The Effect of COVID Lockdowns, Curfews, and Business Closures on Sexual Behavior, Intended and Realized Fertility

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(For review only)

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DRAFT

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Acknowledgements: I gratefully acknowledge financial support from US National Institutes of Health Grant# R01AG071649-01 (PI Lillard). I thank the Cross-National Equivalent File-COVID project collaborators and their respective team members for their comments, criticism, and support, with particular thanks to the OSU-based team. All remaining errors are mine.

ABSTRACT
This paper uses rich longitudinal data to model how fertility decisions and trends in fertility evolved before and during the COVID pandemic. It uses a standard economic model of fertility decisions to frame the analysis. The model needs almost no extra adaptation to include measures of COVID-mitigation policies. I exploit cross-state and temporal variation in COVID policies that potentially affected the time couples spend together. The model predicts differential effects for people with an existing partner versus those not in a marriage or marriage-like relationship. The COVID policies could have affected fertility rates, relative to pre-pandemic rates, if they increased (decreased) the rate of sexual intercourse, led to more (fewer) conceptions, and more (fewer) of those women carried their pregnancies to full-term. Because factors work in both directions, one must investigate this question empirically. To establish empirical patterns and disentangle potentially offsetting predicted effects, I use Panel Study of Income Dynamics data. The analysis exploits temporal and cross-state differences in COVID policy interventions.

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1. INTRODUCTION AND BACKGROUND

There is a robust literature that examines how fertility varies with external shocks that affect whether, when, and how often people engage in sexual intercourse. Many people remember a 1966 New York Times article, authored by Martin Tochin, with the headline, "BIRTHS UP 9 MONTHS AFTER THE BLACKOUT" (Tochin 1966). The outage shut down electric power in New York City for about ten hours on November 9, 1965. Tochin conjecture that births might have increase because the blackout caused people to engage in more sexual intercourse than usual, resulting in a higher than usual number of conceptions and more full-term pregnancies nine months later. Several scholars empirically evaluate and reject the title's claim (Izenman and Zabell 1981, Udry 1970, Menaker 1970).

Despite that evidence, more recent studies supports Tochin's implied logic that connects events to changes in birth rates. However, the effects run in both directions. Some events increase fertility. Some events reduce fertility. Scholars find that future birth rates are statistically higher among people subject to warnings and advisory messages of moderate storms (Evans, Hu and Zhao 2010), power outages lasting from one month (Burlando 2014) to one year (Fetzer and Pardo 2018), and popular local sports teams winning championship games (Montesinos, et al. 2013). Future birth rates are reduced when people are exposed to warnings and advisory messages about severe storms (Evans, Hu and Zhao 2010).

I investigate how future birth rates of US residents changed when their state governments ordered residents to "stay-at-home," imposed curfews, and closed businesses during the COVID-19 pandemic. I exploit variation across states that did and did not intervene. I also exploit the fact that governments enacted and repealed the interventions on different dates. These two features of the COVID-lockdown/curfew restrictions generate geographic and temporal variation in whether or not and when residents faced COVID interventions.

To test for differences in birth rates, I use Panel Study of Income Dynamics (PSID) data on births that occurred between January 2018 and December 2021. I test whether birth rates differed between people in states that did and did not enact COVID-19 restrictions nine months earlier. I also estimate models that compare differences in birth rates of people in the same year and same month who experienced or did not experience an intervention.

Results suggest that the COVID-19 interventions changed the probability of a birth in opposite ways for people with and without a partner. When state governments ordered people to stay-at-home, imposed curfews, and closed businesses related to social activities (bars, restaurants, etc) births increased nine months later for people with a partner and fell for people without a partner.

These results are preliminary. I have yet to control for many factors. For example, the data do not measure differences in whether or not or the extent to which state authorities enforced the restrictions. The analysis does not currently measure differences in location-specific COVID infection rates.

In the rest of the paper unfolds as follows: In Section 2, I describe a simple model that guides the analysis. In Section 3, I present and describe the PSID data, the COVID-19 policies, and how I link the policies to the PSID respondents. Section 4 presents the basic empirical model and the

variants I estimate. Section 5 presents results. In Section 6, I discuss results, analysis limitations, and preliminary (descriptive evidence) about fruitful extensions that will fill some of those gaps.

2. ANALYTICAL FRAMEWORK

Consider first how external events might plausibly affect birth rates nine months later. By describing the logic chain, one can evaluate whether or not an event might plausibly affect each choice that people take that leads to a live birth.

People with no regular partners

Individuals without a regular sexual partner must first find a paramour. That means he or she must decide a) whether or not to seek out a person with whom they might have sex, b) whether or not to court/woo/seduce/be seduced, c) in order to woo a person, a person typically engages in date-related activities that raise the likelihood their paramour agrees to have sex. Date-related activities often include dining at restaurants, seeing a movie together, going to a concert, dancing, and similar activities.

Several COVID-19 interventions plausibly hindered the wooing process. Government-imposed curfews and stay-at-home orders made it more difficult for single people to meet others. Governments also shut down non-essential businesses at which a person might meet potential partners – e.g. gyms and bars – or to which a person might go on a date - restaurants, bars, movie theaters, concert venues, and places people dance. Because these interventions reduce encounters that might lead to sexual intercourse, the restrictions should reduce the probability and frequency of sexual intercourse. One should expect fewer births nine months after a government exposes people to them.

People with regular partners

Individuals who have a sexual partner further decide d) whether or not to have sex on a given day, e) whether and how frequently (per time period) to engage in sexual intercourse, f) for each encounter, whether or not to use birth control methods, and g) conditional on having conceived, whether or not to carry the child to full-term.

When governments order people to stay-at-home, impose a curfew, and shut down businesses and meeting places (bars, churches, gyms, movie theaters, restaurants), couples spend more time together – over a whole day in the case of stay-at-home orders and in the evenings for curfews. If one assumes a drive for regular sex, the extra time together raises the probability a couple engages in sexual intercourse because the partner is present and readily available. The longer governments extend stay-at-home orders or curfews, the higher will be the expected frequency of sex.

-Use of birth control

The above logic suggests fewer births among people without a regular partner because they engage in sexual intercourse less often. It also suggests that people with a sexual partner will be more likely to engage in sex more frequently. For the extra sex to lead to a higher birth rate, couples must conceive and carry the child to full-term.

The probability of conception depends on whether or not people use birth control more or less frequently (compared to their usual sexual encounters). It is unclear whether or how the stay-at-

home orders and curfews affect the probability that either unpartnered or partnered people use birth control. If and to the extent that government covid policies restricted whether and when businesses could sell birth control then those policies will increase the probability that a sexual encounter results in a conception.

-Fertility intentions

To realize a live birth, once a conception occurs, individuals decide to whether to terminate the pregnancy. That decision will depend on (current and future) desired fertility. It is reasonable to assume that the average person with no regular partner does not (currently) want a child because of the substantial time and money costs one must pay when raising a child. By contrast, people with regular partners may have already discussed and agreed on whether and when they would have a child. For such couples, an unintended pregnancy that resulted from extra intercourse confronts them with a decision about whether or not to have their child sooner than they planned. Deciding against that implies that the couple must seek an abortion.

If people bear a desired child sooner, one should observe a subsequent reduction in fertility. One should also see a higher rate of abortions in the intervening months between the COVID-19 interventions up to the latest date that a state permits abortions after conception.

4. DATA

-Dependent and control variables

I use Panel Study of Income Dynamics (PSID) data on the birth date of 1,177 children born to PSID respondents from January 2018 through December 2021. I keep data on the date and state of each child's birth, whether or not the father and mother were present in the household, and, if available, the age of each. I create 48 monthly observations for each child. I code a birth indicator that equals "0" by default. It equals "1" in the month a mother gave birth.

Figure 1 plots the fraction of births in each calendar month. The vertical line separates months before and after the COVID pandemic. The long solid line plots the linear trend over all forty-eight months. The two shorter dashed lines plot the linear trend over the pre- and post-pandemic months. Next to each line, I show the simple linear regression of birth rates over the relevant period. From January 2018 through December 2021 births trend downward. Month-on-month birth rates declined on average at a rate of 0.0159 percentage points each month. In the pre-pandemic period, from January 2018 through February 2020, month-on-month birth rates were effectively constant. They declined on average at a rate of 0.0002 percentage points each month. Post-pandemic, from March 2020 through December 2021, average month-on-month birth rates declined at a rate 215 times faster or 0.043 percentage points each month.

The simple trends in Figure 1 provide prima facie evidence that birth rates fell over the course of the pandemic. However, there is quite a bit of variation in exposure to COVID policies over time and across states. To account for that variation, I use also collect and code COVID-19 policy variables related to social interactions and business/economic situations of respondents in each state.

-COVID-19 policy variables

The empirical analysis takes advantage of state-specific government orders, curfews, mandates, and economic policies that either aimed to mitigate the spread of COVID or that sought to ameliorate the economic consequences of the COVID-mitigation policies. I draw the policy data from the Boston University compilation of state-specific COVID policies available at www.tinyurl.com/statepolicies (Raifman, et al. 2020). The data include the date each government enacted and repealed up to twenty-nine different policies.

Table 1 lists the policies I use. I organize the policies into two groups. In the first group, I include policies that restricted social interactions. In the second group, I include other policies that affected might have affected the employment or economic situation of the potential parents. The second group also includes the minimum wage prevailing in the state. The level of the minimum wage is the higher of the federal or state minimum wage. It is adjusted for inflation to constant January 2024 dollars. I track variation in this second group to control for exposure to policies that governments may have enacted simultaneously or in close temporal proximity with the social interaction policies.

Table 1 - COVID policies

Policies affecting social interactions	Policies affecting individual's business/economic situation	
Evening curfew	Ban on face mask mandates	Ban on elective medical procedures
Bars closed	Ban on personal visits to prisons	Face mask mandate
Churches closed	CARES Act pleading	Mandated reconnection of utilities
Stay-at-home order	Eviction moratorium (CDC)	Moratorium on utilities shutoff
Restaurants closed	Limitations on non-payment actions	Extended public benefits
Movie theaters closed	Required quarantine (out-of-state visitors)	Ban on enforcement of eviction orders
Hair salons closed	Ban on late fees	Ban on initation of evictions
Gyms closed	Limitation for COVID-19 hardship	Moratorium on evictions
	Benefits extended for 20 weeks	Closed retail stores
	Ban on eviction hearings	Closed non essential businesses
	Minimum wage (real 2024$)*	

Source: Boston University State COVID policies (www.tinyurl.com/statepolicies; Raifman, et al. 2020) updated by author.
*Higher of federal or state minimum wage; inflation adjusted to real January 2024 dollars.

In most cases, the data track the date each state government imposed and repealed the policies. In the initial period of the pandemic, every state ordered all "non-essential" businesses to shut but did not refer to a particular type of business. As the pandemic progressed, state governments allowed particular types of business to reopen fully or partially. Subsequently some state governments again closed and later reopened particular types of businesses. In order to track days of exposure, I assume that each particular business type first closed on the date state governments required non-essential businesses to close.

To capture variation over time and across states, I create data with state-year-day observations for each day from January 2018 through December 2021 and columns for each of the above 29 policies. For each of the above policies, I create an indicator variable that equals "0" by default. Each variable takes on a value of "1" on each day that falls between the dates each government enacted and repealed the restrictions. I collapse these data by month, summing the number of days a particular policy was in force in a given state in each calendar month of 2020 and 2021.

3. FACTOR ANALYSIS OF COVID POLICIES

Existing empirical analysis of the effects of COVID policies frequently use variation in specific COVID policies but fail to control for variation across the wider range of COVID policies. The inherent problem is that the studies fail to explore whether the COVID policies of interest vary independently of the other COVID policies. Empirical studies that rely solely on variation in some but not all of the COVID policies run the risk of identifying the joint effect all COVID policies that co-vary.

Table 2 Correlation Matrix - COVID policies (N=1,836)

				Closure days of						
Social interaction policies		**S1**	**S2**	**S3**	**S4**	**S5**	**S6**	**S7**	**S8**	**S9**
S1	Stay-at-home order	1								
S2	Curfew	-0.01	1							
S3	Restaurants closed	0.75	0.00	1						
S4	Gyms closed	0.71	-0.03	0.81	1					
S5	Movie houses closed	0.67	0.01	0.77	0.88	1				
S6	Bars closed	0.54	0.18	0.67	0.68	0.69	1			
S7	Hair salons closed	0.80	-0.05	0.81	0.82	0.71	0.57	1		
S8	Churches closed	0.67	-0.05	0.69	0.68	0.58	0.47	0.79	1	
S9	Retail stores closed	0.75	-0.06	0.80	0.76	0.66	0.54	0.92	0.8041	1
Business/economic policies										
B1	Face mask mandate	0.01	0.35	0.05	0.08	0.16	0.33	-0.05	-0.06	-0.07
B2	Ban on face mask mandate	-0.03	-0.03	-0.04	-0.04	-0.04	-0.05	-0.03	-0.03	-0.03
B3	Quarantine required	0.16	0.14	0.16	0.14	0.19	0.32	0.15	0.18	0.13
B4	Eviction moratorium	0.41	0.19	0.47	0.48	0.55	0.53	0.41	0.34	0.37
B5	Ban on initiation of evictions	0.22	0.18	0.32	0.31	0.34	0.37	0.23	0.21	0.21
B6	Ban on eviction hearings	0.39	0.07	0.38	0.46	0.43	0.39	0.47	0.40	0.41
B7	Ban on enforcement of eviction orders	0.30	0.12	0.33	0.38	0.44	0.41	0.32	0.27	0.28
B8	hous_limit	0.09	0.09	0.16	0.19	0.23	0.21	0.07	0.07	0.07
B9	hous_npay	0.15	0.02	0.20	0.18	0.21	0.22	0.19	0.11	0.14
B10	CARES Act	0.11	0.11	0.11	0.23	0.24	0.21	0.15	0.09	0.14
B11	CDC eviction ban	-0.07	0.25	-0.06	-0.04	-0.05	0.09	-0.08	-0.06	-0.07
B12	Ban on late fees on mortgages	0.09	0.04	0.22	0.23	0.25	0.26	0.14	0.19	0.16
B13	Ban on shutoff of utilities	0.36	0.22	0.36	0.39	0.46	0.45	0.33	0.26	0.29
B14	Reconnection of utilities mandated	0.15	0.15	0.19	0.25	0.29	0.18	0.13	0.05	0.09
B15	Ban on personal visits to prisons	0.08	0.14	0.11	0.12	0.15	0.24	0.13	0.13	0.14
B16	Ban on elective health procedures	0.49	-0.03	0.57	0.49	0.43	0.36	0.60	0.50	0.65
B17	Benefit payments extended	0.07	0.17	0.09	0.16	0.27	0.36	0.02	-0.02	-0.03
B18	Benefits extended 20 weeks	0.01	0.19	0.05	0.08	0.18	0.19	-0.04	-0.07	-0.06
B19	State minimum wage*	0.11	0.12	0.14	0.17	0.19	0.22	0.07	0.09	0.06

Source: Author's compilation using Boston University state COVID policy data base, with corrections and enhancements from state policies/minimum wages. *Higher of state or federal minimum wage.

To get a sense of this potential, Table 2 presents the correlations between the eight social

interaction COVID policies and each of the other 20 COVID policies and the state minimum wage. I highlight partial correlations with absolute values of 0.20 or higher.

The correlations range from 0.20 to 0.55. The higher correlations imply that, to interpret coefficients on social interaction COVID policies cleanly, one should control for variation in the other policies.

Table 3 - Factor loading on COVID policies

A. Policies related to social interactions					
Policies: number of past 30 days state had...	**Uniqueness**	**Factor 1**	**Factor 2**	**Factor 3**	
Evening curfew	0.875	0.004	0.268	0.230	
Bars closed	0.378	0.707	0.326	0.123	
Churches closed	0.334	0.769	-0.264	0.076	
Stay-at-home order	0.296	0.822	-0.142	0.093	
Restaurants closed	0.202	0.892	0.009	0.052	
Movie theaters closed	0.168	0.864	0.237	-0.171	
Hair salons closed	0.120	0.907	-0.236	0.048	
Gyms closed	0.111	0.921	0.097	-0.179	
B. Policies related to Business/economic factors					
Policies: number of past 30 days state had...	**Uniqueness**	**Factor 1**	**Factor 2**	**Factor 3**	**Factor 4**
Ban on face mask mandates	0.916	-0.068	0.005	0.057	0.053
Ban on personal visits to prisons	0.807	0.231	0.002	0.235	-0.118
CARES Act pleading	0.779	0.211	0.049	0.246	0.090
Eviction moratorium (CDC)	0.736	0.085	-0.178	0.350	0.199
Limitations on non-payment actions	0.707	0.389	-0.022	-0.151	0.279
Required quarantine (out-of-state visitors)	0.665	0.300	-0.023	-0.396	-0.017
Ban on late fees	0.649	0.441	-0.101	-0.095	-0.175
Limitation for COVID-19 hardship	0.636	0.369	-0.121	-0.105	0.309
Benefits extended for 20 weeks	0.552	0.455	-0.381	0.141	-0.155
Ban on eviction hearings	0.541	0.574	0.187	0.093	0.089
Ban on elective medical procedures	0.524	0.310	0.586	0.083	-0.003
Face mask mandate	0.489	0.505	-0.407	0.210	0.027
Mandated reconnection of utilities	0.486	0.497	-0.192	-0.261	-0.319
Moratorium on utilities shutoff	0.446	0.658	-0.041	0.011	-0.235
Extended public benefits	0.339	0.555	-0.409	0.292	-0.047
Ban on enforcement of eviction orders	0.373	0.717	-0.020	-0.105	0.094
Ban on initation of evictions	0.297	0.735	-0.145	-0.263	0.047
Moratorium on evictions	0.089	0.900	-0.037	-0.178	0.239
Closed retail stores	0.061	0.483	0.825	0.072	-0.080
Closed non essential businesses	0.056	0.454	0.843	0.064	-0.044
Minimum wage (real 2024$)	0.666	0.411	-0.176	-0.085	-0.140

Source: Author's compilation using enhanced Boston University state COVID policy data base

To reduce the dimensions of the monthly COVID policy data, I run factor analysis separately over the two groups of policies. There are eight policies in the first group. In the second group, there are twenty COVID business/economic-related policies plus the prevailing state minimum wage. The factor analysis of the first set retains four factors only one of which has an eigenvalue larger than one. The factor analysis on the second set retains eleven factors, only one of which has an eigenvalue larger than one. The second factor has an eigenvalue of 0.959.

Table 3 presents the factor loadings for three social interaction policy factors and four business/economic policy factors.

I use the factor loadings and data on j covid policies (counts of days in each month) were in force in a given state in a given month. With those data I create, for each month and state, the index score for each factor that is given by:

$$Factor\ i = \sum_{j=1}^{n} w^j x^j$$

for j = 1 to n; n=8 for social interactions policies; n=21 for business/economic policies.

Factor scores equal 0 for every month before March 2020. I then map the factor scores by state, year, and month to the PSID outcome data on births. In addition to the current month scores, I merge in the scores nine months prior to the month of birth. I label these data, month of conception factor scores.

Table 3a shows the correlation between each of the seven month of conception COVID policy factors (3 social interaction COVID policy factors and 4 business/economic COVID policy factors).

Table 3a Correlation Matrix - COVID policy factors (N=1,836)

Label	Month of conception factors	SF1	SF2	SF3	BF1	BF2	BF3	BF4
SF1	Social interaction factor 1	1						
SF2	Social interaction factor 2	0.6021	1					
SF3	Social interaction factor 3	-0.2231	-0.2281	1				
BF1	Business/economic factor 1	0.7936	0.7129	-0.1913	1			
BF2	Business/economic factor 2	0.2208	-0.3804	0.051	-0.2482	1		
BF3	Business/economic factor 3	-0.003	0.2993	0.0906	0.1911	-0.4542	1	
BF4	Business/economic factor 4	-0.071	-0.0607	0.0957	-0.0505	0.2069	-0.1263	1

Source: Author's compilation using enhanced Boston University state COVID policy data base

The high correlations between the first of the business/economic factors suggests that models that omit controls for those policies will not estimate a "clean" effect of the social interaction COVID policies.

Table 4 Descriptive statistics								
	Full sample		Single moms		Single dads		Two-parents	
Variable	**Mean**	**Std. dev.**	**Mean**	**Std. dev.**	**Mean**	**Std. dev.**	**Mean**	**Std. dev.**
Birth in given month	0.05	(0.21)	0.05	(0.21)	0.04	(0.21)	0.05	(0.21)
Conception month factors								
Social interaction factor 1	2.47	(17.46)	2.90	(19.29)	2.76	(17.93)	2.36	(17.01)
Social interaction factor 2	0.21	(1.55)	0.24	(1.74)	0.30	(2.12)	0.20	(1.47)
Social interaction factor 3	0.00	(0.53)	-0.02	(0.52)	-0.05	(0.65)	0.00	(0.52)
Business/economic factor 1	3.01	(18.04)	3.16	(18.16)	3.11	(17.44)	2.98	(18.05)
Business/economic factor 2	-0.03	(6.20)	-0.04	(6.43)	-0.06	(6.58)	-0.03	(6.13)
Business/economic factor 3	0.14	(2.30)	0.16	(2.13)	0.18	(2.23)	0.13	(2.33)
Business/economic factor 4	-0.05	(1.53)	-0.11	(1.35)	0.13	(1.92)	-0.05	(1.55)
Current month factors								
Social interaction factor 1	7.83	(29.84)	7.49	(28.69)	7.73	(28.27)	7.91	(30.15)
Social interaction factor 2	0.88	(3.27)	0.98	(3.53)	1.14	(3.89)	0.85	(3.17)
Social interaction factor 3	-0.01	(1.22)	0.04	(1.30)	-0.04	(1.49)	-0.02	(1.19)
Business/economic factor 1	11.25	(33.27)	11.38	(33.10)	11.72	(31.97)	11.20	(33.38)
Business/economic factor 2	-1.62	(12.17)	-1.91	(12.79)	-1.84	(11.77)	-1.55	(12.05)
Business/economic factor 3	0.84	(4.92)	0.82	(4.56)	1.28	(5.53)	0.83	(4.96)
Business/economic factor 4	-0.18	(3.31)	-0.23	(2.99)	0.34	(3.75)	-0.19	(3.36)
Time-varying Demographics								
Number co-resident children	2.85	(2.25)	2.74	(1.69)	1.79	(1.11)	2.92	(2.38)
Number mother's children	2.21	(1.41)	2.73	(1.69)	0.03	(0.18)	2.21	(1.27)
Log monthly income	4.27	(4.32)	2.67	(3.59)	3.62	(4.04)	4.65	(4.40)
N (child-month)	**23783**		**4043**		**927**		**18813**	
Demographics								
Mother's age (non missing)	29.20	(5.53)	29.13	(6.01)			29.22	(5.42)
Father's age (non missing)	31.23	(6.56)			28.54	(5.53)	31.38	(6.58)
Time-invariant Demographics								
Educational attainment (HS graduate reference category)								
Mother HS dropout	0.16		0.35				0.12	
Mother GED	0.07		0.16				0.05	
Mother HS graduate	0.75		0.56				0.80	
Mother BA+	0.40		0.19				0.47	
Father HS dropout	0.13				0.19		0.16	
Father GED	0.07				0.10		0.09	
Father HS graduate	0.74				0.67		0.74	
Father BA+	0.30				0.19		0.38	
Race/ethnicity indicators (Caucasian reference category)								
Mother Caucasian	0.67		0.35				0.75	
Mother Black	0.31		0.84				0.21	
Mother American Indian	0.06		0.07				0.06	
Mother Asian	0.04		0.04				0.04	
Mother Hispanic	0.17		0.09				0.20	
Father Caucasian	0.68				0.43		0.69	
Father Black	0.21				0.57		0.24	
Father American Indian	0.04				0.10		0.05	
Father Asian	0.01				0.10		0.01	
Father Hispanic	0.16				0.19		0.20	
Mother data not observed	0.04		0.00		1.00		0.00	
Father data not observed	0.18		1.00		0.00		0.00	
N (unique parents)	**469**		**85**		**21**		**363**	

Table 4 shows the descriptive statistics for the merged PSID outcome and factor score data. Since the theoretical framework suggests a difference in COVID social interaction restrictions for people with and without a partner, I present descriptive statistics for the whole sample and three subsamples based on whether or not one observes data for the mother and father of the child who was born. In the analysis, I run a model that allows for a differential effect for the probability of a birth in a given month when both parents are present and when either the mother or father is not present.

Single mothers are more likely to be high school dropouts and minorities than are mothers who give birth when a partner is present.

5. EMPIRICAL SPECIFICATION

I estimate a model of the probability that a birth occurs in each of the forty-eight months. I specify and estimate five variants of the model. All models include month fixed-effects for the calendar month. The "naïve" model includes only COVID social interaction factors:

$$(1)\ Prob(birth)_{imt} = \beta_0 + \beta_{1-3} SocFactor(1-3)_{im-9} + \tau_t + \varepsilon_{imt}$$

where the subscript (m-9) indicates that the policy variation is measured in the month of conception for the three factors.

The second model controls for demographic characteristics (both time-varying and time-invariant):

$$(2)\ Prob(birth)_{imt} = \beta_0 + \beta_{1-3} SocFactor(1-3)_{im-9} + X_{imt}\gamma + \tau_t + \varepsilon_{imt}$$

where the vector X_{imt} includes demographic characteristics of parents that are both time-varying and time-invariant.

To show the potential specification bias in the coefficients on the social interaction variables that one introduces when one fails to control for variation in other COVID policies, I specify a second model that adds controls for the four factors capturing variation in business/economic COVID policies:

$$(3)\ Prob(birth)_{imt} = \beta_0 + \beta_{1-3} SocFactor(1-3)_{im-9} + \beta_{4-7} Bus_EconFactor(1-4)_{im-9} + X_{imt}\gamma + \tau_t + \varepsilon_{imt}:$$

The fourth specification adds factor variation for the current month. The fifth specification adds a fixed effect for the state of residence.

Finally, I estimate a sixth model specification that allows the effect of the social interaction COVID factors to vary for parents whose partner data one does or does not observe in the PSID data. I estimate all models by Ordinary-Least Squares (as a linear probability model).

6. RESULTS

Table 5 reports results. The naïve model supports the hypothesis that governments increased the

probability of birth nine months after the government restricted social interactions. Results in column one indicate that a one unit increase in each of the three social interaction factors increases the probability of birth nine months later by between 0.05 and 1.24 percentage points.

Table 5 Model results										
Variable	**(1)**		**(2)**		**(3)**		**(4)**		**(5)**	
Month of conception social interaction COVID policies										
Factor 1	0.0005	***	0.0005	***	0.0007	***	0.0006	***	0.0006	**
	(0.0001)		(0.0001)		(0.0002)		(0.0003)		(0.0003)	
Factor 2	0.0124	***	0.0125	***	0.0022		0.0021		0.0019	
	(0.0011)		(0.0011)		(0.0015)		(0.0015)		(0.0015)	
Factor 3	0.0081	***	0.0085	***	0.0023		0.0016		0.0015	
	(0.0027)		(0.0027)		(0.0028)		(0.0028)		(0.0028)	
Month of conception business/economic COVID policies										
Factor 1					0.0006	***	0.0005	**	0.0005	**
					(0.0002)		(0.0002)		(0.0002)	
Factor 2					-0.0019	***	-0.0017	***	-0.0018	***
					(0.0004)		(0.0004)		(0.0004)	
Factor 3					0.0043	***	0.0049	***	0.0049	***
					(0.0007)		(0.0007)		(0.0007)	
Factor 4					-0.0006		-0.0001		0.0000	
					(0.0010)		(0.0010)		(0.0010)	
Demographic controls	no		yes		yes		yes		yes	
Current month factors	no		no		no		yes		yes	
State of residence fixed effects	no		no		no		no		yes	
N	23,783		23,783		23,783		23,783		23,783	
k	14		35		39		46		95	
N-k	23768		23747		23743		23736		23687	
F(k, N-k)	25.45		12.26		14.98		15.37		7.94	
R-squared	0.015		0.018		0.024		0.029		0.031	
Adj. R-sq	0.014		0.016		0.022		0.027		0.027	
Root MSE	0.210		0.210		0.209		0.209		0.209	

Notes: ***, **, and + denote coefficients that statistically differ from zero with p-values ≤ .01, .05, and .10 respectively. All models control for calendar month fixed effects (reference January). Demographic controls include mother and father's age, education (dropout, GED, BA+ - reference HS graduate), race/ethnicity (Black, American Indian, Asian/Pacific Islander, Hispanic - reference Caucasian), the log of the sum of monthly income of the mother and father, and indicators for children whose mother or father's data are not observed.

Results in column two confirm that the variation in COVID social interaction policies are orthogonal to the variation in demographic characteristics. The coefficients on the COVID social interaction factors barely change in column two when one controls for demographic characteristics.

Results in column three confirm the evidence that results are biased by correlations observed in Table 2 and Table 3a between COVID social interaction policies and other COVID policies. Once one controls for variation in the business/economic COVID factors in column 3, the

coefficient on the first COVID social interaction factor increases by sixty percent, 0.0005 to 0.0007.

Table 6 Heterogeneity across partnership status				
Variable	**(5)**		**(6)**	
Month of conception social interaction COVID policies				
Factor 1	0.0006	**	0.0012	***
	(0.0003)		(0.0003)	
Factor 2	0.0019		-0.0004	
	(0.0015)		(0.0017)	
Factor 3	0.0015		-0.0007	
	(0.0028)		(0.0032)	
Factor 1*Single parent			-0.0028	***
			(0.0006)	
Factor 2*Single parent			0.0104	***
			(0.0034)	
Factor 3*Single parent			0.0178	**
			(0.0073)	
Month of conception business/economic COVID policies				
Factor 1	0.0005	**	0.0001	
	(0.0002)		(0.0002)	
Factor 2	-0.0018	***	-0.0024	***
	(0.0004)		(0.0005)	
Factor 3	0.0049	***	0.0058	***
	(0.0007)		(0.0008)	
Factor 4	0.0000		0.0014	
	(0.0010)		(0.0011)	
Factor 1*Single parent			0.0025	***
			(0.0005)	
Factor 2*Single parent			0.0031	***
			(0.0010)	
Factor 3*Single parent			-0.0029	
			(0.0018)	
Factor 4*Single parent			-0.0067	**
			(0.0026)	
Demographic controls	yes		yes	
Current month factors	yes		yes	
State of residence fixed effects	yes		yes	
N	23,783		23,783	
k	95		108	
N-k	23687		23,674	
F(k, N-k)	7.94		7.49	
R-squared	0.031		0.033	
Adj. R-sq	0.027		0.029	
Root MSE	0.209		0.208	
Notes: ***, **, and + denote coefficients that statistically differ from zero with p-values ≤ .01, .05, and .10 respectively. See notes Table 5				

Coefficients are slightly smaller when one adds controls for current month COVID policy factors (column 4). Coefficients do not change when one controls for state of residence fixed effects.

As noted above, the theory suggests that government policies I label "social interaction" variables potentially have different effects for people already with a partner versus those who have not partner. The stay-at-home orders, curfews, and closures of socially oriented businesses plausibly caused couples to spend more time together. By contrast, those policies made it more costly for single people to find and date potential sexual partners. Thus, one should expect that government policies would have opposite effects for the two groups. Table 6 interacts an indicator variable that identifies people for whom only data on one parent is observed versus births where both parents' data are observed.

Results are consistent with the hypothesis. A one unit increase in the first COVID social interaction factor increases the probability of a birth nine months later by 1.2 percentage points. Among people without a partner, a one unit increase in the first COVID social interaction factor ***reduces*** the probability of a birth nine months

later by 1.6 percentage points (given by the sum of the two coefficients = 1.2-2.8).[1]

During the three years 2020, 2021, and 2022 a standard deviation in the first COVID social interaction factor was 17.5. Roughly speaking, that corresponds to days that (collectively) people had to stay-at-home, not go out at night, or were prevented from visiting bars, restaurants, and other businesses. Of course that interpretation is not strictly correct because the index increases not only when one policy was in force for a whole month or when multiple policies were simultaneously in force over a shorter period.

However, one can use the coefficients on the first COVID social interaction factor in column six to compute the implied change in the probability of a birth in nine months if a state government were to restrict social interactions by 17.5 days. Table 7 reports those results. The model predicts that the probability of a birth nine months later would ***increase*** among partnered women by 2.0 percentage points and would ***decrease*** among unpartnered women by 2.8 percentage points. These predicted effects are large, possibly implausibly large. Using a base birth probability of 5.0 percentage points, Table 7 reports the percent change in the probability of a birth in a given calendar month that results predict if state governments restricted social interactions nine months earlier. Focusing only on the first social interaction COVID factor, the model predicts that probability of a birth would be 40.8 percent higher for partnered women and 56.7 percent lower among unpartnered women.

Table 7 Predicted effect of 1 standard deviation increase in COVID social interaction policies

Statistic	Whole sample		Two parents		Single parent	
Factor 1 coefficient	0.0006	**	0.0012	***	-0.0016	***
Predicted (Δ1 std dev)	0.011		0.020		-0.028	
% mean birth probability	22.03%		40.82%		-56.74%	
Factor 2 coefficient	0.0019		-0.0004		0.0100	***
Predicted (Δ1 std dev)	0.003		-0.001		0.015	
% mean birth probability	6.03%		-1.24%		30.99%	
Factor 3 coefficient	0.0015		-0.0007		0.0171	**
Predicted (Δ1 std dev)	0.001		0.000		0.009	
% mean birth probability	1.63%		-0.74%		17.97%	

Notes: Coefficients from Table 5. ***, **, and + denote effects that statistically differ from zero with p-values ≤ .01, .05, and .10 respectively. For single parent births the test is of the joint significance of the main effect and the difference for single parents. Model controls listed in Table 5

7. DISCUSSION

The cottage industry predicting changes in births after external shocks arose because of a newspaper story after a blackout in New York City. Subsequent and careful statistical analysis

[1] Recall that the first COVID social interaction factor loads strongly and positively on seven of the nine policy restrictions.

exposed the fact that the author of that story cherry-picked outcome data from four hospitals in a city of millions. Despite the debunking, the logic seems sound. Anything that alters activities leading to a live birth – increased sexual activity, reduction in use of birth control, reduction in abortions – logically should lead to an increase in births. Subsequent and careful empirical research provides support for this logic using systematic variation in power outages.

Here, I contribute to this newer literature. I provide evidence that governments do affect probabilities of birth when they restrict the activities people normally pursue. Results comport with intuitive understanding and differences in the process that leads people to engage in sex. Specifically, predicted effects differ for partnered and unpartnered individuals in ways consistent with our intuition.

Much remains to be explored. A key question is whether the COVID social interaction restrictions affected decisions taken earlier in the timeline that leads to a realized birth. These decisions include whether or not one…

a. …finds a (short-term) partner (currently unpartnered) or has a (long-term) partner;
b. …has sex;
c. …uses or does not use contraception;

[…conceives]

d. chooses to carry fetus to full-term;

[…does not miscarry]

e. gives birth.

The above results do not answer the question of whether or not the social interaction restrictions affected only the timing of planned fertility (presumably moving planned fertility forward) or if the couples treated by the social interaction restrictions had more children overall than couples not treated (as much) by restrictions. Because the COVID pandemic restricted interactions over a limited and relatively short time, it seems more plausible that the COVID restrictions affected the timing of births but did not affect the levels. That hypothesis remains to be explored.

Appendix B describes preliminary evidence, from the Panel Study of Income Dynamics Transition to Adulthood sample, on the first three points.

Many other factors might affect decisions to terminate pregnancies that I do not explore. Principle among them is COVID infection rates. One might expect women to have been more likely to be more vigilant about birth control or more likely to terminate a pregnancy if when COVID infection rates were higher. That sort of behavior plausibly varies across both time (as knowledge changed) and geographic space. Such behavior might have been more likely at the beginning of the pandemic, when scientists knew less about the health implications for fetuses and pregnant women.

In future work, I will test these and other hypotheses to exploit temporal and geographic variation in COVID infection rates, hospitalizations, and COVID-attributed deaths.

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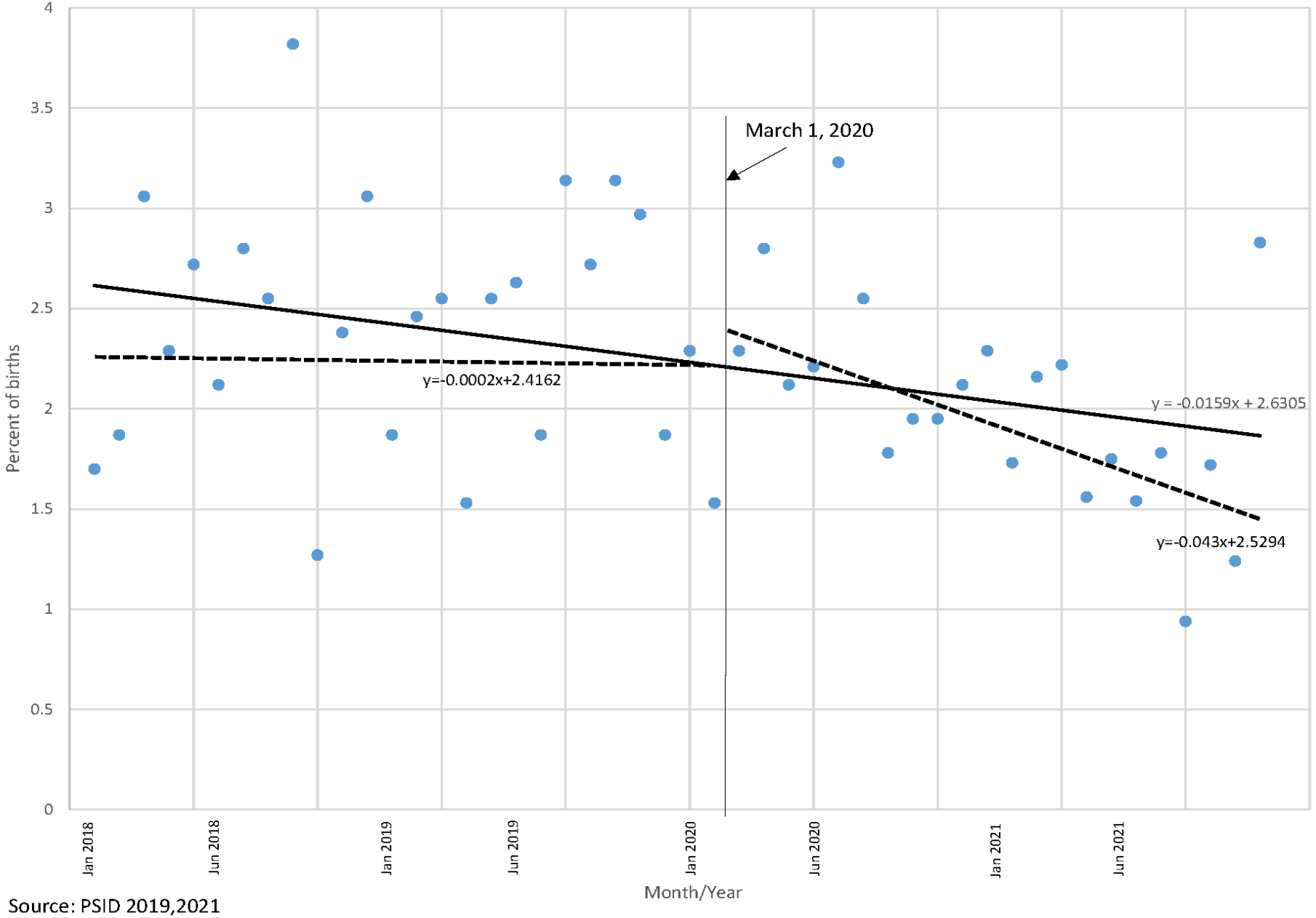
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Figure 1 Birth Rate January 2018 – December 2021



Source: PSID 2019,2021

Appendix A

Appendix Table 1 Full Correlation Matrix - 28 COVID policies and state minimum wage (N=1,836)

				Closure days of																										
Social interaction policies		**S1**	**S2**	**S3**	**S4**	**S5**	**S6**	**S7**	**S8**	**S9**	**B1**	**B2**	**B3**	**B4**	**B5**	**B6**	**B7**	**B8**	**B9**	**B10**	**B11**	**B12**	**B13**	**B14**	**B15**	**B16**	**B17**	**B18**	**B19**
S1	Stay-at-home order	1																											
S2	Curfew	-0.01	1																										
S3	Restaurants closed	0.75	0.00	1																									
S4	Gyms closed	0.71	-0.03	0.81	1																								
S5	Movie houses closed	0.67	0.01	0.77	0.88	1																							
S6	Bars closed	0.54	0.18	0.67	0.68	0.69	1																						
S7	Hair salons closed	0.80	-0.05	0.81	0.82	0.71	0.57	1																					
S8	Churches closed	0.67	-0.05	0.69	0.68	0.58	0.47	0.79	1																				
S9	Retail stores closed	0.75	-0.06	0.80	0.76	0.66	0.54	0.92	0.8041	1																			
Business/economic policies																													
B1	Face mask mandate	0.01	0.35	0.05	0.08	0.16	0.33	-0.05	-0.06	-0.07	1																		
B2	Ban on face mask mandate	-0.03	-0.03	-0.04	-0.04	-0.04	-0.05	-0.03	-0.03	-0.03	-0.08	1																	
B3	Quarantine required	0.16	0.14	0.16	0.14	0.19	0.32	0.15	0.18	0.13	0.22	-0.03	1																
B4	Eviction moratorium	0.41	0.19	0.47	0.48	0.55	0.53	0.41	0.34	0.37	0.44	-0.07	0.20	1															
B5	Ban on initiation of evictions	0.22	0.18	0.32	0.31	0.34	0.37	0.23	0.21	0.21	0.35	-0.05	0.15	0.74	1														
B6	Ban on eviction hearings	0.39	0.07	0.38	0.46	0.43	0.39	0.47	0.40	0.41	0.17	-0.04	0.27	0.55	0.33	1													
B7	Ban on enforcement of eviction orders	0.30	0.12	0.33	0.38	0.44	0.41	0.32	0.27	0.28	0.33	-0.05	0.20	0.74	0.57	0.47	1												
B8	hous_limit	0.09	0.09	0.16	0.19	0.23	0.21	0.07	0.07	0.07	0.27	-0.03	0.01	0.46	0.25	0.17	0.25	1											
B9	hous_npay	0.15	0.02	0.20	0.18	0.21	0.22	0.19	0.11	0.14	0.16	-0.03	0.06	0.42	0.41	0.24	0.27	0.27	1										
B10	CARES Act	0.11	0.11	0.11	0.23	0.24	0.21	0.15	0.09	0.14	0.13	0.11	0.11	0.16	0.11	0.20	0.17	0.02	0.03	1									
B11	CDC eviction ban	-0.07	0.25	-0.06	-0.04	-0.05	0.09	-0.08	-0.06	-0.07	0.28	0.08	0.15	0.06	0.00	0.00	-0.03	0.12	0.06	0.13	1								
B12	Ban on late fees on mortgages	0.09	0.04	0.22	0.23	0.25	0.26	0.14	0.19	0.16	0.27	-0.03	0.08	0.34	0.46	0.19	0.27	0.08	0.18	-0.01	0.06	1							
B13	Ban on shutoff of utilities	0.36	0.22	0.36	0.39	0.46	0.45	0.33	0.26	0.29	0.34	-0.05	0.28	0.57	0.47	0.36	0.45	0.17	0.20	0.17	-0.03	0.28	1						
B14	Reconnection of utilities mandated	0.15	0.15	0.19	0.25	0.29	0.18	0.13	0.05	0.09	0.29	-0.03	-0.06	0.41	0.39	0.19	0.36	0.16	0.13	0.05	-0.09	0.28	0.48	1					
B15	Ban on personal visits to prisons	0.08	0.14	0.11	0.12	0.15	0.24	0.13	0.13	0.14	0.12	-0.03	0.23	0.12	0.09	0.17	0.15	0.07	0.01	0.03	0.05	0.18	0.20	0.02	1				
B16	Ban on elective health procedures	0.49	-0.03	0.57	0.49	0.43	0.36	0.60	0.50	0.65	-0.03	-0.02	0.08	0.24	0.10	0.26	0.19	0.05	0.10	0.14	-0.02	0.07	0.14	0.06	0.08	1			
B17	Benefit payments extended	0.07	0.17	0.09	0.16	0.27	0.36	0.02	-0.02	-0.03	0.54	-0.04	0.25	0.45	0.39	0.24	0.38	0.19	0.20	0.21	0.22	0.23	0.40	0.32	0.20	-0.05	1		
B18	Benefits extended 20 weeks	0.01	0.19	0.05	0.08	0.18	0.19	-0.04	-0.07	-0.06	0.41	-0.04	0.17	0.34	0.33	0.20	0.29	0.20	0.10	0.07	0.14	0.25	0.30	0.37	0.13	-0.06	0.55	1	
B19	State minimum wage*	0.11	0.12	0.14	0.17	0.19	0.22	0.07	0.09	0.06	0.30	-0.03	0.17	0.38	0.35	0.17	0.23	0.21	0.10	-0.05	0.06	0.29	0.26	0.33	0.11	0.04	0.21	0.25	1

Source: Author's compilation using enhanced Boston University state COVID policy data base. *Higher of state or federal minimum wage.

Appendix Table 2 Full model results (Linear probability model coefficients)												
Variable	**(1)**		**(2)**		**(3)**		**(4)**		**(5)**		**(6)**	
Month of conception social interaction COVID policies												
Factor 1	0.0005	***	0.0005	***	0.0007	***	0.0006	***	0.0006	**	0.0012	***
	(0.0001)		(0.0001)		(0.0002)		(0.0003)		(0.0003)		(0.0003)	
Factor 2	0.0124	***	0.0125	***	0.0022		0.0021		0.0019		-0.0004	
	(0.0011)		(0.0011)		(0.0015)		(0.0015)		(0.0015)		(0.0017)	
Factor 3	0.0081	***	0.0085	***	0.0023		0.0016		0.0015		-0.0007	
	(0.0027)		(0.0027)		(0.0028)		(0.0028)		(0.0028)		(0.0032)	
Factor 1*Single parent											-0.0028	***
											(0.0006)	
Factor 2*Single parent											0.0104	***
											(0.0034)	
Factor 3*Single parent											0.0178	**
											(0.0073)	
Month of conception business/economic COVID policies												
Factor 1					0.0006	***	0.0005	**	0.0005	**	0.0001	
					(0.0002)		(0.0002)		(0.0002)		(0.0002)	
Factor 2					-0.0019	***	-0.0017	***	-0.0018	***	-0.0024	***
					(0.0004)		(0.0004)		(0.0004)		(0.0005)	
Factor 3					0.0043	***	0.0049	***	0.0049	***	0.0058	***
					(0.0007)		(0.0007)		(0.0007)		(0.0008)	
Factor 4					-0.0006		-0.0001		0.0000		0.0014	
					(0.0010)		(0.0010)		(0.0010)		(0.0011)	
Factor 1*Single parent											0.0025	***
											(0.0005)	
Factor 2*Single parent											0.0031	***
											(0.0010)	
Factor 3*Single parent											-0.0029	
											(0.0018)	
Factor 4*Single parent											-0.0067	**
											(0.0026)	
Current month social interaction COVID policies												
Factor 1							0.0005	***	0.0005	***	0.0005	***
							(0.0001)		(0.0001)		(0.0001)	
Factor 2							-0.0021	***	-0.0022	***	-0.0012	
							(0.0007)		(0.0008)		(0.0009)	
Factor 3							-0.0022	+	-0.0023	+	-0.0025	+
							(0.0013)		(0.0013)		(0.0015)	
Factor 1*Single parent											0.0001	
											(0.0003)	
Factor 2*Single parent											-0.0036	**
											(0.0018)	
Factor 3*Single parent											0.0001	
											(0.0030)	

Appendix Table 2 Full model results cont.

Variable	(1)		(2)		(3)		(4)		(5)		(6)	
Current month business/economic COVID policies												
Factor 1							0.0001		0.0001		0.0001	
							(0.0001)		(0.0001)		(0.0001)	
Factor 2							-0.0008	***	-0.0008	***	-0.0008	***
							(0.0002)		(0.0002)		(0.0002)	
Factor 3							0.0006	+	0.0005		0.0003	
							(0.0003)		(0.0003)		(0.0004)	
Factor 4							0.0000		0.0000		-0.0003	
							(0.0004)		(0.0005)		(0.0005)	
Factor 1*Single parent											-0.0001	
											(0.0003)	
Factor 2*Single parent											0.0003	
											(0.0006)	
Factor 3*Single parent											0.0017	**
											(0.0009)	
Factor 4*Single parent											0.0019	
											(0.0012)	
Demographic characteristics												
Number of children, household			-0.0001		-0.0001		0.0001		-0.0002		-0.0004	
			(0.0011)		(0.0011)		(0.0011)		(0.0011)		(0.0011)	
Number of children, mother			-0.0018		-0.0017		-0.0016		-0.0021		-0.0019	
			(0.0017)		(0.0017)		(0.0017)		(0.0018)		(0.0018)	
Mother's age			0.0020	***	0.0020	***	0.0018	***	0.0020	***	0.0014	***
			(0.0004)		(0.0004)		(0.0004)		(0.0004)		(0.0003)	
Father's age			0.0004		0.0004		0.0004		0.0005		0.0010	***
			(0.0003)		(0.0003)		(0.0003)		(0.0003)		(0.0002)	
Log monthly labor income			-0.0007	**	-0.0004		-0.0010	***	-0.0010	***	-0.0011	***
			(0.0003)		(0.0003)		(0.0003)		(0.0003)		(0.0003)	
Educational attainment (HS graduate reference category)												
Mother high school dropout			0.0004		0.0013		0.0015		0.0002		-0.0019	
			(0.0052)		(0.0052)		(0.0052)		(0.0054)		(0.0054)	
Mother GED			0.0019		0.0016		0.0014		0.0041		0.0055	
			(0.0072)		(0.0072)		(0.0072)		(0.0075)		(0.0075)	
Mother BA+			-0.0091	**	-0.0099	**	-0.0097	**	-0.0107	***	-0.0101	**
			(0.0039)		(0.0039)		(0.0039)		(0.0040)		(0.0040)	
Father high school dropout			-0.0007		-0.0006		-0.0014		0.0008		0.0021	
			(0.0062)		(0.0062)		(0.0061)		(0.0066)		(0.0066)	
Father GED			-0.0031		-0.0039		-0.0032		-0.0074		-0.0082	
			(0.0079)		(0.0079)		(0.0079)		(0.0082)		(0.0082)	
Father BA+			-0.0077	+	-0.0078	**	-0.0071	+	-0.0080	**	-0.0070	+
			(0.0040)		(0.0040)		(0.0040)		(0.0041)		(0.0041)	

Appendix Table 2 Full model results cont.												
Variable	**(1)**		**(2)**		**(3)**		**(4)**		**(5)**		**(6)**	
Race/ethnicity indicators (Caucasian reference category)												
Mother Black			0.0035		0.0030		0.0034		0.0029		-0.0019	
			(0.0047)		(0.0047)		(0.0047)		(0.0049)		(0.0046)	
Mother American Indian			0.0050		0.0048		0.0049		0.0029		0.0020	
			(0.0062)		(0.0062)		(0.0062)		(0.0063)		(0.0063)	
Mother Asian			-0.0068		-0.0062		-0.0056		-0.0084		-0.0112	
			(0.0077)		(0.0077)		(0.0076)		(0.0079)		(0.0079)	
Mother Hispanic			-0.0062		-0.0078		-0.0097	**	-0.0074		-0.0072	
			(0.0048)		(0.0048)		(0.0048)		(0.0051)		(0.0051)	
Father Black			-0.0023		-0.0021		-0.0027		-0.0042		0.0000	
			(0.0047)		(0.0047)		(0.0047)		(0.0049)		(0.0046)	
Father American Indian			0.0001		-0.0014		-0.0015		-0.0043		-0.0036	
			(0.0070)		(0.0069)		(0.0069)		(0.0072)		(0.0071)	
Father Asian			0.0110		0.0107		0.0086		0.0099		0.0105	
			(0.0110)		(0.0109)		(0.0109)		(0.0113)		(0.0113)	
Father Hispanic			-0.0004		0.0003		-0.0009		0.0017		0.0020	
			(0.0052)		(0.0051)		(0.0051)		(0.0053)		(0.0053)	
Mother's data not observed[1]			0.0469	***	0.0457	***	0.0415	***	0.0474	***	0.0263	***
			(0.0128)		(0.0127)		(0.0127)		(0.0131)		(0.0065)	
Father's data not observed			0.0062		0.0059		0.0048		0.0034			
			(0.0117)		(0.0117)		(0.0117)		(0.0122)			
Calendar month indicators (January reference month)												
February	-0.0007		-0.0008		-0.0032		-0.0031		-0.0031		-0.0034	
	(0.0060)		(0.0060)		(0.0060)		(0.0060)		(0.0060)		(0.0060)	
March	0.0202	***	0.0199	***	0.0137	**	0.0118	+	0.0116	+	0.0114	+
	(0.0061)		(0.0061)		(0.0061)		(0.0061)		(0.0061)		(0.0061)	
April	0.0153	**	0.0150	**	0.0082		0.0011		0.0008		0.0008	
	(0.0062)		(0.0062)		(0.0062)		(0.0064)		(0.0064)		(0.0064)	
May	0.0180	***	0.0176	***	0.0119	+	0.0046		0.0042		0.0046	
	(0.0062)		(0.0062)		(0.0063)		(0.0063)		(0.0063)		(0.0063)	
June	0.0144	**	0.0139	**	0.0088		0.0023		0.0020		0.0021	
	(0.0063)		(0.0063)		(0.0063)		(0.0064)		(0.0064)		(0.0064)	
July	0.0222	***	0.0217	***	0.0170	***	0.0100		0.0099		0.0099	
	(0.0064)		(0.0064)		(0.0064)		(0.0064)		(0.0064)		(0.0064)	
August	0.0288	***	0.0282	***	0.0243	***	0.0176	***	0.0177	***	0.0177	***
	(0.0065)		(0.0065)		(0.0065)		(0.0065)		(0.0065)		(0.0065)	
September	0.0286	***	0.0280	***	0.0247	***	0.0195	***	0.0196	***	0.0199	***
	(0.0066)		(0.0066)		(0.0066)		(0.0066)		(0.0066)		(0.0066)	
October	0.0248	***	0.0241	***	0.0207	***	0.0159	**	0.0161	**	0.0163	**
	(0.0067)		(0.0067)		(0.0067)		(0.0067)		(0.0067)		(0.0067)	
November	0.0305	***	0.0300	***	0.0265	***	0.0228	***	0.0232	***	0.0231	***
	(0.0068)		(0.0068)		(0.0068)		(0.0068)		(0.0068)		(0.0068)	
December	0.0185	***	0.0180	***	0.0190	***	0.0177	**	0.0182	***	0.0179	***
	(0.0069)		(0.0069)		(0.0069)		(0.0069)		(0.0069)		(0.0069)	

Appendix Table 2 Full model results cont.												
Variable	**(1)**		**(2)**		**(3)**		**(4)**		**(5)**		**(6)**	
State of residence indicators												
Alabama									-0.0041		-0.0036	
									(0.0247)		(0.0247)	
Alaska									-0.0778	**	-0.0779	**
									(0.0395)		(0.0395)	
Arizona									-0.0474	**	-0.0451	+
									(0.0233)		(0.0233)	
Arkansas									-0.0230		-0.0229	
									(0.0249)		(0.0249)	
California									-0.0423	+	-0.0428	**
									(0.0219)		(0.0219)	
Colorado									-0.0257		-0.0261	
									(0.0233)		(0.0233)	
Connecticut									-0.0338		-0.0323	
									(0.0279)		(0.0279)	
Delaware									-0.0468		-0.0423	
									(0.0306)		(0.0306)	
District of Columbia									-0.0229		-0.0200	
									(0.0274)		(0.0275)	
Florida									-0.0329		-0.0333	
									(0.0224)		(0.0224)	
Georgia									-0.0241		-0.0255	
									(0.0226)		(0.0226)	
Idaho									-0.0364		-0.0348	
									(0.0301)		(0.0300)	
Illinois									-0.0400	+	-0.0398	+
									(0.0227)		(0.0227)	
Indiana									-0.0258		-0.0266	
									(0.0229)		(0.0229)	
Iowa									-0.0269		-0.0261	
									(0.0234)		(0.0234)	
Kansas									-0.0244		-0.0249	
									(0.0240)		(0.0240)	
Kentucky									-0.0386		-0.0373	
									(0.0240)		(0.0240)	
Louisiana									-0.0258		-0.0270	
									(0.0239)		(0.0239)	
Maine									-0.0571		-0.0584	+
									(0.0351)		(0.0351)	
Maryland									-0.0249		-0.0240	
									(0.0228)		(0.0227)	
Massachusetts									-0.0494	**	-0.0481	**
									(0.0243)		(0.0243)	
Michigan									-0.0322		-0.0313	
									(0.0222)		(0.0221)	
Minnesota									-0.0191		-0.0191	
									(0.0255)		(0.0255)	
Mississippi									-0.0345		-0.0371	
									(0.0227)		(0.0226)	
Missouri									-0.0250		-0.0256	
									(0.0223)		(0.0223)	

Appendix Table 2 Full model results cont.

Variable	(1)		(2)		(3)		(4)		(5)		(6)	
State of residence indicators cont.												
Montana									0.0589		0.0615	
									(0.0565)		(0.0564)	
Nebraska									-0.0410	+	-0.0420	+
									(0.0244)		(0.0244)	
Nevada									-0.0529	**	-0.0521	**
									(0.0248)		(0.0248)	
New Hampshire									-0.0661	**	-0.0652	+
									(0.0334)		(0.0334)	
New Jersey									-0.0414	+	-0.0415	+
									(0.0244)		(0.0244)	
New Mexico									-0.0108		-0.0096	
									(0.0360)		(0.0360)	
New York									-0.0381	+	-0.0381	+
									(0.0225)		(0.0224)	
North Carolina									-0.0267		-0.0271	
									(0.0223)		(0.0222)	
North Dakota									-0.0415		-0.0391	
									(0.0337)		(0.0337)	
Ohio									-0.0213		-0.0223	
									(0.0224)		(0.0224)	
Oklahoma									-0.0218		-0.0215	
									(0.0259)		(0.0259)	
Oregon									-0.0279		-0.0275	
									(0.0251)		(0.0251)	
Pennsylvania									-0.0259		-0.0267	
									(0.0229)		(0.0229)	
South Carolina									-0.0365	+	-0.0360	
									(0.0221)		(0.0221)	
South Dakota									0.0063		0.0071	
									(0.0328)		(0.0328)	
Tennessee									-0.0338		-0.0337	
									(0.0245)		(0.0245)	
Texas									-0.0224		-0.0244	
									(0.0221)		(0.0221)	
Utah									-0.0197		-0.0190	
									(0.0252)		(0.0251)	
Vermont									-0.0121		-0.0115	
									(0.0619)		(0.0618)	
Virginia									-0.0279		-0.0290	
									(0.0232)		(0.0232)	
Washington									-0.0340		-0.0349	
									(0.0237)		(0.0237)	
West Virginia									-0.0068		-0.0057	
									(0.0548)		(0.0548)	
Wisconsin									-0.0245		-0.0247	
									(0.0259)		(0.0259)	
Wyoming									-0.0378		-0.0389	
									(0.0363)		(0.0362)	
Intercept	0.0260	***	-0.0306	***	-0.0272	***	-0.0210	**	0.0075		0.0084	
	(0.0043)		(0.0098)		(0.0098)		(0.0098)		(0.0237)		(0.0236)	
N	23,783		23,783		23,783		23,783		23,783		23,783	
k	14		35		39		46		95		108	
N-k	23768		23747		23743		23736		23687		23674	
F(k, N-k)	25.45		12.26		14.98		15.37		7.94		7.49	
R-squared	0.0148		0.0178		0.024		0.0289		0.0308		0.0331	
Adj. R-sq	0.0142		0.0163		0.0224		0.027		0.027		0.0286	
Root MSE	0.20998		0.20975		0.2091		0.2086		0.20861		0.20843	

Notes: ***, **, and + denote coefficients that statistically differ from zero with p-values ≤ .01, .05, and .10 respectively.

[1] Indicator for model 6 identifies single parents (mother or father's data not observed)

Appendix B Preliminary evidence from Transition to Adulthood (TA) Sample 2005-2023
This appendix describes evidence relevant.

Figure 1 shows the distribution of interviews, by month for the Transition to Adulthood samples interviewed every other year from 2005 to 2023. Because the interviews occur in different months, I will evaluate the probability a person first has sex in a given month as a function of temporal and geographic variation in COVID restrictions on social interactions. The same applies to sex over the past 30 days from the interview date.

Figure 2 shows that the fraction of the TA sample that is married and/or in a romantic relationship fell in 2021 and 2023.

Figure 3 shows that, starting in 2020, TA respondents waited longer before they first had sex.

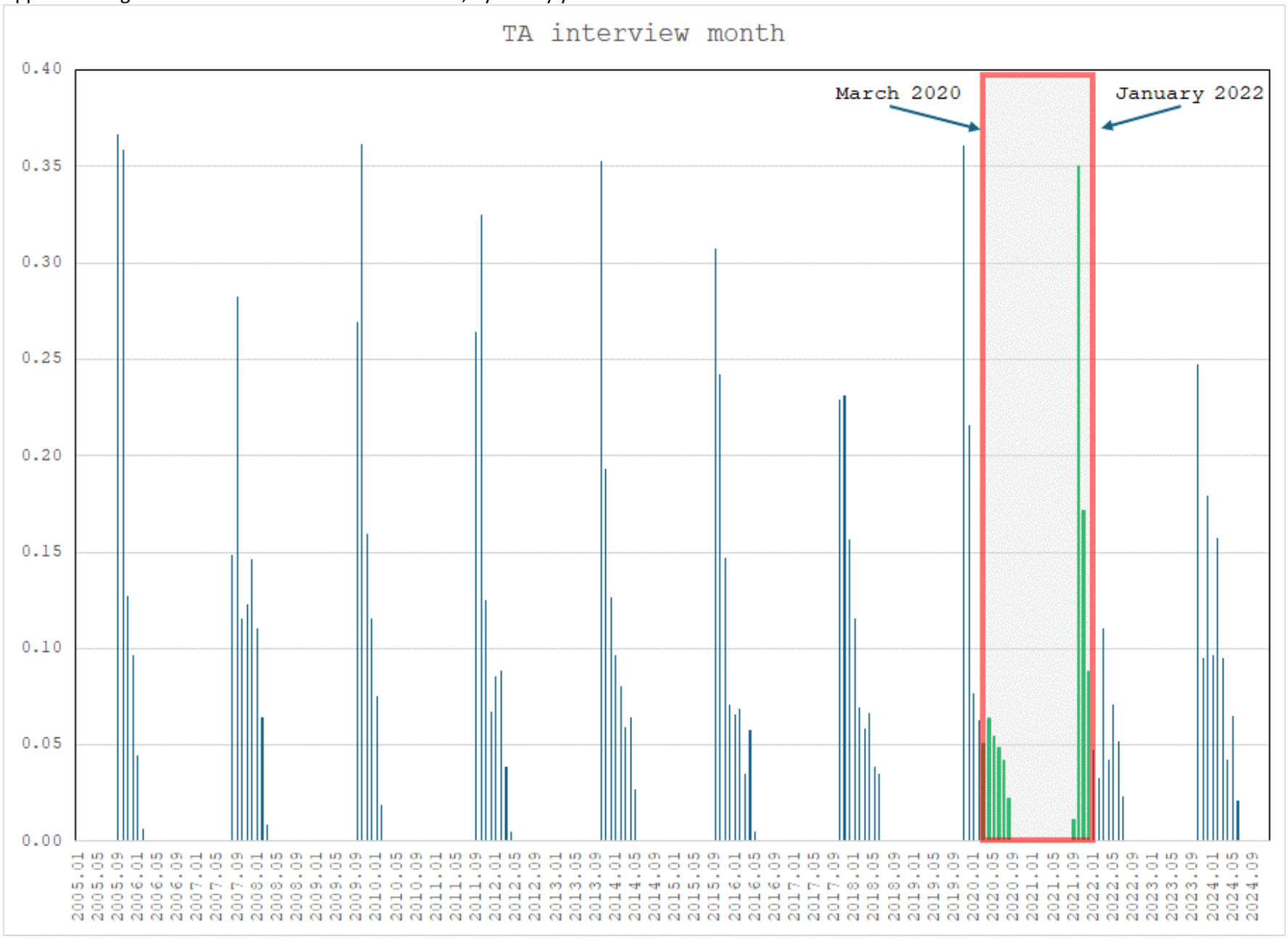
Figure 4 shows systematic variation in the probability people used each of eleven types of birth control either the first time they had sex or, among those having sex in the past thirty days.

Figure 5 shows pregnancy desires for people interviewed between 2013 and 2021, overall and by sex

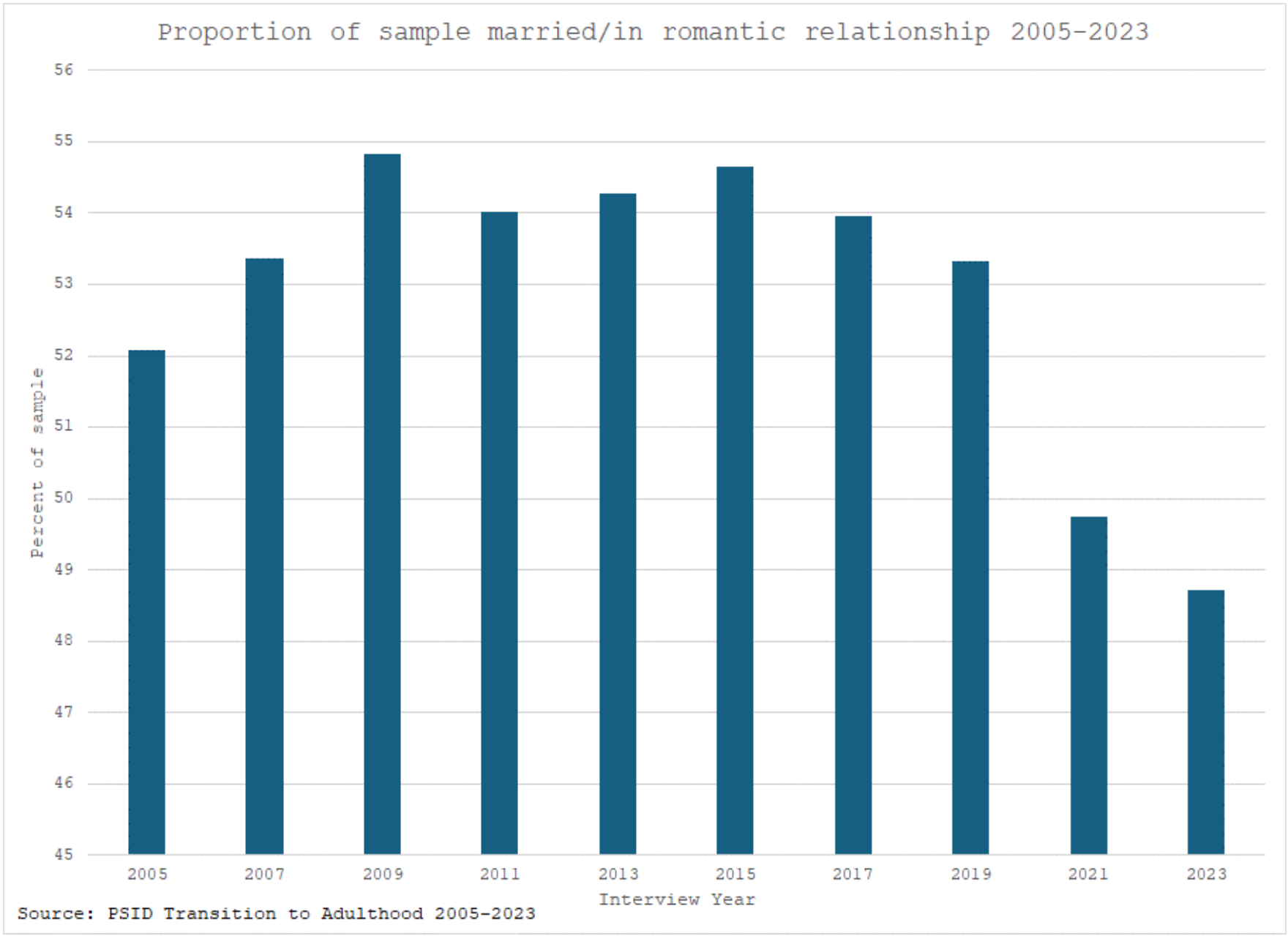
Together, these preliminary data support the idea that the social interaction restrictions associated with COVID led people to take decisions that reduced the likelihood single people married or had a romantic partner, delayed the age people first had sex, systematically altered the use of birth control, and increased desire for more children.

I will exploit systematic variation in exposure to restricted social interactions to identify the causal effect of those restrictions on each outcome.

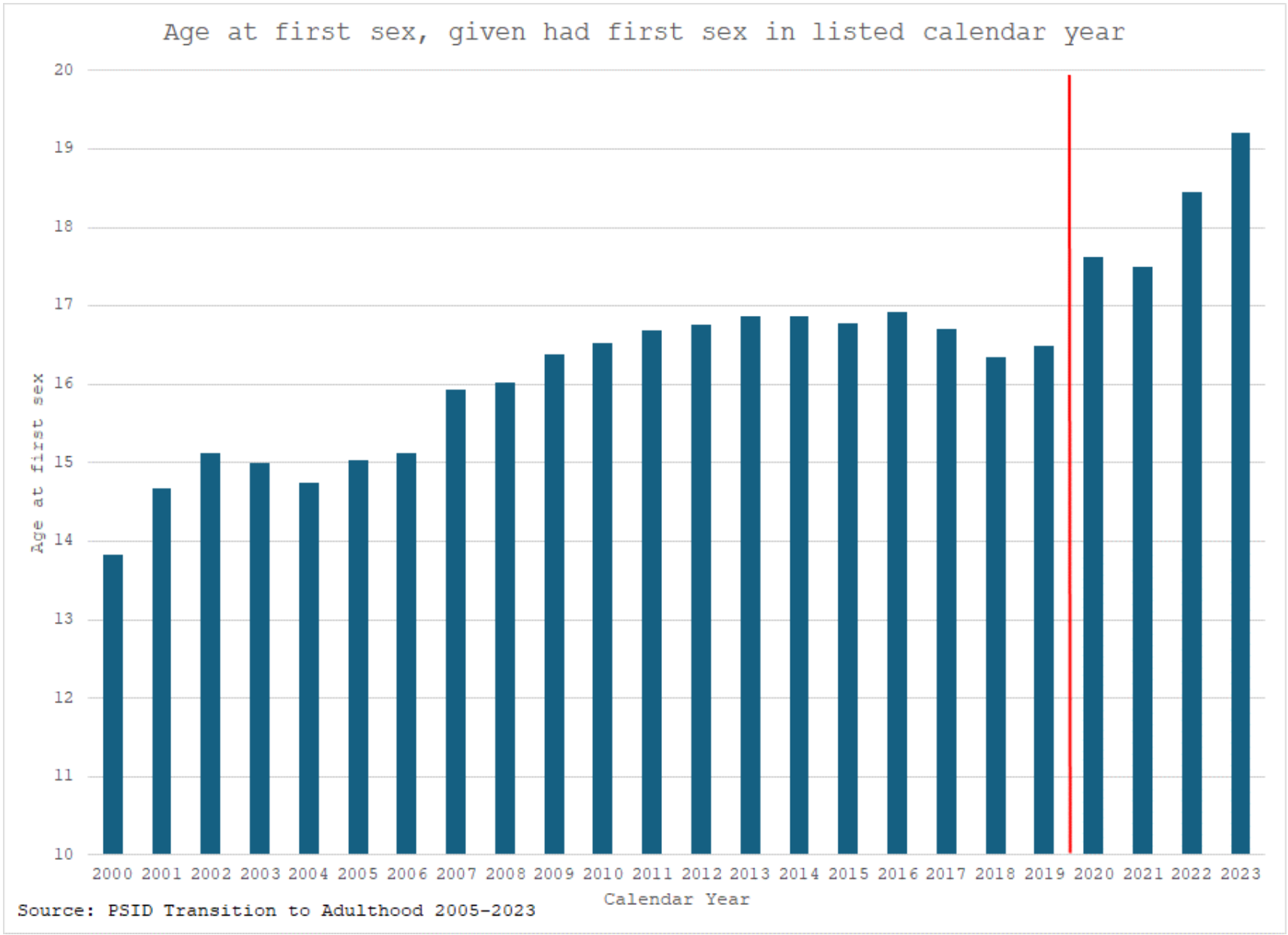
Appendix B Figure 1 Distribution of interview months, by survey year 2005-2023



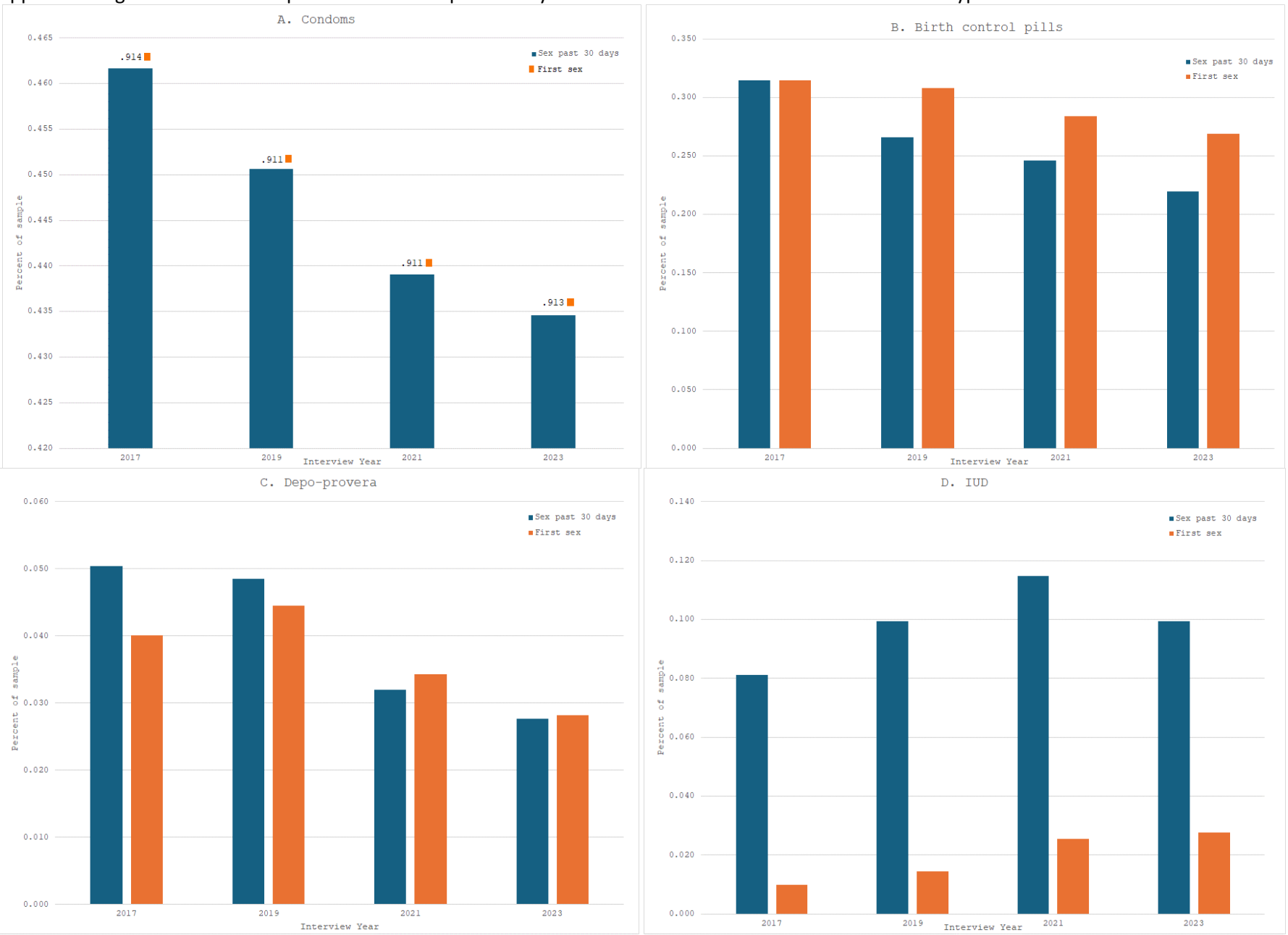
Appendix B Figure 2 Transition to Adulthood sample married or in a romantic relationship



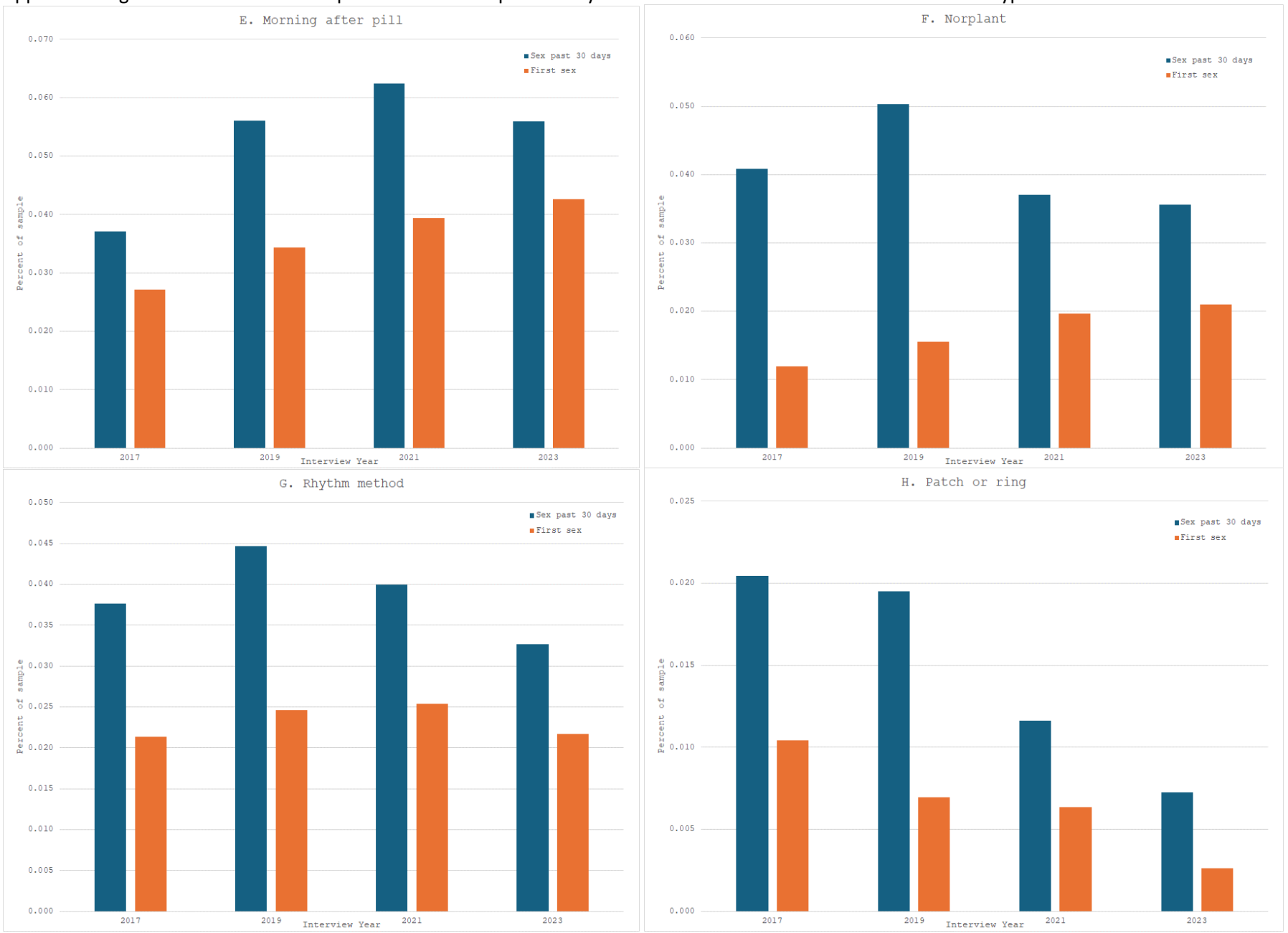
Appendix B Figure 3 Average age of sample that first had sex in a given calendar year 2000-2023



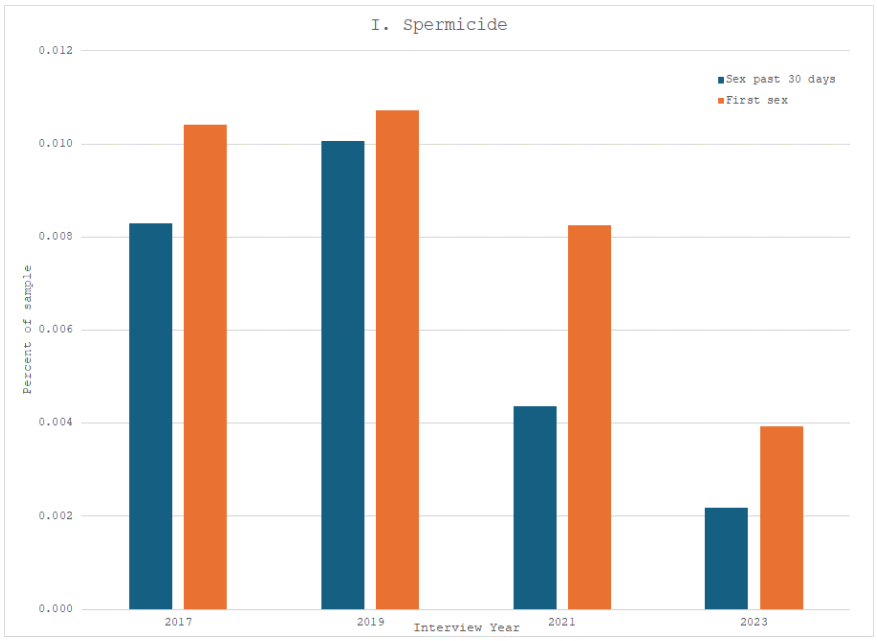
Appendix B Figure 4 Share of sample that had sex in past 30 days or for first time that used listed birth control type

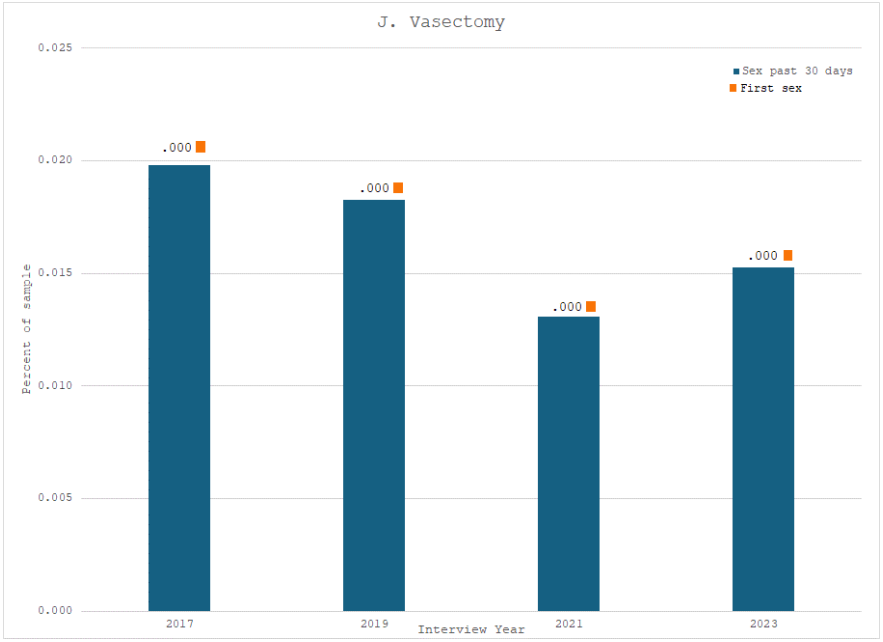


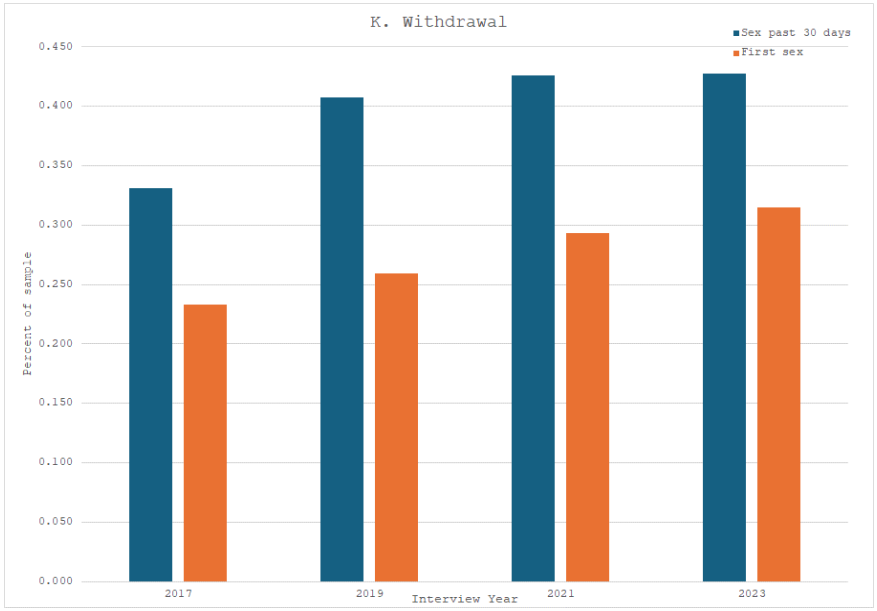
Appendix B Figure 4 cont. Share of sample that had sex in past 30 days or for first time that used listed birth control type



Appendix B Figure 4 cont. Share of sample that had sex in past 30 days or for first time that used listed birth control type







Source: Transition to Adulthood 2017-2023

Appendix B Figure 5 Pregnancy intentions, overall and by sex

