relationship - Single (t-1)	0.399	0.068	0.361	0.086	0.612	0.056
Relationship - Cohabitating (t-1)	0.367	0.074	0.400	0.093	0.459	0.062
Years Education	-0.091	0.013	-0.014	0.014	0.034	0.011
Employment - FT PY (t-1)	0.144	0.057	0.156	0.065	0.003	0.046
Employment - PT FY (t-1)	0.198	0.086	-0.003	0.103	-0.080	0.072
Employment - PT PY (t-1)	0.180	0.064	0.146	0.073	0.035	0.053
Employment - Not working (t-1)	0.056	0.097	0.073	0.113	-0.231	0.084
Cigarette prices	0.017	0.038	-0.148	0.044	0.054	0.031
Cigarette packs per capita	-0.237	0.138	-0.279	0.158	-0.134	0.122
Rate of marijuana use	-0.003	0.016	0.079	0.018	0.002	0.013
Wine prices	0.048	0.025	-0.016	0.029	-0.038	0.021
Beer prices	-0.004	0.029	0.006	0.033	0.022	0.026
Avg college tuition	3.354	1.009	1.565	1.024	0.204	1.003
Grocery Store Price Index	0.007	0.213	0.179	0.247	0.162	0.194
Grocery stores per 100,000	0.283	0.231	-0.296	0.257	-0.125	0.205
Farmers markets per 100,000	-2.873	1.038	2.866	1.063	-2.833	1.035
Gyms per 100,000	-0.307	0.495	0.700	0.607	0.766	0.441
Parks per 100,000	-0.081	0.028	0.038	0.034	0.002	0.024
Unemployment Rate	-0.204	0.093	-0.146	0.110	-0.238	0.076
Sex ratio	0.754	0.261	-0.823	0.321	0.097	0.235
Percent access to abortion clinic	0.535	0.163	-0.385	0.184	-0.064	0.142
PCPs per 100,000	0.074	0.865	0.037	0.957	0.777	0.739
Hospital beds per 100,000	0.113	0.064	0.130	0.077	0.208	0.055
Missing market vars	0.322	0.191	-0.517	0.244	-0.380	0.186
Time trend	-0.089	0.108	0.301	0.124	-0.270	0.091
Time trend squared	0.006	0.013	-0.042	0.015	0.028	0.011
Time trend cubed	-0.000	0.001	0.002	0.001	-0.001	0.000
Constant	-5.692	1.532	0.515	0.989	-5.173	0.883

Notes: Demographic characteristics aren't shown for the sake of spacing but are available upon request.

Table 6: Unobserved heterogeneity parameter estimates

	Estimated mass points				
	Permanent			Time-varying	
	μ_2	μ_3	μ_4	ν_2	ν_3
Smoking	0.564	-0.121	-0.106	0.062	2.710
	(0.074)	(0.073)	(0.217)	(0.113)	(0.087)
Binge Drinking	-0.054	0.370	1.247	0.212	2.685
	(0.064)	(0.064)	(0.199)	(0.107)	(0.086)
Marijuana use	0.055	-0.043	-1.874	0.247	2.685
	(0.077)	(0.087)	(0.233)	(0.134)	(0.090)
BMI	-0.247	-0.118	8.111	6.549	-0.137
	(0.038)	(0.035)	(0.409)	(0.082)	(0.083)
SRHS - Very good	-0.673	-1.668	-3.734	0.190	0.021
	(0.064)	(0.057)	(0.289)	(0.112)	(0.110)
SRHS - Good	-1.081	-2.847	-3.532	0.346	-0.101
	(0.082)	(0.057)	(0.251)	(0.123)	(0.141)
SRHS - Fair or poor	-1.779	-3.740	-3.276	0.577	-0.308
	(0.106)	(0.125)	(0.327)	(0.157)	(0.202)
Any sex	0.515	0.091	-2.671	0.482	0.889
	(0.060)	(0.058)	(0.170)	(0.107)	(0.066)
Birth control use	-0.564	0.094	-1.453	-0.423	0.458
	(0.076)	(0.070)	(0.205)	(0.099)	(0.078)
Employment - FT PY	-0.686	-0.050	-4.527	-0.091	-0.080
	(0.059)	(0.063)	(0.177)	(0.108)	(0.068)
Employment - PT FY	0.042	-0.041	-7.659	0.043	-0.209
	(0.078)	(0.085)	(0.302)	(0.154)	(0.101)
Employment - PT PY	-0.602	-0.013	-4.364	0.057	-0.043
	(0.068)	(0.070)	(0.259)	(0.127)	(0.077)
Employment - Not working	-0.379	-0.055	-3.037	0.241	-0.224
	(0.068)	(0.075)	(0.209)	(0.125)	(0.083)
Relationship - Single	0.763	0.111	-2.908	0.553	-1.122
	(0.091)	(0.094)	(0.275)	(0.161)	(0.141)
Relationship - Cohabitating	0.715	-0.113	-1.935	0.443	-0.515
	(0.069)	(0.074)	(0.223)	(0.118)	(0.088)
Not enrolled in school	2.194	0.065	-1.707	0.408	-0.105
	(0.063)	(0.058)	(0.157)	(0.101)	(0.063)
Pregnant	0.083	-0.051	-4.298	1.212	0.964
	(0.065)	(0.064)	(0.172)	(0.097)	(0.156)
Abortion	-0.069	0.355	-8.619	-0.435	0.019
	(0.243)	(0.260)	(0.699)	(0.411)	(0.462)
Live birth	-0.234	0.012	8.121	1.699	1.429
	(0.217)	(0.270)	(0.953)	(0.571)	(0.450)
Low birth weight	-0.098	-0.280	-10.195	-1.360	-2.231
	(0.244)	(0.306)	(0.924)	(0.523)	(0.541)
Gestational age at birth	0.236	0.054	-0.057	-1.099	1.397
	(0.287)	(0.291)	(0.953)	(0.704)	(0.350)
Estimated probability weight	0.331	0.318	0.001	0.035	0.217

Notes: Standard errors are in parentheses. The first mass points (μ_1, ν_1) are normalized to zero and have probability weights of 0.352 and 0.748, respectively. Unobserved heterogeneity also enters the attrition and initial condition equations.

Table 7: Impact of different smoking histories on cumulative pregnancy outcomes at age 30

Measure	Never smoker	Quit at 18	Quit at 25	Always smoker
Number of pregnancies	1.353	1.472	1.427	1.184
Number of LBW births	0.068	0.096	0.148	0.139
Number of abortions	0.110	0.154	0.156	0.158
Number of live births	1.085	1.222	1.043	0.791

Notes: Each measure is calculated using the simulated data for different histories of smoking. All numbers are calculated for women simulated through the age of 30. As an example, the average number of pregnancies when women are fixed to never smoke is 1.353, and it is 1.184 when they always smoke.

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7 Appendix

7.1 Data

7.1.1 Market level data details

I augment the individual level survey data with market level characteristics that aid in identification. Supply side and market level variables that shift health behaviors that have no independent effect on pregnancy and birth outcomes conditional on the behaviors include cigarette prices, per capita cigarette pack consumption, alcohol prices, marijuana use rates, a grocery store price index, and per capita measures for number of grocery stores, gyms, and parks. Sex ratios are included to help identify the pregnancy behaviors. Unemployment rates, per capita rates of state colleges and community colleges, and average tuition are included to identify other confounders. Finally, access to abortion clinics, and hospital bed and primary care rates are used to aid in identifying abortion and birth outcome equations. The market characteristics are summarized in Table 8.

When a year is unavailable, I impute the value by taking the average of the two closest years if there are years on either side of the year. Otherwise, I take the closest available year and extrapolate.

Table 8: Market Data Description

Variable	Data Source	Observation Level	Years Available
Related to health behaviors			
Cigarette prices	TBT Data	County	1997-2011
Cigarette packs consumed per capita	TBT Data	County	1997-2011
Rate of marijuana use	NSDUH	State	2002-2011
Wine prices	ACCRA	CBSA	1997-2011
Beer prices	ACCRA	CBSA	1997-2011
Grocery store price index	ACCRA	CBSA	1997-2011
Num. grocery stores per 100,000	CBP	County	1997-2011
Num. gyms per 100,000	CBP	County	1997-2011
Num. parks per 100,000	CBP	County	1997-2011
Num. farmers markets per 100,000	CBP	County	1997-2011
Related to pregnancy behaviors			
Sex ratios	Census Bureau	County	1997-2011
Population	Census Bureau	County, CBSA, State	1997-2011
Related to confounders			
Unemployment Rate	NLSY97	County	1997-2011
State colleges per 100,000	CBP	County	1997-2011
Community colleges per 100,000	CBP	County	1997-2011
Average tuition in 1000s of dollars	NCES	State	2000-2011
Related to abortion/birth outcomes			
Percent with access to abortion clinic	Guttmacher Institute	State	2000, 2005, 2008, 2011
Primary care providers per 100,000	AHRF	County	1997-2011
Hospital beds per 100,000	AHRF	County	1997-2011

7.1.2 Health behavior data details

In each survey wave, NLSY97 respondents are asked whether they have smoked a cigarette, and then there are follow up questions about frequency and intensity of use. I define a woman as being a smoker in the period if she had smoked a cigarette at least once in the 30 days leading up to the interview. Similarly, respondents are asked if they use marijuana, then there are follow up questions about frequency and intensity of use. I define a woman as using marijuana in the period if she had used marijuana at least once in the 30 days leading up to the interview. Respondents are also asked how many days they've had (if any) at least five drinks in the 30 days leading up to the interview. This measure is used to determine binge drinking. The CDC defines binge drinking for women to be an occasion on which they have at least four drinks and this measure in the survey is the closest to that definition.

7.1.3 Pregnancy and live birth data details

In every survey wave, NLSY97 women are asked whether they have ever had sexual intercourse. If they answer yes, then they are asked questions about birth control and any pregnancies. For pregnancy, they are first asked if they have been pregnant since the date of the last interview, and then they are asked if they are currently pregnant. I also utilize information on birth dates when there is a reported biological child in the household with no matching pregnancy. To determine in what survey wave a pregnancy occurred, I use the survey interview date, birth dates, and if a pregnancy is reported to have ended, any date information that is provided.[23] Below is the priority list for pregnancy assignment.

- If a woman answers yes to being currently pregnant, she is pregnant in that survey wave.
- If a woman answers yes to having been pregnant since the date of the last interview (DLI), and a date can be provided based on her follow up responses or a birth date, she is assigned to be pregnant on whichever survey wave is closest to her approximate pregnancy start date.
- If a woman reports having a child with a birth date in between survey waves, the pregnancy is assigned to whichever survey is closest to her approximate pregnancy start date.

[23] If a woman reports that a pregnancy ended between survey dates, there is a follow up question asking what month and year it ended.

- If a woman answers yes to having been pregnant since the DLI, but no further date can be provided to determine when the pregnancy started, the pregnancy is assigned to the previous survey wave.

Once a pregnancy is assigned to a survey wave, the pregnancy outcome is assigned to the next survey wave.

7.1.4 Estimation Sample

The estimation sample includes women who (1) provide at least two consecutive years of data and (2) have not been pregnant prior to the first observed year of data. All consecutive years of data are included until the first year of non-response to important dependent variables. Specifically, if there is no recorded answer to whether or not a respondent has smoked, used marijuana, or drank alcohol in the last 30 days then that year and all subsequent years are dropped. This leaves 3,675 women (84% of full sample) who contribute 40,797 person-years of data.

Table 9: Comparison of estimation sample and excluded sample by select variables

Variable	Estimation Sample	Full Sample	Mean Difference
Age	15.85	15.90	−0.040
Race: White	0.534	0.514	0.020*
Race: Black	0.265	0.276	−0.010
Hispanic[24]	0.201	0.211	−0.010
BMI	22.47	22.55	−0.082
Any sex	0.287	0.307	−0.020*
Any birth control	0.266	0.291	−0.025**
Any smoking	0.257	0.254	0.004
Any marijuana use	0.106	0.102	0.004
Any binge drinking	0.144	0.130	0.013*

Notes: Column 1 and 2 report means of selected variables for each sample at the first survey wave. Column 3 reports statistical significance of T-tests for difference in means between the two samples. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

At the time of the first survey wave the women entering estimation are slightly more likely to be white, are less likely to have had sex, are less likely to have used birth control, and are slightly more likely to have binge drank than the full sample.

7.2 Derived Empirical Model

Below I depict a woman's optimization problem during her fecund years in the form of a Bellman equation where the woman decides about her health behaviors, sexual activity, and abortion. The information set, Ω_t includes the vector B_t of health behavior histories up to period t that affect her own health outcome(s) (H_t) entering period t, the vector N_t of the histories of pregnancies and children, the vector X_t of exogenous demographic characteristics in t, and a vector of exogenous prices and supply side characteristics, Z_t, that also influence values of each alternative. The lifetime values of behaviors $(b_t = b)$, sexual activities $(s_t = s)$, and abortion $(a_t = a)$ at time t, given information Ω_t, are:

$$
\begin{aligned}
V^{bsa}(\Omega_t, u_t) = \sum_{p=0} & p(P_t = p)U(b_t, c_t, l_t, s_t, a_t; H_t, N_t, P_t = p) + u_t^{bsa} + \\
& \beta\Big[(1 - a_t)[(1 - p(L_{t+1} = 1) \sum_{h=0}^{H} p(H_{t+1} = h)V(\Omega_{t+1}|N_{t+1} = N_t) + \\
& \int_{O^1}\int_{O^2} p(L_{t+1} = 1) \sum_{h=0}^{H} p(H_{t+1} = h)V(\Omega_{t+1}|N_{t+1} = N_t + 1)]df(O^1)df(O^2)] + \\
& a_t \cdot \sum_{h=0}^{H} p(H_{t+1} = h)V(\Omega_{t+1}|N_{t+1} = N_t)\Big] \quad t = 1..., T^F
\end{aligned}
\tag{18}
$$

where utility is constrained by a per-period time and budget constraint.[25] The uncertainties of a woman's $t + 1$ health evolution (H_{t+1}) and her birth outcomes (L, O^1, O^2) impact her b, s, a decisions in t. The probabilities of health outcomes, live birth, and birth outcomes depend on elements of the updated state space, Ω_{t+1}, and are delineated in equations 6-9 of Section 7.2 of the main paper. The parameter β reflects how much a woman discounts her future outcomes. $V(\Omega_{t+1})$ is the maximal expected value of lifetime utility in period $t + 1$. T^F marks the end of her fertile period. Rather than model all decisions after the fertile period, $t = T^{F+1}, ..., T$, the theoretical motivation simply assumes that the future value, $V(\Omega_{T^F+1})$, is a function of the state vector at the end of T^F. Women choose the combination of alternatives b, s, a that maximizes the value of lifetime utility at each period t. The resulting demand equations depend on all information available to the woman

[25]The prices of health behaviors enter the budget constraint, and supply-side exogenous factors that affect health behaviors may enter the time constraint or augment the utility derived from each behavior.

at the point of decisionmaking, summarized by $\Omega_t = [B_t, H_t, N_t, X_t, Z_t]$.

7.3 Likelihood Function

The vector Θ defines the parameters of the model and all probabilities are represented by a logit or multinomial logit specification. The unconditional likelihood function for an individual i is:

$$
\begin{aligned}
\mathcal{L}_i(\Theta) = \sum_{m=1}^{J} \lambda_m & \prod_{h^1=0}^{1} Pr(H_1^1 = h^1 | \mu_m^{H^1}) \cdot \prod_{h^2=0}^{1} Pr(H_1^2 = h^2 | \mu_m^{H^2}) \cdot \prod_{s^1=0}^{1} Pr(s_1 = s | \mu_m^{s}) \\
& \cdot \prod_{b^1=0}^{1} Pr(b_1^1 = b^1 | \mu_m^{b^1}) \cdot \prod_{b^2=0}^{1} Pr(b_1^2 = b^2 | \mu_m^{b^2}) \cdot \prod_{b^3=0}^{1} Pr(b_1^3 = b_3 | \mu_m^{b^3}) \cdot \prod_{se=0}^{1} Pr(se_1 = se | \mu_m^{se}) \\
& \cdot \prod_{t=1}^{T} \Bigg[\sum_{k=1}^{K} \phi_k \prod_{b^1=0}^{1} Pr(b_t^1 = b^1 | \mu_m^{b^1}, \nu_{k,t}^{b^1}) \cdot \prod_{b^2=0}^{1} Pr(b_t^2 = b^2 | \mu_m^{b^2}, \nu_{k,t}^{b^2}) \cdot \prod_{b^3=0}^{1} Pr(b_t^3 = b^3 | \mu_m^{b^3}, \nu_{k,t}^{b^3}) \\
& \cdot \prod_{s^1=0}^{1} Pr(s_t^1 = s^1 | \mu_m^{s^1}, \nu_{k,t}^{s^1}) \cdot \prod_{s^2=0}^{1} Pr(s_t^2 = s^2 | \mu_m^{s^2}, \nu_{k,t}^{s^2}) \\
& \cdot \prod_{r=0}^{2} Pr(r_t = r | \mu_m^{r}, \nu_{k,t}^{r}) \cdot \prod_{se=0}^{1} Pr(se_t = se | \mu_m^{se}, \nu_{k,t}^{se}) \cdot \prod_{e=0}^{3} Pr(e_t = e | \mu_m^{e}, \nu_{k,t}^{e}) \\
& \cdot \prod_{p=0}^{1} Pr(P_t = p | \mu_m^{P}, \nu_{k,t}^{P}) \cdot \prod_{a=0}^{1} Pr(a_t = a | \mu_m^{a}, \nu_{k,t}^{a}, P_t = 1) \cdot \prod_{l=0}^{1} Pr(L_{t+1} = l | \mu_m^{L}, \nu_{k,t}^{L}, P_t = 1, a_t = 0) \\
& \cdot f^{O^1}(O_{t+1}^1 | \mu_m^{O^1}, \nu_{k,t}^{O^1}, P_t = 1, a_t = 0, L_{t+1} = 1) \cdot \prod_{o^2=0}^{1} Pr(O_{t+1}^2 = l | \mu_m^{O^2}, \nu_{k,t}^{O^2}, P_t = 1, a_t = 0, L_{t+1} = 1) \\
& \cdot f^{H_1}(H_{t+1}^1 | \mu_m^{H^1}, \nu_{k,t}^{H^1}) \cdot \prod_{H^2=0}^{3} Pr(H_{t+1}^2 | \mu_m^{H^2}, \nu_{k,t}^{H^2}) \Bigg]
\end{aligned}
$$

7.4 Model Estimates

Table 10 displays model estimates for the probability of pregnancy, the probability of live birth, and the probability of an abortion. Table 11 displays model estimates for the BMI equation, and Table 12 displays model estimates for self-reported health status.

Table 10: Pregnancy, abortion, and live birth equation parameters

	Pregnancy		Abortion		Live Birth	
	Coef.	SE	Coef.	SE	Coef.	SE
Smoked cigarettes (t)	-0.710	0.069	0.097	0.241	-0.811	0.223
Smoked cigarettes (t-1)	1.147	0.267	-0.401	0.993	1.771	0.943
Ever smoke	0.257	0.071	-0.286	0.275	0.132	0.264
Smoked cigarettes (t-1) x age	-0.036	0.012	0.039	0.045	-0.087	0.043
Years smoking cessation	-0.029	0.011	0.038	0.043	-0.005	0.039
Used marijuana (t)	-0.612	0.081	0.179	0.259	-1.143	0.250
Used marijuana (t-1)	0.664	0.346	1.018	1.151	-1.123	0.997
Ever use marijuana	0.272	0.070	0.352	0.246	0.651	0.250
Used marijuana (t-1) x age	-0.023	0.016	-0.043	0.053	0.031	0.046
Years marijuana cessation	-0.037	0.011	0.046	0.041	-0.078	0.039
Binge drank (t)	-1.005	0.079	0.608	0.241	-1.502	0.232
Binge drank (t-1)	-0.365	0.303	-0.579	1.020	-1.298	0.984
Ever binge drank	0.283	0.069	-0.424	0.257	0.094	0.235
Binge drank (t-1) x age	0.014	0.013	0.077	0.045	0.024	0.043
Years binge drink cessation	-0.064	0.016	0.130	0.063	-0.067	0.054
Any sex (t)			-0.150	0.331	0.458	0.280
Birth control use (t)	-0.626	0.047	0.462	0.194	-0.087	0.171
BMI (t-1)	0.075	0.019	-0.023	0.086	0.011	0.064
BMI squared (t-1)	-0.001	0.000	-0.000	0.002	-0.000	0.001
Ever poor BMI	0.024	0.051	0.250	0.190	0.083	0.184
Years healthy BMI	0.004	0.009	-0.060	0.039	0.003	0.036
SRHS - Very Good (t-1)	-0.012	0.054	-0.149	0.206	-0.104	0.219
SRHS - Good (t-1)	0.042	0.061	0.148	0.220	-0.454	0.230
SRHS - Fair or Poor (t-1)	0.093	0.082	0.099	0.297	-0.988	0.284
Number Pregnancies	0.185	0.068	-0.160	0.232	-0.407	0.192
Number Live Births	-0.154	0.070	0.228	0.243	0.499	0.205
Ever had LBW birth	0.179	0.096	-0.182	0.367	-0.431	0.297
Ever had abortion	0.029	0.110	0.718	0.328	0.462	0.342
Pregnant (t-1)	-0.726	0.090				
Relationship- Single	-0.820	0.054	2.001	0.248	-1.359	0.199
Relationship- Cohabitating	-0.423	0.056	1.360	0.259	-0.421	0.218
Not enrolled in school	-0.807	0.059	0.082	0.211	-0.720	0.204
Years Education	-0.014	0.012	0.132	0.051	-0.071	0.043
Employment- FT PY	-0.023	0.055	0.390	0.194	-0.134	0.202
Employment- PT FY	0.170	0.077	-0.759	0.290	0.556	0.252
Employment- PT PY	0.068	0.064	-0.229	0.225	0.848	0.233
Employment- Not working	0.104	0.065	-0.798	0.242	1.335	0.234
Age	-0.143	0.088	0.554	0.383	-0.333	0.276
Age squared	0.002	0.002	-0.012	0.008	0.007	0.006
Race/Ethnicity Black	0.471	0.051	0.019	0.186	-0.346	0.181
Race/Ethnicity Hispanic	0.115	0.053	-0.332	0.208	-0.338	0.192
Sex ratio	0.398	0.248				
Percent access to abortion clinic	-0.070	0.092	-2.067	0.350		
PCPs per 100,000	0.989	0.903	-11.522	5.537	4.681	1.172
Hospital beds per 100,000	0.070	0.063	0.102	0.252	0.327	0.233
Time trend	0.132	0.084	0.878	0.368	-0.336	0.312
Time trend squared	-0.024	0.010	-0.116	0.045	0.068	0.038
Time trend cubed	0.001	0.000	0.004	0.002	-0.003	0.002
Constant	-0.009	1.004	-12.003	4.354	7.752	2.988

Table 11: BMI equation parameters

	Coefficient	Std. Error
Smoked cigarettes (t)	-0.097	0.043
Smoked cigarettes (t-1)	0.093	0.151
Ever smoke	-0.026	0.041
Smoked cigarettes (t-1) x age	0.003	0.007
Years smoking cessation	0.008	0.007
Used marijuana (t)	-0.064	0.047
Used marijuana (t-1)	-0.094	0.200
Ever use marijuana	-0.120	0.044
Used marijuana (t-1) x age	0.006	0.009
Years marijuana cessation	0.009	0.008
Binge drank	0.064	0.041
Binge drank (t-1)	0.064	0.171
Ever binge drank	-0.110	0.043
Binge drank (t-1) x age	0.003	0.007
Years binge drink cessation	0.008	0.012
Any sex (t)	0.188	0.046
Birth control use (t)	-0.135	0.039
BMI (t-1)	0.905	0.011
BMI squared (t-1)	0.000	0.000
Ever poor BMI	0.146	0.029
Years healthy BMI	-0.048	0.006
SRHS - Very Good (t-1)	0.023	0.030
SRHS - Good (t-1)	0.028	0.034
SRHS - Fair or Poor (t-1)	0.051	0.051
Abortion (t)	-0.015	0.131
LBW birth (t)	0.130	0.153
Number Pregnancies	-0.008	0.045
Number Live Births	-0.113	0.047
Ever had LBW birth	0.155	0.072
Ever had abortion	-0.019	0.075
Live birth (t)	-0.239	0.064
Pregnant (t)	0.429	0.045
Relationship- Single	-0.132	0.037
Relationship- Cohabitating	0.035	0.043
Not enrolled in school	-0.066	0.031
Years Education	-0.041	0.008
Employment- FT PY	-0.041	0.033
Employment- PT FY	-0.017	0.052
Employment- PT PY	-0.014	0.039
Employment- Not working	-0.111	0.040
Age	0.026	0.045
Age squared	-0.001	0.001
Race/Ethnicity Black	0.205	0.029
Race/Ethnicity Hispanic	0.088	0.030
Time trend	-0.091	0.043
Time trend squared	0.012	0.006
Time trend cubed	-0.000	0.000
Constant	2.95789	0.4527

Table 12: Self-reported health status equation parameters

	Very Good		Good		Fair or Poor	
	Coef.	SE	Coef.	SE	Coef.	SE
Smoked cigarettes (t)	0.206	0.057	0.444	0.069	0.721	0.098
Smoked cigarettes (t-1)	0.265	0.228	0.675	0.255	0.265	0.361
Ever smoke	-0.077	0.061	-0.016	0.075	0.073	0.107
Smoked cigarettes (t-1) x age	-0.009	0.010	-0.031	0.012	-0.019	0.016
Years smoking cessation	0.009	0.010	-0.018	0.012	-0.030	0.018
Used marijuana (t)	0.162	0.066	0.262	0.078	0.418	0.108
Used marijuana (t-1)	0.109	0.312	0.498	0.351	0.943	0.481
Ever use marijuana	0.135	0.067	0.103	0.080	0.161	0.110
Used marijuana (t-1) x age	-0.011	0.014	-0.031	0.016	-0.052	0.022
Years marijuana cessation	-0.017	0.011	-0.013	0.013	-0.024	0.018
Binge drank (t)	0.062	0.056	0.100	0.069	0.059	0.099
Binge drank (t-1)	-0.036	0.253	-0.029	0.292	0.790	0.417
Ever binge drank	0.028	0.066	0.116	0.078	0.003	0.106
Binge drank (t-1) x age	0.002	0.011	-0.003	0.013	-0.036	0.018
Years binge drink cessation	-0.004	0.016	-0.012	0.018	-0.008	0.024
Any sex (t)	0.047	0.068	0.331	0.078	0.376	0.105
Birth control use (t)	0.055	0.056	-0.118	0.063	-0.023	0.084
BMI (t-1)	0.060	0.019	0.065	0.021	0.076	0.025
BMI squared (t-1)	-0.001	0.000	-0.000	0.000	-0.000	0.000
Ever poor BMI	0.146	0.046	0.263	0.054	0.406	0.075
Years healthy BMI	-0.012	0.009	-0.031	0.011	-0.048	0.015
SRHS - Very Good (t-1)	1.250	0.042	1.075	0.050	0.799	0.094
SRHS - Good (t-1)	1.085	0.051	1.899	0.055	1.909	0.092
SRHS - Fair or Poor (t-1)	0.872	0.101	2.051	0.098	3.488	0.120
Abortion (t)	-0.109	0.194	-0.222	0.216	-0.368	0.303
LBW birth (t)	0.495	0.243	0.646	0.258	0.681	0.341
Num Pregnancies	0.080	0.087	0.134	0.097	0.217	0.114
Num Live Births	-0.063	0.091	-0.073	0.101	-0.142	0.119
Ever had LBW birth	0.056	0.130	0.101	0.143	0.356	0.169
Ever had abortion	-0.044	0.134	0.027	0.150	-0.112	0.189
Live birth (t)	-0.287	0.109	-0.314	0.122	-0.738	0.156
Pregnant (t)	-0.076	0.057	-0.057	0.064	-0.047	0.089
Relationship- Single	-0.002	0.056	0.135	0.067	0.240	0.092
Relationship- Cohabitating	0.113	0.064	0.186	0.075	0.347	0.102
Not enrolled in school	0.148	0.044	-0.034	0.052	-0.361	0.077
Years Education	0.029	0.012	-0.047	0.014	-0.198	0.020
Employment- FT PY	0.053	0.047	0.050	0.057	0.215	0.083
Employment- PT FY	-0.074	0.074	-0.038	0.084	0.236	0.116
Employment- PT PY	-0.034	0.056	-0.027	0.065	0.296	0.093
Employment- Not working	-0.136	0.059	-0.054	0.068	0.292	0.094
Age	-0.222	0.064	-0.192	0.073	0.103	0.099
Age squared	0.005	0.001	0.005	0.002	-0.001	0.002
Race/Ethnicity Black	-0.154	0.050	0.084	0.064	0.313	0.085
Race/Ethnicity Hispanic	0.033	0.052	0.280	0.067	0.327	0.090
Time trend	0.162	0.061	0.198	0.071	0.311	0.106
Time trend squared	-0.011	0.008	-0.017	0.009	-0.028	0.013
Time trend cubed	0.000	0.000	0.001	0.000	0.001	0.001
Constant	0.781	0.656	0.153	0.747	-3.873	0.978

Notes: The category of comparison is self-reported health status of "Excellent".

7.5 Other Simulations

In this section, I discuss other simulations that were considered. The simulation process is the same process described in the main paper.

Figure 8 compares the impact of a history of smoking, marijuana use, and binge drinking. The impact of a history of binge drinking follows a similar pattern as the impact of a history of marijuana use.

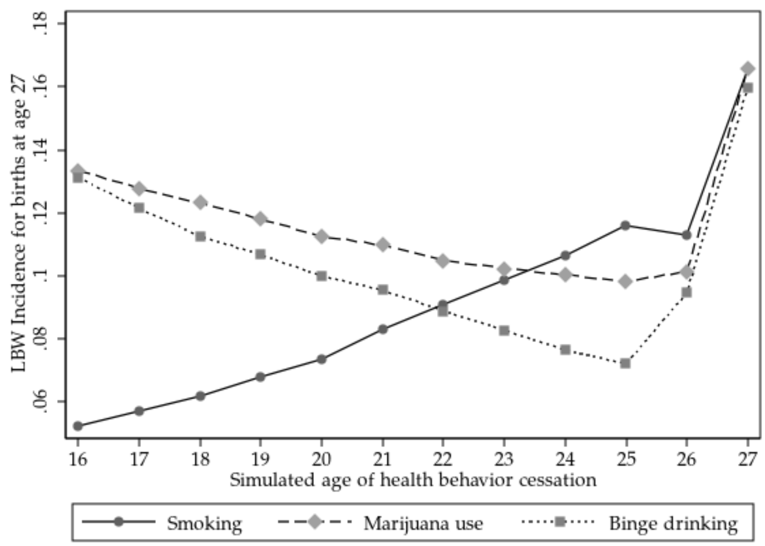

Figure 8: Impact of age of health behavior cessation on low birth weight incidence for women giving birth at age 27 and started the behavior at age 15

To evaluate how smoking, marijuana use, and binge drinking might impact the probability of a low birth weight birth when done together I hold fixed the pattern of each as a pair, and then all three. The results of these four simulations are presented in Figure 9. Possibly as expected, women who do two of the three or all three behaviors have a higher incidence of low birth weight births relative to only smoking or using marijuana. Note that there is no interaction effect allowed for in the model, so all that is observed is an additive effect across behaviors.

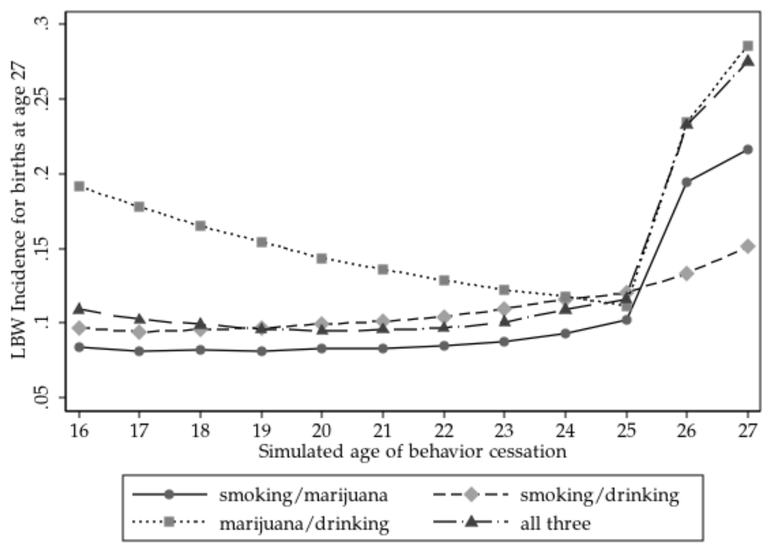

Figure 9: Impact of age of health behavior cessation on low birth weight incidence for women giving birth at age 27 and started the behavior at age 15