Biodemography and Social Biology

ISSN: 1948-5565 (Print) 1948-5573 (Online) Journal homepage: https://www.tandfonline.com/loi/hsbi20

Breakfast Skipping, Extreme Commutes, and the Sex Composition at Birth

Bhashkar Mazumder & Zachary Seeskin

Biodemography and Social Biology, 61:187–208, 2015

ISSN: 1948-5565 print / 1948-5573 online
DOI: 10.1080/19485565.2015.1007335

Breakfast Skipping, Extreme Commutes, and the Sex Composition at Birth

BHASHKAR MAZUMDER[1] AND ZACHARY SEESKIN[2]

[1]Federal Reserve Bank of Chicago, Research Department, Chicago, Illinois, USA
[2]Department of Statistics, Northwestern University, Evanston, Illinois, USA

A growing body of literature has shown that environmental exposures in the period around conception can affect the sex ratio at birth through selective attrition that favors the survival of female conceptuses. Glucose availability is considered a key indicator of the fetal environment, and its absence as a result of meal skipping may inhibit male survival. We hypothesize that breakfast skipping during pregnancy may lead to a reduction in the fraction of male births. Using time use data from the United States we show that women with commute times of 90 minutes or longer are 20 percentage points more likely to skip breakfast. Using U.S. census data we show that women with commute times of 90 minutes or longer are 1.2 percentage points less likely to have a male child under the age of 2. Under some assumptions, this implies that routinely skipping breakfast around the time of conception leads to a 6 percentage point reduction in the probability of a male child. Skipping breakfast during pregnancy may therefore constitute a poor environment for fetal health more generally.

Introduction

Breakfast skipping is a common and growing phenomenon among American women. Approximately 40 percent of women of childbearing age are attempting to lose weight (Cohen and Kim 2009), and rates of breakfast skipping have grown steadily over time, especially for adolescent women (Haines, Guilkey, and Popkin 1996; Siega-Riz, Popkin, and Carson 1998). Holtzman (2010) finds that 75 percent of women aged 18 to 26 skip breakfast at least one day a week, 58 percent skip breakfast at least four days a week, and 29 percent skip breakfast every day. Using detailed time use data we find that on a given day, 51 percent of employed women between the ages of 15 and 45 report not eating between the hours of 5 a.m. and 10 a.m.[1] Even among pregnant women, 24 percent report skipping meals (Siega-Riz et al. 2001).

Given the vast and growing literature documenting the profound and lasting effects of the prenatal environment on long-term health and socioeconomic success (e.g., Almond and Currie 2011), one might be concerned that the rising incidence of breakfast skipping among women of childbearing age might have important intergenerational ramifications. Pregnant women who extend the overnight fast by skipping breakfast experience a sharp drop in glucose levels and other associated biochemical changes referred to as “accelerated

Address correspondence to Bhashkar Mazumder, Federal Reserve Bank of Chicago, 230 S. La Salle Street, Chicago, IL 60604, USA. E-mail: bhash.mazumder@gmail.com

[1]This is based on the Eating and Health module subsample of the data, which includes all primary and secondary activities.

Color versions of one or more of the figures in the article can be found online at www.tandfonline.com/hsbi.

starvation" (Metzger et al. 1982). Declines in glucose levels as a result of overnight fasts of 10 to 12 hours in length have been observed in women as early as the sixth to tenth weeks of pregnancy (Mills et al. 1998). The availability of glucose is a key indicator of the fetal environment, and its absence is thought to alter the trajectory of fetal development (Gluckman and Hanson 2005). Recent studies have linked Ramadan fasting during pregnancy to reduced birth weight, fewer male births, and adverse long-term outcomes for the offspring such as lower test scores, poor adult health, and higher rates of disability (Almond and Mazumder 2011; van Ewijk 2011; Almond, Mazumder, and van Ewijk 2014).

We investigate whether the effects of breakfast skipping are apparent among an exposed cohort for one specific marker for poor fetal health, namely, the sex composition at birth.[2] A well-known theory, the Trivers-Willard hypothesis, has argued that women experiencing worse environmental conditions are less likely to have male offspring and has been validated by some empirical studies (e.g., Almond and Edlund, 2007). Previous research has also specifically linked environmental exposures around the time of conception to fewer male births either because fewer males are conceived or because fewer male embryos survive (e.g., Hansen, Mǿller, and Olsen 1999). In a provocative study, Mathews, Johnson, and Neil (2008) find that poor nutrition around the time of conception results in fewer male births and suggest that breakfast skipping could explain their findings.[3] Almond and Mazumder (2011) also find that maternal fasting around the time of conception sharply lowers the share of male births. These studies, taken in combination, suggest that women skipping breakfast around the time of conception may lead to fewer surviving male fetuses and could potentially affect long-term outcomes. Recent research has specifically linked in utero nutritional conditions at the time of conception to alterations in gene expression among humans (Dominguez-Salas et al. 2014), suggesting a precise mechanism between such exposures and long-term outcomes.

We use an indirect approach to estimating the effect of breakfast skipping on the sex of the child at birth. This is primarily because no one dataset that we are aware of contains large samples of women with information on both breakfast consumption and the sex of subsequently born children. In addition, we may be concerned about the unobservable characteristics of women who selectively choose to skip breakfast. Instead, we use "extreme" commuting lengths of 90 minutes or more as a plausibly exogenous source of variation in breakfast skipping once all other observable characteristics of women are controlled for. Extreme commuting is a growing phenomenon in the United States. Approximately 1.7 million workers, or 2.4 percent of the nation's full-time workers, experience such commutes (Rapino and Fields 2013). Our approach can be viewed within an instrumental variables (IV) framework, in which separate datasets allow us to estimate (1) the "first stage" effect of an extreme commute on the probability of skipping breakfast and (2) the "reduced form" effect of having an extreme commute on the probability of a male child. If we have a valid instrument, the ratio of the reduced form to the first stage delivers a causal estimate of the effect of skipping breakfast on the probability of a male child.

[2]For example, the Centers for Disease Control and Prevention considers the sex ratio at birth to be "an important demographic indicator" that is useful in understanding trends in infant morbidity (Matthews and Hamilton 2005).

[3]Among the 133 food items analyzed by Mathews et al. only breakfast cereal "was strongly associated with infant sex"; the researchers suggest that breakfast cereal consumption may simply serve as a proxy for whether women eat breakfast. They write: "Skipping breakfast extends the normal period of nocturnal fasting, depresses circulating glucose levels and may be interpreted by the body as indicative of poor environmental conditions." They also cite Larson et al. (2001), who show that among bovine embryos, in vitro provision of glucose enhances the growth and development of male conceptuses while inhibiting that of females.

Methods

ATUS Sample

We use the American Time Use Survey (ATUS) data from 2003 to 2009 to estimate the effect of extreme commutes on the likelihood of skipping breakfast among women of child-bearing age. The ATUS uses a nationally representative sample of the U.S. population.[4] ATUS respondents are asked to provide a time diary, which is an account of the respondent's primary activities starting at 4 a.m. of the previous day until 4 a.m. of the interview day. For each activity, respondents are asked between what times the activity occurred and where the activity took place, enabling a determination of when eating and commuting takes place. In addition, a rich set of demographic and economic information is available from linked Current Population Survey data. We restrict our sample to 8,233 women between the ages of 15 and 45 who commuted to a job on the day of the diary and began work before 11 a.m. The commute time is based on the reported length of the first work-related commute occurring between 4 a.m. and 11 a.m. of the diary day.[5] We divide commuting time into 8 bins: 0 minutes, 1 to 14 minutes, 15 to 29 minutes, 30 to 44 minutes, 45 to 59 minutes, 60 to 74 minutes, 75 to 89 minutes, and extreme commutes of 90 minutes or more. We measure breakfast skipping by using an indicator variable that takes the value of 1 if the respondent did not have any primary eating activities ending between 5 a.m. and 10 a.m. of the diary day and takes the value of 0 otherwise. In the Appendix we use a second outcome that is an indicator variable for whether the estimated length of the overnight fast is greater than 16 hours. Metzger et al. (1982) show that there are sharp declines in blood glucose and other pronounced biochemical changes in the intrauterine environment ("accelerated starvation") when pregnant women extend the overnight fast beyond 16 hours. We use both graphical plots and multivariate ordinary least squares (OLS) regressions to show the effect of extreme commutes on the probability of skipping breakfast.

Census/ACS Sample

In order to estimate the effect of extreme commutes on the sex composition of offspring we combine samples from the 1980, 1990, and 2000 decennial censuses with the 2005 through 2009 American Community Surveys (ACS).[6] We link children aged 2 or less to their biological mothers and condition that selection on cases in which the mother is working and the current commuting time is known and is positive.[7] Our final sample consists of over 700,000 observations. The data contain a rich set of covariates, including family income, education, race, marital status, part-time work, family structure, home ownership, type of

[4]See the American Time Use Survey User's Guide for more information (http://www.bls.gov/tus/atususersguide.pdf).

[5]We include all days of the week, but our results are robust to excluding weekend days. For a small subsample of respondents data were collected in an Eating and Health Module, which asked about any eating and drinking on the diary day that was not listed as a primary activity in the main interview. As we discuss later, including secondary eating reduces our measured rate of breakfast skipping but doesn't alter the pattern of the timing of eating over the course of the day. Since the samples are too small to obtain precise estimates, we exclude these data.

[6]Specifically, we use the 1980 5 percent state sample, the 1980 1 percent metro sample, the 1990 5 percent state sample, the 1990 1 percent metro sample, the 2000 5 percent sample, the 2000 1 percent sample, and the 2005 to 2009 ACS 1 percent samples.

[7]We found similar results using samples based on children of age 1 or less or children aged 3 or less. We also found similar results if we included noncommuters in the analysis.

school attended, departure time, and mode of transit to work. Our outcome of interest is an indicator variable for whether or not the child's sex is male, and our key explanatory variable is an indicator for extreme commutes (those of 90 minutes or longer). We initially use both graphical plots and OLS regressions to examine the effects of extreme commutes on the fraction of male births.

In order to more successfully eliminate any potential confounding influences, we also use propensity score estimation and inverse probability weighting (IPW) with regression adjustment. Hirano and Imbens (2001) propose this method for estimating causal effects when observable variables affect assignment to treatment, which in our case is the probability of an extreme commute. This method is implemented in two stages. In the first stage, we estimate a logit for which the covariates include the number of children, race, marital status, part-time work, time of departure for work, mode of transit to work, income, birth order of child, age, mother's and father's education, year indicators, and metropolitan area fixed effects. The propensity scores are the predicted values from the logit. In the second stage, we estimate a weighted least squares specification using the inverse of the propensity scores from the first stage as weights.[8] The intuition is that the reweighted samples for those with and without a long commute have comparable characteristics. If one assumes that the covariates fully explain all differences in treatment selection, then the IPW estimate is an unbiased estimator of the average treatment effect.[9]

Results

We begin by showing the pattern of eating over the course of a day for the ATUS sample in Figure 1. There are notable peaks that occur at 12 p.m. and 6 p.m. that correspond to lunch and dinner. There is a much smaller peak during the morning hours, however, indicating significantly lower rates of breakfast consumption. Overall, among women in our sample, 67 percent record no primary eating activity between the hours of 5 a.m. and 10 a.m., and 51 percent report not eating at all during this time period. The summary statistics for the ATUS sample are shown in the top panel of Table 1 and include women with a commute length of zero minutes. The summary statistics for the census/ACS sample are shown in the bottom of Table 1 and only include those individuals with a positive commute length.[10]

Effect of Extreme Commutes on Breakfast Skipping

Figure 2 illustrates how breakfast skipping differs across the different commute time bins. Among those women who commute, there is a gradual increase in breakfast skipping rates as commute time increases. Table 2 shows that the effect of extreme commutes on breakfast skipping that is already apparent in the raw data is unaffected by the inclusion of a large set of variables that control for the day of the week, demographics, family structure, education, economic status, departure time, geographic area, or metropolitan area. In Figure A1, we

[8]In the second stage, interactions of the treatment with each of the demeaned covariates (except for metro area fixed effects) are included, along with all of the first-stage covariates.

[9]An advantage of the Hirano and Imbens approach compared to other propensity score methods is that there is a straightforward algorithm that limits subjective decisions by the researcher in modeling the first and second stages.

[10]We drop those individuals from the census with a commute time of zero minutes because we can only utilize the information on the mode of commute for our IPW strategy if individuals actually commute to work. The conditional distribution of commute times for the ATUS sample is provided in the notes to Table 1.

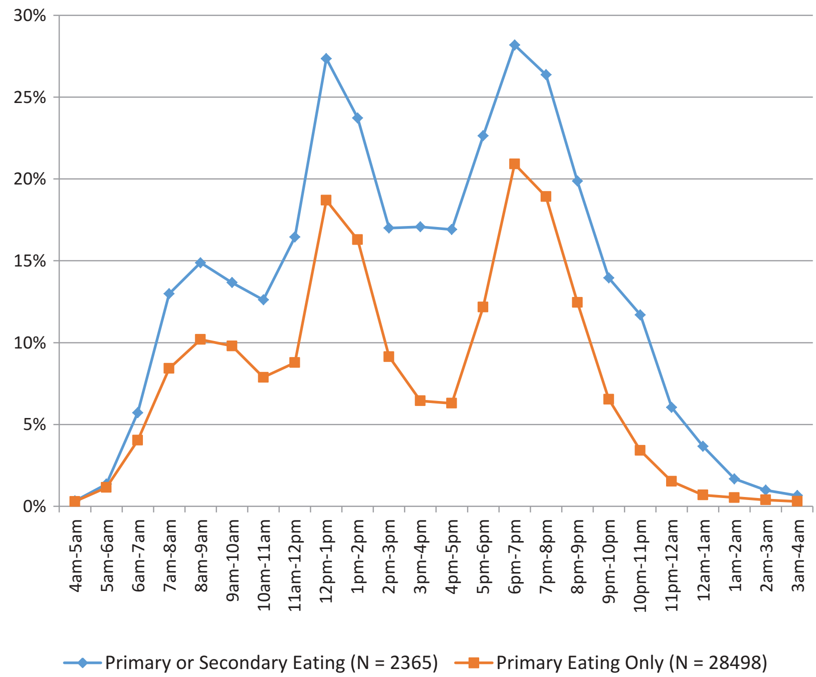

Figure 1. Primary and secondary eating by time of day.

show that in the ATUS data, rates of college-going are higher among extreme commuters than the sample average and rates of dropping out of high school are lower, suggesting that education is not a confounding influence and that extreme commuters are, if anything, positively selected. In Table A1, we show a larger set of mean characteristics by commute time length for the census/ACS sample.

To further lend credence to our estimates, we find that if we divide our sample by women who drove versus women who were either passengers in the car or used another mode of commuting, our effect is vastly larger and only statistically significant for women who drove. This suggests that among extreme commuters, it is the driving per se that impedes eating and also implies that there is not a more general selection issue among women who are extreme commuters. In Table A2, we show the same pattern of results for an alternative measure of breakfast skipping, namely, whether a woman goes 16 hours or longer without any primary eating activity.

Evidence on Trivers-Willard

Using our census/ACS sample, we begin by presenting evidence in support of the Trivers-Willard hypothesis in Figure 3, where we plot the fraction of male children under the age of 2 by family income quintile and by the education level of the mother. Here we see evidence consistent with the notion that women of poorer socioeconomic status have a smaller share of male children. This is important for our purposes, since women who are extreme commuters have higher socioeconomic status. As a result, our estimates may be biased away from finding a negative effect of extreme commuting on the fraction of male children if we do not condition on socioeconomic status.

Table 1
Summary statistics

	Mean	*SD*	*N*
2003–2009 American Time Use Survey (ATUS)			
No primary eating 5 a.m.–10 a.m.	67.4%	46.9%	8,233
No primary eating for >16 hours	64.5%	47.8%	8,233
Minutes with no primary eating	1,062.7	292.5	7,785
No primary or secondary eating 5 a.m.–10 a.m.	51.1%	50.0%	2,099
No primary or secondary eating for >16 hours	14.0%	34.7%	2,099
Minutes with no primary or secondary eating	756.1	203.5	2,099
Commute time (min.)	15.9	16.9	8,233
No commute time	19.5%	39.6%	8,233
1–14-min. commute	31.5%	46.4%	8,233
15–29-min. commute	28.1%	45.0%	8,233
30–44-min. commute	13.4%	34.1%	8,233
45–59-min. commute	3.9%	19.3%	8,233
60–74-min. commute	2.6%	15.8%	8,233
75–89-min. commute	0.4%	6.2%	8,233
90+-min. commute	0.7%	8.2%	8,233
Black	13.0%	33.7%	8,233
Hispanic	13.6%	34.3%	8,233
Works part time	21.3%	40.9%	8,233
Number of children	1.33	1.13	8,233
Less than high school completed	7.9%	26.9%	8,233
College graduate	38.4%	48.6%	8,233
1980–2000 Census and 2005–2009 American Community Survey			
Male child	51.1%	50.0%	725,032
Commute time (min.)	23.1	19.1	725,032
1–14-min. commute	31.1%	46.3%	725,032
15–29-min. commute	36.2%	48.1%	725,032
30–44-min. commute	19.5%	39.6%	725,032
45–59-min. commute	7.2%	25.8%	725,032
60–74-min. commute	3.9%	19.3%	725,032
75–89-min. commute	0.6%	8.0%	725,032
90+-min. commute	1.5%	12.0%	725,032
Black	10.6%	30.8%	725,032
Hispanic	10.6%	30.8%	725,032
Works part time	25.7%	43.7%	725,032
Total number of children	2.0	1.0	725,032
Less than high school completed	6.9%	25.3%	725,032

(*Continued*)

Table 1
(*Continued*)

1980–2000 Census and 2005–2009 American Community Survey			
	Mean	*SD*	*N*
College graduate	32.2%	46.7%	725,032
Carpool	16.9%	37.5%	725,032
Public transportation	3.7%	18.8%	725,032
Bike/walk	2.1%	14.4%	725,032
Other transportation	0.4%	6.3%	725,032

Notes: Conditional on having a nonzero commute time, the average commute time in the ATUS sample is 19.8 minutes, and the fraction of the sample in each commuting bin is as follows: 1–14 min., 39.1 percent; 15–29 min., 34.9 percent; 30–44 min., 16.6 percent; 45–59 min., 4.8 percent; 60–74 min., 3.2 percent; 75–89 min., 0.5 percent; and 90 min. or longer, 0.8 percent (9.2%).

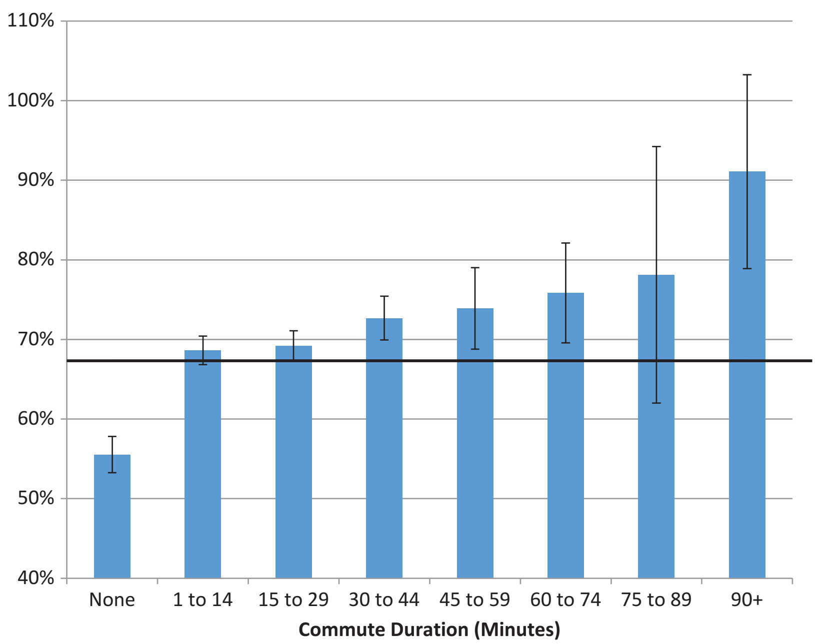

Figure 2. Percent "skipping breakfast" by commute duration.

Effect of Extreme Commutes on the Fraction of Male Children

Figure 4 presents the raw data on the fraction of male children by commute time bin.[11] Women with extreme commutes are about 0.7 percentage points less likely to have a male child than the sample average. In the raw data no other commute time bin has a statistically

[11]For this figure, we have included noncommuters, even though they are not in our estimation sample.

Table 2
Effects of long commute times on breakfast skipping, selected coefficients

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
90+-min commute	0.218***	0.215***	0.217***	0.210***	0.206***	0.206***	0.213***	0.282***	0.082
	(0.063)	(0.063)	(0.062)	(0.062)	(0.062)	(0.062)	(0.063)	(0.072)	(0.138)
Black		0.096***	0.094***	0.093***	0.093***	0.092***	0.097***	0.065***	0.171***
		(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.017)	(0.020)	(0.033)
Number of children		0.020***	0.018***	0.023***	0.023***	0.022***	0.023***	0.021***	0.024**
		(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.010)
Age 15–17		−0.109**	−0.041	−0.007	−0.003	−0.007	−0.052	−0.155**	0.103
		(0.045)	(0.051)	(0.053)	(0.053)	(0.053)	(0.055)	(0.074)	(0.091)
Age 39–41		−0.055**	−0.053**	−0.063***	−0.063***	−0.064***	−0.050**	−0.064**	0.026
		(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.024)	(0.028)	(0.049)
Age 42–45		−0.098***	−0.096***	−0.107***	−0.108***	−0.109***	−0.100***	−0.113***	−0.054
		(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.023)	(0.027)	(0.047)
Less than high school education			−0.053**	−0.044*	−0.044*	−0.043*	−0.029	0.003	−0.051
			(0.026)	(0.026)	(0.026)	(0.026)	(0.027)	(0.036)	(0.046)
College education or more			−0.038**	−0.057***	−0.056***	−0.055***	−0.060***	−0.072***	−0.047
			(0.017)	(0.018)	(0.018)	(0.018)	(0.020)	(0.023)	(0.040)
Log wage				0.020*	0.018*	0.022**	0.019*	0.017	0.020
				(0.011)	(0.011)	(0.011)	(0.012)	(0.014)	(0.022)
Weekly hours				0.003***	0.003***	0.003***	0.003***	0.002***	0.005***
				(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Departs after 9 a.m.					−0.041**	−0.040**	−0.037**	−0.033*	−0.038
					(0.018)	(0.018)	(0.018)	(0.020)	(0.047)
West						−0.041***	−0.046***	−0.051***	−0.031
						(0.016)	(0.016)	(0.019)	(0.032)
Observations	8,233	8,233	8,233	8,233	8,233	8,233	8,233	5,741	2,492

R-squared	0.019	0.033	0.039	0.047	0.048	0.049	0.096	0.100	0.171
Controls									
Day of week fixed effects	X	X	X	X	X	X	X	X	X
Demographic/family variables		X	X	X	X	X	X	X	X
Education			X	X	X	X	X	X	X
Economic status				X	X	X	X	X	X
Departure time					X	X	X	X	X
Geographic						X	X	X	X
Metro area fixed effects							X	X	X
Drivers only								X	
Nondrivers only									X

Notes: Standard errors in parentheses. The full list of baseline covariates includes other commuting time bins, day of week fixed effects, demographic and family variables (race, number of children in household under 18, whether there are two parents present in the household, and age bin dummies), educational attainment, economic variables (log wage and hours worked), dummies for departure time bins, dummies for geographic area of the United States, and metropolitan area fixed effects. Column 8 estimates the model with the full set of regressors for drivers only. Column 9 estimates the model with the full set of regressors for nondrivers only.

$^{***}p < .01$, $^{**}p < .05$, $^{*}p < .1$.

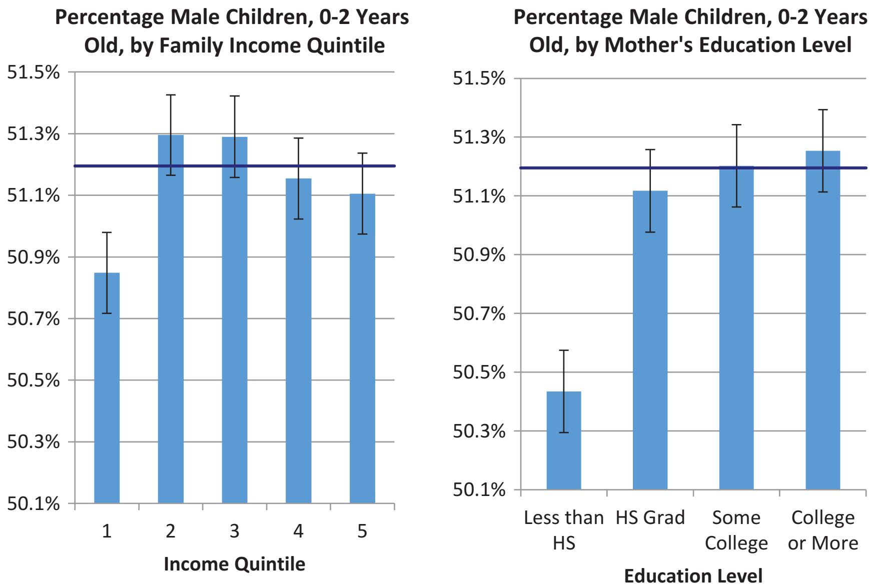

Figure 3. Percentage male children by socioeconomic characteristics.

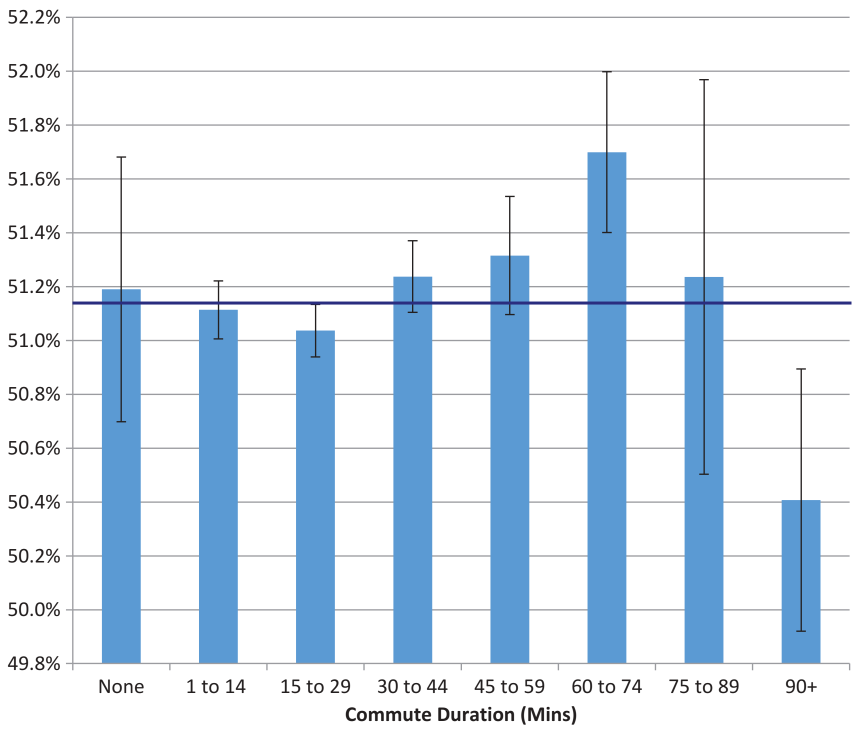

Figure 4. Percentage male children aged 0–2 years old, by mother's commuting time.

significant departure from the mean except for the 60–74 minute commute bin, which is 0.6 percentage points more likely to have a male child. However, these results may not represent the causal effect of long commutes on the likelihood of having a male child if there are confounding factors affecting which women have long commutes. The first approach to address this concern is to use OLS with a wide variety of covariates available in the census/ACS sample. The OLS results for the effects of an extreme commute are shown in Table 3. To better deal with any lingering confounding factors that are not well addressed by a simple linear regression model, we use Hirano and Imbens's (2001) inverse probability weighting procedure (IPW). The first-stage logit results are shown in Table A3. We find several variables are helpful for predicting the likelihood of an extreme commute, including the number of children, race, ethnicity, the presence of the father, the departure time, and the mode of transport to work. The distribution of propensity scores of extreme commuters and nonextreme commuters are shown in Figure 5. We find for example, that the 5th to the 95th percentile of the propensity score distribution for nonextreme commuters covers 66 percent of the propensity score distribution of extreme commuters, suggesting considerable overlap. The first column of Table 4 shows our preferred results using the IPW procedure. We find that the effect of an extreme commute is to lower the fraction of male children by 1.2 percentage points, an effect that is statistically significant at the 10 percent level. In Table A4, we show analogous results using IPW for the other commuting time bins. We find no other statistically significant effects. Unlike the case of extreme commutes, in which the negative effect on the fraction of male children is accentuated by using IPW, we find that the positive effect of a 60–74-minute commute time found in the raw data shown in Figure 4 is now dramatically reduced when using IPW to just 0.3 percentage points and is not close to statistically significant. This set of findings is consistent with the idea that both 60–74-minute commuters and extreme commuters are positively selected on socioeconomic status and that once one properly conditions on observable characteristics through IPW, the procedure produces more accurate estimates.

Discussion

Previous research has linked nutritional conditions in utero to the sex composition at birth. Provocative studies by Mathews, Johnson, and Neil (2008) and Almond and Mazumder (2011) highlight the potential role of intermittent fasting and suggest the usefulness of exploring additional sources of variation in fasting or meal skipping. The study by Mathews, Johnson, and Neil (2008) is purely observational, and it would therefore be helpful to replicate their findings using a research design that may more plausibly utilize exogenous variation in breakfast skipping. Second, their sample only utilized 740 women. Gelman and Weakliem (2009) have shown that studies of the sex ratio at birth are subject to the concern that with smaller sample sizes, only implausibly sized estimates that may be due purely to chance can be found to be statistically significant. Almond and Mazumder (2011) arguably use a more compelling research design paired with a large sample consisting of all births in Michigan over an 18-year period, but one may question whether repeated *diurnal* fasting over a 30-day period among American Muslims generalizes to non-Muslim American women who may occasionally skip breakfast and extend the overnight fast.

Using time use data, we find that women who have extreme commutes of 90 minutes or longer are about 20 percentage points more likely to skip breakfast. Using very large census/ACS samples we also show that the fraction of male offspring among women who have extreme commutes is reduced by about 1.2 percentage points. Combining these estimates in an instrumental variables framework by taking the ratio of the reduced form to

Table 3
Basic OLS, effects of 90+-minute commute on fraction of male births

	(1)	(2)	(3)	(4)	(5)	(6)
90+-min. commute	−0.007	−0.007	−0.007	−0.007	−0.007	−0.007
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Number of kids	−0.001	−0.001	−0.001	−0.001	−0.001	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Black	−0.004*	−0.004*	−0.004*	−0.004*	−0.004**	−0.004**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Asian	0.000	0.000	0.000	0.000	0.000	0.000
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Father absent		−0.005	−0.005	−0.005	−0.005	−0.005
		(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Parents married,		0.005	0.005	0.005	0.005	0.005
father absent		(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Separated		−0.010**	−0.010**	−0.010**	−0.010**	−0.010**
		(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Divorced		0.003	0.002	0.003	0.003	0.002
		(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Widowed		−0.0275**	−0.0275**	−0.0275**	−0.0275**	−0.0274**
		(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Part-time worker	−0.004**	−0.004**	−0.004**	−0.004**	−0.003**	−0.003**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	0.519***	0.519***	0.519***	0.519***	0.518***	0.518***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
Observations	729122	729122	729122	729122	729122	729122
R-squared	0.001	0.001	0.001	0.001	0.001	0.001
Controls						
Marital status	X	X	X	X	X	X
Additional race		X	X	X	X	X
Home ownership			X	X	X	X
Type of school				X	X	X
Birth order					X	X
Departure time						X

Notes: Standard errors in parentheses. The full list of covariates includes 90+-minute commute time, income bin dummies, number of children, race, part-time employment status, age bin dummies, dummies for years of education and father's years of education, and indicators for census year. Marital status includes variables for absent father, parents married with absent father, separated, divorced, and widowed. Type of school includes an indicator for private school enrollment. Birth order includes dummies for order of birth within family. Departure time adds dummies for morning departure time bins.

$^{***}p < .01$, $^{**}p < .05$, $^{*}p < .1$.

the first stage (–1.2/0.2) yields an estimate of about –6 percentage points. This implies that from a baseline fraction of 51 percent male births, skipping breakfast would lower that fraction to about 45 percent. The magnitude of the estimate is comparable to estimates from previous studies. Almond and Mazumder (2011) find that complete exposure to Ramadan

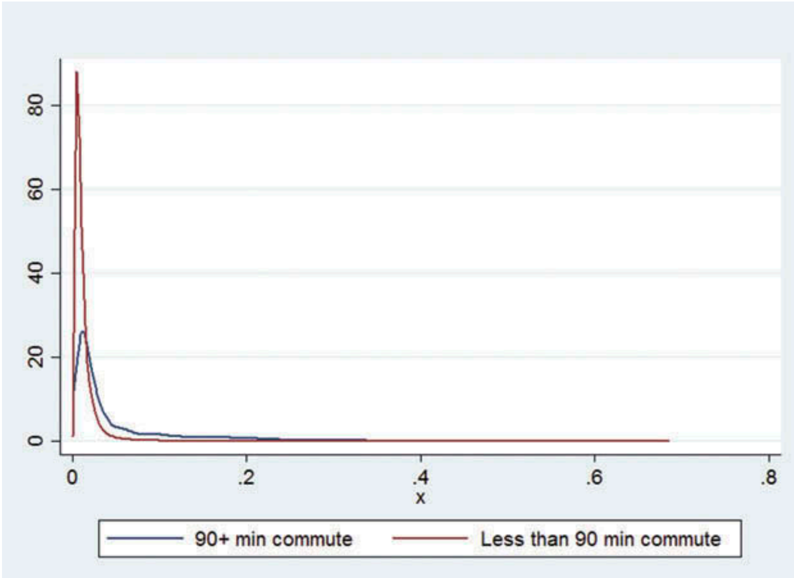

Figure 5. Distribution of propensity score by commute time.

Table 4
Inverse probability weighted effect on fraction of male births

	(1) Full sample	(2) Drivers only	(3) All others
90+-min. commute	−0.012*	−0.019**	0.006
	(0.007)	(0.009)	(0.045)
Observations	725,032	546,999	178,033
R-squared	0.001	0.001	0.004

Notes: Standard errors in parentheses. The full list of covariates includes 90+-minute commute; income bin dummies; number of children; race; absent father; married parents and absent father; parents separated, divorced, or widowed; part-time employee status; home ownership; private school enrollment; birth order dummies; morning departure time; mode of transportation (carpool, public transportation, biking or walking, or other); age and educational attainment; father's educational attainment; census year dummies; and metropolitan area fixed effects.
$^{**}p < .05$, $^{*}p < .1$.

fasting in the first month of pregnancy reduces the fraction of male births by 6.1 percentage points. Mathews, Johnson, and Neil (2008) find that moving from the top to the bottom tercile in nutrition around the time of conception (possibly as a result of breakfast skipping) reduces the probability of male birth by 11 percentage points.

We have also implemented several robustness checks. In one set of results we have limited both our ATUS sample and our census/ACS sample to those with commute times of 60 minutes or longer. By narrowing the sample to only those with long commutes we arguably limit the potential for our results to be driven by unobservable factors. We find that relative to those with 60–89-minute commutes, depending on our specification, extreme commuters are about 10 to 15 percent more likely to skip breakfast and about 1.1 to 1.2 percentage points less likely to have male births. In a second set of results we include controls for occupation and find nearly identical results to our main estimates. Finally, we also experimented with dropping the 1980 census from our reduced form analysis so that the timing of the first-stage analysis using the 2003–2009 ATUS sample more closely corresponds to the timing of the census/ACS sample. We find that the fraction of male births is reduced by 0.9 percentage points, a point estimate that is slightly lower than our baseline estimate but is not statistically significant.

There are some limitations to our approach. First, we use a sample of women whose commuting time is measured *after* the birth of their children. Thus, we rely on a potentially selected sample of women who chose to return to a job after childbirth, and we assume the commuting time of these mothers is the same as it was prior to birth. Our identification strategy assumes that these choices are independent of the sex of their children. Lundberg and Rose (2002) find that the women's labor supply in the United States is unrelated to the sex composition of their children.[12] We also test this finding directly using our very large census samples and confirm that there are no effects of the sex composition of births on either the likelihood of working or the number of hours worked by mothers.[13] This lessens our concern that commuting time is influenced by the sex of the child.

A second possible issue is whether extreme commuting might have a direct effect on the sex composition at birth that does not operate through breakfast skipping. One alternative hypothesis is that women who commute long distances in cars might be exposed to more pollution emitted by vehicles. Currie and Walker (2011) show that women who live near areas with high traffic congestion experience worse pregnancy outcomes. Sanders and Stoecker (2015) find that prenatal exposure to ambient air pollution is also associated with fewer male births. To address this possibility we show that the effects of extreme commutes on both breakfast skipping and the fraction of male children are concentrated almost exclusively on women who are drivers. We find little effect on nondriving passengers who are also in a vehicle for 90 minutes or longer and who would presumably be exposed to the same levels of pollutants. In columns 8 and 9 of Table 2 and Table A2 we show a set of results when we divide the ATUS sample by whether women were drivers or not on the day of the time diary. Among drivers, extreme commuters are 28 percentage points more likely to skip breakfast, whereas among nondrivers, extreme commuters are only 8 percentage points more likely to do so. The latter estimate is not statistically significant. We also find that among drivers, extreme commuters are 26 percentage points more likely to have a 16-hour or longer fast, but that among nondrivers, extreme commuters only experience a statistically insignificant 1.5 percentage point increase. In the census/ACS sample, we cannot cleanly divide the sample into drivers and passengers, since the data refer to the prior week. However, we can identify a subset of women who report that they usually drove alone to work and can compare the effects of extreme commuting in this subgroup to the rest of the sample. The results using the IPW estimation are reported in columns 2 and 3 of Table 4. Among those who usually drove alone the effect of extreme commutes is to lower the fraction of male children by 1.9 percentage points, an effect that is statistically

[12]Lundberg and Rose (2002) do present evidence that fathers' labor supply is related to the sex of their children.

[13]One possible mechanism linking the sex of the child to the mother's labor supply is through marital dissolution prompted by a bias for sons on the part of fathers (for the first child), as argued by Ichino, Lindstrom, and Viviano (2012). We find even larger effects of extreme commuting when we restrict our sample to still-married women, suggesting that our results are not driven by this mechanism. These results are available upon request.

significant at the 5 percent level. In contrast, among the rest of the sample we find a statistically insignificant positive effect of 0.6 percentage points. Our consistent finding of effects of extreme commuting on drivers and not passengers also suggests that any confounding factor or alternative explanation to breakfast skipping as the mechanism would also have to explain this pattern. As an added check, we also find that our effects are robust to removing from our sample women living in cities with the highest levels of highway pollutants according to data from the Environmental Protection Agency (EPA).

On the other hand, we cannot definitively rule out other possible factors that might be associated with being a driver during long commutes. It might be the case that there is increased stress associated with being a driver and that this activates responses in the neuroendocrine system that might result in selective attrition of male fetuses. Unfortunately, we are unable to measure stress in the ATUS to show whether or not there are similar levels of stress for drivers and nondrivers among those women with extreme commutes in the same way we can show definitive evidence with breakfast consumption. It is worth noting that even if it is the case that extreme commutes have a direct effect on the sex of offspring that does not operate only through breakfast skipping, our "reduced form" analysis still provides a useful contribution to the literature and highlights the value of future research to better understand the mechanisms. Similarly, our finding of large effects of extreme commuting on the propensity to skip breakfast may also be of independent interest, since skipping breakfast may also lead to poor health outcomes such as eating disorders, obesity, and metabolic syndrome (e.g. Ma et al. 2003; Wennberg et al. 2015).

In summary, we present new evidence suggesting that the skipping of breakfast by women of childbearing age can affect the sex composition of surviving births. This implies that the infant health of children born to these women may be compromised as a result of nutritional deficiencies very early in pregnancy—perhaps even before women are aware that they are pregnant. Given the growing body of evidence linking early-life exposures to the development of adult health conditions such as heart disease and diabetes, low-cost policies that encourage breakfast consumption could potentially yield large long-term benefits. While our analysis adds to the growing literature linking prenatal nutrition to the sex of the child at birth, we acknowledge that our approach is necessarily indirect and that it would be useful for future research to corroborate these findings.

Acknowledgments

We thank Adem Dugalic and Arian Seifoddini for excellent research assistance. We also thank two anonymous reviewers as well as Douglas Almond, Eric French, Ricarda Schmidl, and seminar participants at the "Long-Run Impacts of Early Life Events IV" conference at the University of Michigan, University of Essex, and University of Mannheim for helpful comments. The views expressed here do not reflect those of the Federal Reserve system.

References

Almond, D., and J. Currie. 2011. Human capital development before age five. In *Handbook of labor economics*, vol. 4B, ed. O. Ashenfelter and D. Card. San Diego, CA: North Holland/Elsevier.

Almond, D., and L. Edlund. 2007. Trivers–Willard at birth and one year: Evidence from US natality data 1983–2001. *Proceedings of the Royal Society of London B: Biological Sciences* 274:2491–96.

Almond, D., and B. Mazumder. 2011. Health capital and the prenatal environment: The effect of Ramadan observance during pregnancy. *American Economic Journal: Applied Economics* 3 (4): 56–85. doi:10.1257/app.3.4.56.

Almond, D., B. Mazumder, and R. van Ewijk. 2014. In utero Ramadan exposure and children's academic performance. *The Economic Journal*. doi:10.1111/ecoj.12168

Cohen, J. H., and H. Kim. 2009. Sociodemographic and health characteristics associated with attempting weight loss during pregnancy. *Preventing Chronic Disease* 6 (1): 1–9.

Currie, J., and R. Walker. 2011. Traffic congestion and infant health: Evidence from E-ZPass. *American Economic Journal: Applied Economics* 3 (1): 65–90. doi:10.1257/app.3.1.65.

Dominguez-Salas, P., S. E. Moore, M. S. Baker, A. W. Bergen, S. E. Cox, R. A. Dyer, A. J. Fulford, et al. 2014. Maternal nutrition at conception modulates DNA methylation of human metastable epialleles. *Nature Communications* 5:4746. doi:10.1038/ncomms4746.

Gelman, A., and D. Weakliem. 2009. Of beauty, sex and power. *American Scientist* 97 (4): 310–16.

Gluckman, P., and M. Hanson. 2005. *The fetal matrix: Evolution, development and disease*. Cambridge, UK: Cambridge University Press.

Haines, P. S., D. K. Guilkey, and B. M. Popkin. 1996. Trends in breakfast consumption of US adults between 1965 and 1991. *Journal of the American Dietetic Association* 96 (5): 464–70. doi:10.1016/S0002-8223(96)00130-7.

Hansen, D., H. Møller, and J. Olsen. 1999. Severe periconceptional life events and the sex ratio in offspring: Follow up study based on five national registers. *British Medical Journal* 319: 548–49.

Hirano, K., and G. Imbens. 2001. Estimation of causal effects using propensity score weighting: An application to data on right heart catheterization. *Health Services and Outcomes Research Methodology* 2 (3/4): 259–78. doi:10.1023/A:1020371312283.

Holtzman, N. S., 2010. *To skip or not to skip? Varying definitions of breakfast skipping and associations with disordered eating, obesity, and depression*. Undergraduate thesis, Wesleyan College.

Ichino, A., E. Lindstrom, and E. Viviano. 2012. *Hidden consequences of a first-born boy for mothers: New evidence and a critical assessment of the literature*. Unpublished manuscript. Firenze, Italy: European University Institute.

Larson, M. A., K. Kimura, H. M. Kubisch, and R. M. Roberts. 2001. Sexual dimorphism among bovine embryos in their ability to make the transition to expanded blastocyst and in the expression of the signaling molecule IFN-t. *Proceedings of the National Academy of Sciences* 98 (17): 9677–82. doi:10.1073/pnas.171305398.

Lundberg, S., and E. Rose. 2002. The effects of sons and daughters on men's labor supply and wages. *Restat* 84 (2): 251–68.

Ma, Y., E. R. Bertone, E. J. Stanek III, G. W. Reed, J. R. Hebert, N. L. Cohen, P. A. Merriam, and I. S. Ockene. 2003. Association between eating patterns and obesity in a free-living US adult population. *American Journal of Epidemiology* 158 (1): 85–92. doi:10.1093/aje/kwg117.

Mathews, F., P. J. Johnson, and A. Neil. 2008. You are what your mother eats: Evidence or maternal preconception diet influencing foetal sex in humans. *Proceedings of the Royal Society of London B: Biological Sciences* 275: 1661–68.

Matthews, T. J., and B. E. Hamilton. 2005. Trend analysis of the sex ratio at birth in the United States. *National Vital Statistics Report* 53 (20): 1–20.

Metzger, B. E., R. Vileisis, V. Ravnikar, and N. Freinkel. 1982. Accelerated starvation and the skipped breakfast in late normal pregnancy. *Lancet* 319 (8272): 588–92. doi:10.1016/S0140-6736(82)91750-0.

Mills, J. L., L. Jovanovic, R. Knopp, J. Aarons, M. Conley, E. Park, Y. J. Lee, L. Holmes, J. L. Simpson, and B. Metzger. 1998. Physiological reduction in fasting plasma glucose concentration in the first trimester of normal pregnancy: The diabetes in early pregnancy study. *Metabolism—Clinical and Experimental* 47 (9): 1140–44. doi:10.1016/S0026-0495(98)90290-6.

Rapino, M. A., and A. K. Fields. 2013. Mega commuters in the U.S.: Time and distance in defining long commute using the American community survey. Social, Economic, and Housing Statistics Division, U.S. Census Bureau Working Paper 2013–03.

Sanders, N. J., and C. Stoecker. 2015. Where have all the young men gone? Using sex ratios to measure fetal death rates. *Journal of Health Economics* 41: 30–45.

Siega-Riz, A. M., T. S. Hermann, D. A. Savitz, and J. M. Thorp. 2001. Frequency of eating during pregnancy and its effect on preterm delivery. *American Journal of Epidemiology* 153 (7): 647–52. doi:10.1093/aje/153.7.647.

Siega-Riz, A. M., B. M. Popkin, and T. Carson. 1998. Trends in breakfast consumption for children in the United States from 1965 to 1991. *American Journal of Clinical Nutrition* 67 (Suppl): 748S–56S.

van Ewijk, R. 2011. Long-term health effects on the next generation of Ramadan fasting during pregnancy. *Journal of Health Economics* 30: 1045–58.

Wennberg, M., P. E. Gustafsson, P. Wennberg, and A. Hammarström. 2015. Poor breakfast habits in adolescence predict the metabolic syndrome in adulthood. *Public Health Nutrition* 18: 122–129. doi:10.1017/S1368980013003509.

Appendix

Table A1
Mean characteristics by commute time

	Commute length in minutes						
	1–14	15–29	30–44	45–59	60–74	75–89	90+
Works part time	32.3%	25.8%	20.8%	17.4%	17.4%	18.3%	18.5%
Lives in metro area	36.9%	43.0%	46.3%	47.9%	49.5%	51.2%	50.1%
Number of children	2.02	1.94	1.91	1.88	1.92	1.90	1.97
Age	29.3	29.9	30.4	30.7	31.0	31.3	31.0
High school dropout	8.1%	6.9%	5.9%	4.6%	5.6%	3.6%	7.0%
College graduate	28.0%	31.8%	35.8%	38.0%	38.5%	42.1%	33.9%
Black	8.3%	10.7%	11.6%	12.6%	15.8%	12.5%	19.2%
Hispanic	10.1%	10.7%	10.9%	10.3%	12.6%	10.0%	13.2%
Family income	$53,800	$59,549	$65,094	$69,353	$71,880	$79,310	$68,406
Carpool	13.5%	17.1%	19.4%	20.8%	21.3%	19.9%	19.6%
Public transportation	0.7%	1.7%	4.7%	9.0%	19.3%	21.8%	25.7%
Bike/walk	5.0%	1.1%	0.5%	0.3%	0.3%	0.4%	0.6%
Other transportation	0.5%	0.3%	0.3%	0.3%	0.3%	0.4%	1.3%

Note: Based on census/ACS sample.

Table A2
Effects of long commute times on fast duration of 16 hours, selected coefficients

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
90+-min. commute	0.189***	0.188***	0.189***	0.189***	0.197***	0.197***	0.193***	0.261***	0.015
	(0.065)	(0.064)	(0.064)	(0.064)	(0.064)	(0.064)	(0.065)	(0.075)	(0.137)
Black		0.091***	0.087***	0.084***	0.085***	0.084***	0.084***	0.060***	0.142***
		(0.016)	(0.016)	(0.016)	(0.016)	(0.017)	(0.017)	(0.021)	(0.032)
Number of children		0.025***	0.021***	0.025***	0.025***	0.024***	0.023***	0.024***	0.020**
		(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.010)
Age 15–17		−0.050	−0.014	0.023	0.020	0.015	−0.023	−0.053	0.002
		(0.046)	(0.053)	(0.054)	(0.054)	(0.054)	(0.056)	(0.077)	(0.090)
Age 39–41		−0.031	−0.032	−0.038	−0.036	−0.037	−0.031	−0.034	0.009
		(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.029)	(0.049)
Age 42–45		−0.072***	−0.073***	−0.080***	−0.078***	−0.080***	−0.072***	−0.072***	−0.053
		(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.024)	(0.028)	(0.047)
Less than high school education			−0.020	−0.016	−0.016	−0.014	0.009	0.011	0.009
			(0.026)	(0.027)	(0.027)	(0.027)	(0.028)	(0.037)	(0.045)
College education or more			−0.059***	−0.071***	−0.074***	−0.074***	−0.061***	−0.056**	−0.081**
			(0.017)	(0.018)	(0.018)	(0.018)	(0.020)	(0.024)	(0.040)
Log wage				0.016	0.016	0.019*	0.020*	0.006	0.044**
				(0.011)	(0.011)	(0.011)	(0.012)	(0.015)	(0.022)
Weekly hours				0.002***	0.002***	0.002***	0.002**	0.002**	0.002
				(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Departs after 9 a.m.					0.009	0.010	0.011	0.026	−0.040
					(0.018)	(0.018)	(0.018)	(0.021)	(0.047)
West						−0.060***	−0.063***	−0.070***	−0.042
						(0.016)	(0.016)	(0.020)	(0.031)
Observations	8,233	8,233	8,233	8,233	8,233	8,233	8,233	5,741	2,492

R-squared	0.008	0.026	0.030	0.035	0.035	0.037	0.091	0.103	0.182
Controls									
Day of week fixed effects	X	X	X	X	X	X	X	X	X
Demographic/family variables		X	X	X	X	X	X	X	X
Education			X	X	X	X	X	X	X
Economic status				X	X	X	X	X	X
Departure time					X	X	X	X	X
Geographic area						X	X	X	X
Metro area fixed effects							X	X	X
Drivers only								X	
Nondrivers only									X

Notes: Standard errors in parentheses. The full list of baseline covariates includes all commuting time bins, though they are not displayed in the table. Other included covariates include day of week fixed effects, demographic and family variables (race, number of children in household under 18, whether there are two parents present in the household, and age bin dummies), educational attainment, economic variables (log wage and hours worked), dummies for departure time bins, dummies for geographic area of the United States, and metropolitan area fixed effects. Column 8 estimates the model with the full set of regressors for drivers only. Column 9 estimates the model with the full set of regressors for nondrivers only.

$^{***}p < .01$, $^{**}p < .05$, $^{*}p < .1$.

Table A3
First-stage logit results for prediction of 90+-minute commute

Variables	
Number of children	−0.025**
	(0.011)
Black	0.267***
	(0.032)
Asian	0.127***
	(0.047)
American Indian	−0.045
	(0.120)
Hispanic	−0.166***
	(0.042)
Other race	0.046
	(0.048)
Father absent	0.384*
	(0.223)
Part-time	−0.119***
	(0.027)
Departs before 6 a.m.	0.886***
	(0.034)
Departs 6–7 a.m.	0.567***
	(0.027)
Departs 7–8 a.m.	−0.579***
	(0.036)
Departs after 9 a.m.	−0.348***
	(0.033)
Takes public transit	2.051***
	(0.030)
Bikes or walks	−0.755***
	(0.127)
Takes other transit	1.454***
	(0.090)
Constant	−5.167***
	(0.076)
Pseudo R2	0.118
Observations	725032

Notes: Standard errors in parentheses. The full list of covariates includes income bin dummies, number of children, race, absent father, married parents and absent father, parents separated, parents divorced or widowed, part-time employee status, home ownership, private school enrollment, birth order dummies, morning departure time, mode of transportation (carpool, public transit, biking or walking, or other), age, educational attainment, father's educational attainment, census year dummies, and metropolitan area fixed effects.

$^{***}p < .01$, $^{**}p < .05$, $^{*}p < .1$.

Table A4

Inverse probability weighted results for alternate commute times on fraction of male births

	(1) 75–90 min.	(2) 60–75 min.	(3) 45–60 min.	(4) 30–45 min.	(5) 15–30 min.	(6) 0–15 min.
Commute time	−0.007	0.003	0.003	0.001	−0.002	−0.001
	(0.011)	(0.004)	(0.003)	(0.002)	(0.001)	(0.002)
Number of children	0.001	−0.001	0.000	−0.001	0.000	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Black	−0.004	−0.006*	−0.006*	−0.006**	−0.001	−0.003
	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.004)
Asian	−0.001	−0.001	−0.001	0.001	0.003	−0.004
	(0.006)	(0.006)	(0.005)	(0.004)	(0.004)	(0.005)
Father absent	0.009	0.027	0.007	0.007	−0.016	−0.014
	(0.023)	(0.023)	(0.022)	(0.018)	(0.018)	(0.023)
Parents married, father absent	−0.018	−0.003	0.011	0.008	0.005	−0.003
	(0.012)	(0.012)	(0.011)	(0.010)	(0.009)	(0.013)
Separated	−0.021***	−0.012*	−0.009	−0.008	−0.003	0.001
	(0.008)	(0.007)	(0.007)	(0.006)	(0.006)	(0.008)
Divorced	0.004	−0.005	0.003	0.003	0.003	0.004
	(0.007)	(0.006)	(0.006)	(0.005)	(0.005)	(0.007)
Widowed	−0.027	−0.014	−0.019	−0.013	−0.018	−0.039*
	(0.021)	(0.023)	(0.021)	(0.017)	(0.017)	(0.022)
Part-time worker	−0.002	−0.003	−0.002	−0.002	−0.003	−0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Constant	0.514***	0.522***	0.518***	0.525***	0.514***	0.523***
	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
Observations	709,718	724,251	724,982	725,032	725,032	725,032
R-squared	0.001	0.001	0.001	0.001	0.001	0.001

Notes: Robust standard errors in parentheses.
$^{***}p < .01$, $^{**}p < .05$, $^{*}p < .1$.

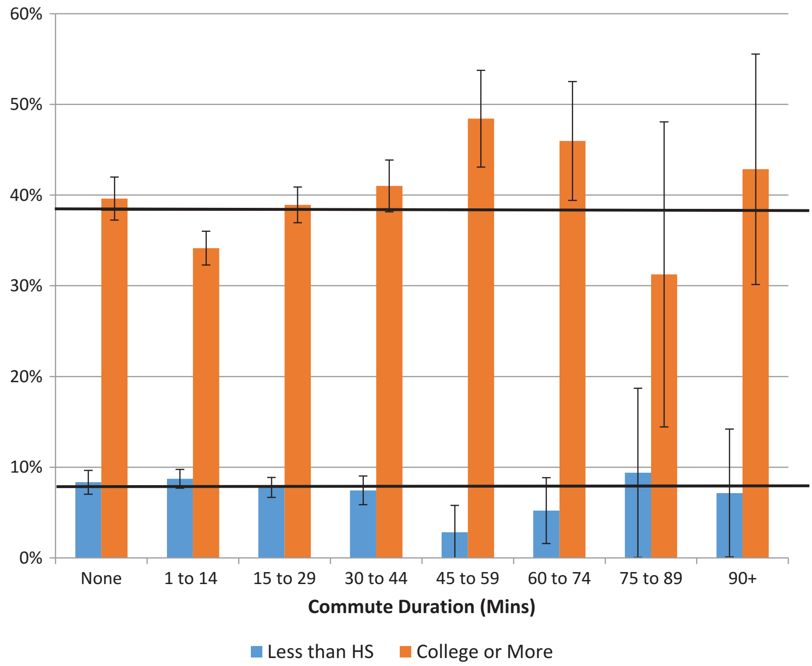

Figure A1. Educational attainment of women by commute duration.