Stable Income, Stable Family*

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Abstract

We document the effect of unemployment insurance generosity on divorce and fertility, using an identification strategy that leverages state-level changes in maximum benefits over time and comparisons across workers who have been laid off and those that have not been laid off. The results indicate that higher benefit levels reduce the probability of divorce and increase the probability of having children for laid-off men. In contrast, for laid-off women we find little evidence of effects of unemployment insurance generosity on divorce and we find suggestive evidence that it reduces their fertility.

JEL classification: J12, J13, J16, J65, H53, I38
Keywords: unemployment insurance, job loss, marriage, divorce, fertility, gender, family

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The recent economic downturn, which has seen record-breaking monthly unemployment insurance (UI) claims, has brought renewed attention to the effects of negative economic shocks and how policy can ameliorate the effects of such shocks. In this study, we focus on the degree to which UI generosity promotes family stability.

UI plays a key role in allowing individuals and their families to meet their financial needs during spells of unemployment, particularly when unemployment insurance is relatively generous and during recessions (Gruber, 1997; Kroft and Notowidigdo, 2016; East and Kuka, 2015). Causal estimates of the effects of UI indicate that UI expansions during the Great Recession prevented more than 1.3 million foreclosures (Hsu et al., 2018). Naturally, this evidence suggests that UI may be important to individuals and their families in many other ways that are not captured by standard economic indicators. In light of evidence that that job losses increase the risk of divorce (Charles and Stephens, Jr., 2004; Schaller, 2013, 2016), UI may play a significant role in promoting family stability.

We evaluate the effect of UI generosity using an empirical strategy that considers how the probability of divorce changes as a function of state-level changes in UI generosity, for individuals who have lost a job relative to individuals who have not lost a job. Our results indicate that individuals are significantly more likely to divorce after losing their jobs, but UI benefit generosity significantly mitigates this elevated risk for laid-off men. Specifically, they indicate that a $100 increase in maximum weekly UI benefits decreases the probability of divorce by a third of a percentage point, which represents 14 percent of the heightened risk of divorce associated with their layoffs. Our causal interpretation of this finding is supported by evidence that the changes in UI benefit generosity we exploit are unrelated to divorce rates for individuals who are employed and they are unrelated states' economic conditions and other social assistance programs. We also find that UI benefit generosity increases the probability of having children for laid-off men, and we find some suggestive evidence of an opposite-signed effect of UI benefit generosity on the fertility of laid-off women.

1 Background on Potential Mechanisms

As we noted above, the primary reason to think UI may promote family stability is because prior research has shown that job loss increases the risk of divorce (Charles and Stephens, Jr., 2004; Schaller, 2016) and because UI ameliorates the income shock associated with job loss.

An extensive body of research on the effects of unexpected income shocks on childbearing also suggests family income is important for families. In particular, studies in this literature find that positive (negative) shocks to men's earnings increase (decrease) fertility and also that housing wealth has a positive effect on fertility.[1] To the degree to which having children reflects stable families, these studies are consistent with the notion that families are more stable when they have access to greater economic resources.

There are a number of reasons why income support may affect family stability. First, resource scarcity may add to stress in a manner that strains relationships. Consistent with the notion that unemployment insurance helps mitigate the documented negative health consequences of job loss (Sullivan and von Wachter, 2009; Eliason and Storrie, 2009; Lindo, 2011), Cylus et al. (2014) find that higher UI generosity reduces suicide rates and Kuka (Forthcoming) shows that higher UI generosity increases health insurance coverage and self-reported health, though it does not have statistically significant effects on specific measures of health conditions. Along similar lines, Ahammer and Packham (2020) find evidence that extended UI benefits reduce opioid and antidepressant prescriptions among women; however they also find evidence that extended UI benefits increase the likelihood of a cardiac event for men.[2]

[1]For studies on the causal effects of shocks to men's earnings, see Lindo (2010), Black et al. (2013), Kearney and Wilson (2018). Also note that Schaller (2016) finds evidence of an opposite-signed effect of employment shocks affecting women. For studies evaluating the effects of housing wealth, see Lovenheim and Mumford (2013) and Dettling and Kearney (2014). Also note that fertility is generally positively related with aggregate measures of local economic conditions (Schaller et al., 2020). Research also indicates that new marriages and divorces are also positively associated with economic conditions (Schaller, 2013).

[2]Research on the effects of expanded earned income tax credit benefits also indicates that relieving financial constraints improves mental health (Evans and Garthwaite, 2014; Boyd-Swan et al., 2016). Similarly, research on stock market wealth also indicates the importance of economic circumstances for mental health (McInerney et al., 2013; Cotti et al., 2015; Cotti and Simon, 2017; Schwandt, 2018).

Second, UI benefit generosity affects time use. They lead to longer unemployment spells (Katz and Meyer, 1990; Kroft and Notowidigdo, 2016) and increased college enrollment (Barr and Turner, 2015) among job losers, and increases in labor supply of spouses (Cullen and Gruber, 2000). These effects have the potential to promote or detract from family stability.

Third, income support may affect the economic benefits of being married relative to the economic benefits of being divorced. This may occur because it alters the benefits of having access to the resources that a spouse brings to the household, or because of the benefits of economies of scale that can be achieved through partnering.

We think it also important to recognize that the effects may be different depending on the gender of the person losing their job. In particular, prior research indicates that domestic violence, marital satisfaction, time spent on household chores, and divorce depends on men's and women's *relative* earnings (Aizer, 2010; Bertrand et al., 2015). Also consistent with the potential for asymmetric effects, several studies examining children's outcomes have found evidence of detrimental effects of men's job losses and positive (or null) effects of women's job losses (Page et al., 2017; Lindo et al., 2018; Schaller and Zerpa, 2019; Regmi and J. Henderson, 2019).

2 Data

Our primary data sources are the Survey of Income and Program Participation (SIPP) and state-specific schedules of unemployment insurance benefits. SIPP is a household survey that provides nationally representative measures of individual and household income, employment status, employment characteristics, family and household dynamics, program participation, and a range of individual and household characteristics.[3] Our analysis uses the 1990, 1991, 1993 1996, 2001, 2004, and 2008 panels of the SIPP. Within each panel, households are surveyed over the course of 30 to 64 months with interviews occurring every four months. The interview

[3]SIPP is a multistage stratified sample of housing units with a sample population that includes civilian non-institutionalized population.

questions in each survey typically reference the months between interview dates.

SIPP data are well-suited for our purposes because they include frequent measures of employment status, marital status, and fertility as well as state identifiers, which allow us to identify the unemployment insurance benefit schedule that is relevant to the individual.[4] Note that while we refer to "divorce" throughout the paper, our empirical analyses evaluate whether an individual reports being separated or divorced. We take this approach in an effort to better capture the timing with which marriages dissolve.

To identify unemployment spells that are most likely to meet UI eligibility requirements, we define a layoff as being currently separated from a primary job after reporting three consecutive months of employment. Like prior studies, we condition on prior employment in this manner to avoid including in this group new labor market entrants that would not be eligible for UI benefits. We note that the broad definition of layoff that we use does include individuals who report being temporarily laid off.[5] While this might seem inconsistent with the fact that state UI eligibility standards typically require an individual to be actively searching for a job, it is consistent with evidence that temporarily laid-off individuals expecting recall make up a large fraction of UI recipients (Katz and Meyer, 1990) and our own investigation of the SIPP data which confirms that many of these individuals report receiving UI benefits. In addition to documenting the effects using this broad definition of a layoff, we also examine the effects using an alternative definition that uses stated reasons for the job loss, as in (Kuka, Forthcoming).[6]

Our analysis also uses individual and household variables available in SIPP including the age, race, and educational attainment of the survey respondent as well as the number of children

[4]An important exception to this statement is that prior to 1996, SIPP did not distinguish between individuals residing in Vermont and Maine, between individuals residing in Alaska, Idaho, Montana, and Wyoming, and between individuals residing in Iowa, North Dakota,South Dakota. We omit these observations from our analysis.

[5]Specifically, our definition includes all individuals in groups 3 through 7 of the SIPP's RMSER variable, which describes their employment circumstances.

[6]This alternative approach defines an individual as having been laid off if they report that they lost a job because of the following reasons: "on layoff," "employer bankrupt," "employer sold business, "job was temporary and ended," or "slack work." This is not our preferred measure because the reasons for job separation are often unreported and because the latter four categories were only included in SIPP panels after 1995.

and ages of children. We restrict our SIPP sample to individuals that are married, employed, and at least age 20 in the first month in which they are observed in the data. Our analysis of divorce further restricts the sample to individuals ages 65 or under in the last month they are observed while our analysis of fertility restricts the sample to individuals who are younger than 35.

Our sample includes both always-employed individuals and individuals that experience a layoff sometime during the survey period. For those experiencing a layoff, we focus on the first layoff observed in the data because subsequent layoffs are less likely to be exogenous (Stevens, 1997). In an effort to improve the balance of the sample around the time of the relevant event, our analyses of divorce use observations for laid-off individuals up to 12 months prior to the layoff and 24 months after the layoff. Out of respect for the lagged nature of childbearing, we adjust this window by nine months when we analyze fertility.[7]

We merge our SIPP sample with state-by-year schedules for unemployment insurance benefits from the U.S. Department of Labor reports published in January of each year.[8] Similar to previous studies, we use the maximum weekly benefits as a measure of unemployment insurance generosity which is a strong predictor of benefits received (Hsu et al., 2018).

Appendix Table A1 includes descriptive statistics for our sample, comparing individuals that report a layoff in the past 24 months to individuals that report being employed, with separate panels for the sample of husbands and the sample of wives.[9] Though not particularly stark, similar patterns appear across the panels when comparing those that experience a layoff to those that do not. The statistics indicate workers that do experience a layoff at some point in our sample are slightly less educated, younger, more likely to be a minority, and live in states that have slightly higher UI benefits and unemployment rates.[10] Moreover, the probability of

[7] Specifically, our analysis sample for fertility outcomes includes observations that are within 3 months prior to and 33 months after the month of the layoff for those that experience a layoff.

[8] The reports identify "Significant Provisions of State UI Laws", and can be found at https://oui.doleta.gov/unemploy/statelaws.asp#sigprouilaws.

[9] We apply sample survey weights when calculating summary statistics.

[10] Unemployment rates are from the Bureau of Labor Statistics.

divorce is higher for both men and women after a layoff, and the probability of having a new child is lower after a layoff for men.

3 Empirical Strategy

Though we also show results from more parsimonious models, our preferred estimates are based on a triple-differences design.[11] Specifically, this research design leverages variation in UI generosity across states and over time (as would be typical in a difference-in-differences design) and also compares laid-off and non-laid-off workers. The third difference involving non-laid-off workers allows us to control flexibly for idiosyncratic shocks that are specific to any given state in any given year (via the inclusion of state-by-year fixed effects) and also to control for systematic differences between laid-off workers in different states (via the inclusion of state-by-group fixed effects where one group is workers who experience layoffs and the other group is workers who do not experience layoffs). We implement this research design using the following model:

$$y_{igsym} = \beta_1 MaxUI_{sy} \times \mathbb{1}[AfterLayoff_{igsym}] + \beta_2 \mathbb{1}[AfterLayoff_{igsym}] + \lambda_{sy} + \psi_{gs} + \epsilon_{igsym}, \quad (1)$$

where y_{igsym} is an outcome observed for individual i from group g residing in state s in year y and month m; $MaxUI_{sy}$ is the maximum amount of weekly UI benefits in state s and year y measured in hundreds of dollars; $\mathbb{1}[AfterLayoff_{igsym}]$ is an indicator variable that takes the value of one following an individual's layoff; λ_{sy} are state-by-year fixed effects; ψ_{gs} are state fixed effects that vary across the group of individuals that experience layoffs and the group that does not experience layoffs; and ϵ_{igsym} is a random error term. We also estimate a version of this model that controls for additional covariates. Our models use survey weights and adjust the standard-error estimates to allow for clusters at the state level.

[11] Our approach closely parallels Hsu et al. (2018) and is also similar to Kuka (Forthcoming).

The coefficient of interest from this model is β_1, which captures the effect of UI generosity on outcomes of individuals who have been laid off. The identifying assumption underlying a causal interpretation of this parameter is that changes in state UI generosity are not correlated with other changes that differentially affect laid-off individuals relative to non-laid-off individuals. In support of the validity of this assumption, we show that there is no significant correlation between the changes in UI generosity that we exploit and changes in divorce probabilities among non-laid off workers. We also show that there is no significant link between the changes in UI generosity that we exploit and changes in states' economic conditions and social assistance programs.

We also report estimates from models that explore the dynamic effects leading up to and following a job loss. Moreover, we report the results from a large number of specification checks, including those that control for individual fixed effects, those that use an alternative definition of layoffs, and those that use different approaches to controlling for state trends, among others.

4 Results

Table 1 shows our main results, with separate panels reporting our analyses of men and women. In Column (1), we report the estimated effect of UI benefit generosity on workers who have been laid off (via the interaction between MaxUI and $\mathbb{1}$[After Layoff]), while controlling for the main effects of having been laid off and UI benefit generosity, in addition to state fixed effects, year fixed effects, and group fixed effects—where the relevant groups are individuals who experience layoffs and individuals who do not experience layoffs. This estimated effect is negative and statistically significant in our analysis of men who are laid off (Panel A), indicating that UI generosity reduces divorce for laid-off men. There is no such evidence of effects on laid-off women (Panel B).

The coefficients on the other variables reported in the table also have meaningful interpretations and provide context for our estimated effects of UI benefit generosity for workers who

Table 1
Effect of UI Benefit Generosity on Divorce

	(1)	(2)	(3)
Panel A: Men			
MaxUI×𝟙[After Layoff]	-0.0040***	-0.0035***	-0.0034***
	(0.0010)	(0.0010)	(0.0010)
𝟙[After Layoff]	0.0262***	0.0248***	0.0245***
	(0.0035)	(0.0035)	(0.0035)
MaxUI	-0.0011		
	(0.0015)		
Panel B: Women			
MaxUI ×𝟙[After Layoff]	-0.0008	-0.0005	-0.0005
	(0.0013)	(0.0015)	(0.0015)
𝟙[After Layoff]	0.0133***	0.0124**	0.0125**
	(0.0049)	(0.0053)	(0.0053)
MaxUI	-0.0013		
	(0.0013)		
Year Fixed Effects	Y	-	-
State Fixed Effects	Y	-	-
Group Fixed Effects	Y	-	-
State-Year Fixed Effects	N	Y	Y
State-Group Fixed Effects	N	Y	Y
Individual Controls	N	N	Y

Notes: Estimates are based on the 1990, 1991, 1992, 1993, 1996, 2001, 2004, and 2008 panels of the Survey of Income and Program Participation. The dependent variable is an indicator variable for being separated or divorced. The variable 𝟙[After Layoff] is an indicator that takes the value of one following a job loss. The variable MaxUI is the state maximum amount of weekly UI benefits in hundreds of dollars. Regression models use survey weights and adjust the standard-error estimates to allow for clusters at the state level.
*, **, and ***, indicate statistical significance at the ten-, five-, and one-percent levels, respectively.

have been laid off. The coefficient on the variable "After Layoff" captures the additional risk of divorce following a layoff. It is positive and statistically significant in our analysis of men and women, which indicates that these individuals are at heightened risk of divorce after they are laid off. Thus, the interacted effect of UI generosity on these individuals can be viewed as mitigating this elevated risk. The coefficient on the variable for maximum weekly UI benefits (MaxUI) is not statistically significant and is close to zero in our analyses of both men and women. This indicates that there is no link between UI benefit generosity and divorce, outside of the effect we identify for laid-off men, and thus provides evidence in support of the validity of our research design.

In Column (2), we report the estimated effects from a model that operationalizes the triple-differences research design. This model includes state-by-year fixed effects to control flexibly for changes in divorce probabilities across states and over time. This model also includes state-by-group fixed effects to control for any differences in divorce probabilities across these groups that are constant over time within states.[12] Finally, in Column (3) we report estimates from our preferred model, which is similar but also controls for demographics and levels of education.[13] The results from these models are extremely similar to those reported in Column (1). They indicate that individuals are more likely to divorce after being laid off, and that UI benefit generosity mitigates this elevated risk for men's layoffs but not for women's layoffs.

The estimated effect for laid-off men from our preferred model indicates that a \$100 increase in maximum weekly UI benefits decreases their probability of divorce by a third of a percentage point. This represents 14 percent of the heightened risk of divorce associated with their layoffs.

In Figure 1 we present estimated effects over time. These estimates are based on a

[12]For example, this would control for persistent high divorce probabilities among individuals experiencing layoffs in State A.

[13]These controls include indicators for White, Black, and other race, a quadratic in age, and indicators for having less than or equal to a high school degree, some college, a bachelor's degree, and a master's degree or beyond.

modified version of our preferred model that includes a full set of interaction terms that capture the effects of UI benefit generosity on laid-off workers leading up to and following the layoff, rather than a single interaction term that captures the average effect of UI benefit generosity across all periods following a layoff.[14] Like the results presented in Table 1, these results indicate that UI benefit generosity significantly reduces the incidence of divorce for laid-off men (Panel A) but not for laid-off women (Panel B).

There is also some evidence of effects one—and perhaps two—quarters prior to men's layoffs. This is consistent with the fact that a significant share of workers anticipate layoffs before they happen (Stephens, 2004), which is not surprising because many workers are forewarned about upcoming layoffs and others may suspect the possibility if they know their firm is in distress or if they experience wage stagnation, reduced overtime, etc. That individuals "feel the effects" of an impending layoff is a consistent pattern in the literature on laid-off workers going back to Jacobson et al. (1993). Specifically, Jacobson et al. (1993) reported "evidence that the events that lead to workers' separations cause their earnings to depart from their expected levels even before they leave their firms." They showed evidence of such divergence up to three years prior to separation and that the divergence accelerated during the quarters immediately prior to separation. The existence of a pre-displacement dip is a common feature of studies on the effects of job loss on earnings, though the severity varies across studies.[15]

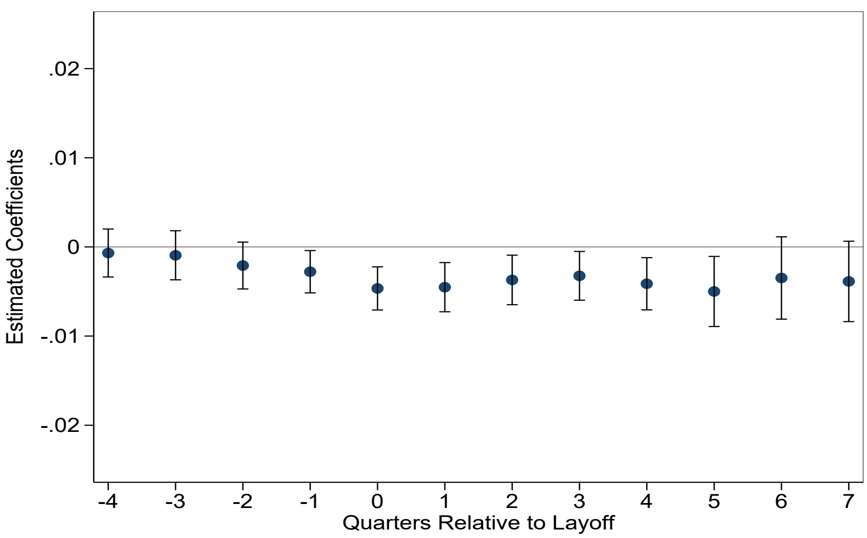
To verify the robustness of the effects we find for laid-off men, we have also estimated these effects with different combinations of state-year adjustments, including models with state fixed effects, year fixed effects, state-linear trends, state-quadratic trends, state-by-year fixed effects, and state-by-group fixed effects. We have also estimated models with different combinations of individual-level adjustments including none, covariates for demographics and state unemployment rates, and individual fixed effects. We have also estimated models with the nar-

[14]The model also includes indicators for quarters before and after the layoff that are not interacted with the measure of UI benefits.

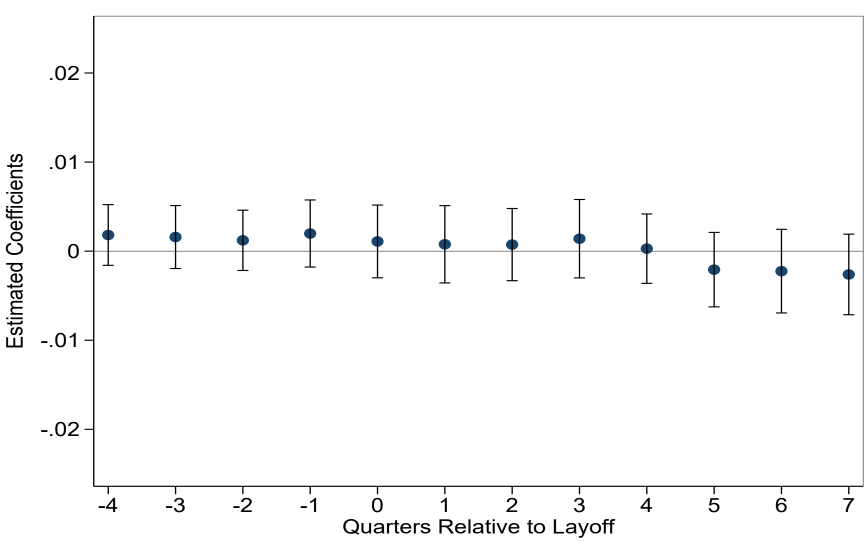
[15]For examples beyond Jacobson et al. (1993), see Sullivan and von Wachter (2009), Lindo (2010), and Couch and Placzek (2010).

Figure 1
Event Study: Effects of UI generosity over time on divorce

Panel A: Men



Panel B: Women



Notes: The dependent variable is an indicator variable for divorce or separation in each survey month. This figure reports estimated coefficients and 95 percent confidence intervals for interactions between indicator variables for quarters relative to layoff and the variable for maximum weekly UI benefits in hundreds of dollars (MaxUI). The regression model additionally includes individual demographic and education controls (age, race, and educational attainment), state-by-year fixed effects, and state-by-group fixed effects. Moreover, we use survey weights and adjust the standard-error estimates to allow for clusters at the state level. Estimates are based on the 1990, 1991, 1992, 1993, 1996, 2001, 2004, and 2008 panels of the Survey of Income and Program Participation.

rower definition of a layoff used in Kuka (Forthcoming). Finally, we have estimated models with UI benefits measured in real (2010) dollars.

In Appendix Figure A1 we report 96 estimates—ordered by magnitude—for all of the possible combinations of these different approaches to controlling for state-year changes over time, individual characteristics, defining layoffs, and measuring UI benefits. These estimates are always negative; they are statistically significant at the five-percent level in 67 of 96 specifications; and they are statistically significant at the ten-percent level in 82 of 96 specifications. There is no clear pattern regarding which approaches lead to bigger or smaller estimates, except that it appears as if using the more-narrow definition of a layoff leads to a wider range of estimated effects.[16]

To further support the validity of our main results, we have also investigated whether our measure of UI benefit generosity might be capturing the effects of other aspects of economic conditions or program generosity. We note such confounding effects would have been evident in the results presented in Table 1 if they they affected workers who had not been laid off, but those results instead indicated that our UI benefit generosity measure was *not* significantly related to divorce for such individuals. Nonetheless, it would be a concern for our identification strategy if the UI benefit measure was significantly related to measures of economic conditions or program generosity and if such measures differentially affect laid off workers. To address this possible concern, we have regressed our measure of UI benefit generosity on various measures of state economic conditions (separately and jointly), controlling for year fixed effects and state fixed effects, and we have regressed our measure of UI benefit generosity on various measures related to state social programs (separately and jointly).[17] The results of these analyses, shown

[16]Notably, if we use this narrower definition of a layoff but otherwise use our preferred specification, the coefficient estimate is -0.058 (versus -0.034 using our preferred definition).

[17]Social program measures include the participation rate in Workers' Compensation, the Supplemental Nutrition Assistance Program (previously known as food stamps), Social Security Disability Insurance (SSDI), and Medicaid. The participation rate is defined as the number of recipients in a state divided by the state's population. These data are from the University of Kentucky Center for Poverty Research (UKCPR). State GDP growth rates are from the Bureau of Economic Analysis' national economic accounts, union coverage data are from unionstats.com which updates data based on Hirsch et al. (2001), and average income is from the Quarterly Census of Employment and Wages (QCEW) program data.

in Appendix Table A2, are reassuring. They indicate that our UI benefit generosity measure is not significantly related to these other measures.

5 Effects By Presence of Children and on Fertility

Given that decisions to divorce may be more complex for couples with children and also given that the financial distress associated with layoffs may be greater for couples with children, it is reasonable to think that the effects of UI benefit generosity may differ for households with and without children. We investigate this possibility (using our preferred model) by separately analyzing the effects for individuals who do not report any children, those who report having children, and those who report having children under age 18.[18]

The results of this analysis for men, shown in Panel A of Table 2, indicate that individuals who have been laid off have a significantly higher probability of divorce whether one considers those without children, those with children, or those with children under age 18. However, this heightened risk of divorce is highest for those without children and it is lowest for those with children under age 18 (for whom the estimate is only statistically significant at the ten-percent level). These findings provide important context for our estimated effects of UI benefit generosity, because they suggest that there is the greatest scope for such benefits to reduce divorce for individuals without children and there is the smallest scope for such benefits to reduce divorce for individuals with young children.

Along these lines, the estimated effects of UI benefit generosity do indicate that UI benefit generosity reduces divorce most among individuals without children. The effects are also statistically significant for individuals with children, but they are not statistically significant for individuals with children under age 18.

We have also investigated the effects for laid-off women, the results of which are shown in

[18]We identify these groups based on responses to the questions asking respondents "the number of own children in the family" and the "number of own children under 18 in the family."

Table 2
Effects on divorce for those with and without children

	(1) No Children	(2) Children	(3) Children < age 18
Panel A: Men			
MaxUI $\times \mathbb{1}$[After Layoff]	-0.0064**	-0.0026***	-0.0003
	(0.0027)	(0.0008)	(0.0009)
$\mathbb{1}$[After Layoff]	0.0475***	0.0153***	0.0051*
	(0.0096)	(0.0023)	(0.0028)
Panel B: Women			
MaxUI $\times \mathbb{1}$[After Layoff]	0.0030	-0.0021	-0.0019
	(0.0022)	(0.0020)	(0.0022)
$\mathbb{1}$[After Layoff]	0.0035	0.0170**	0.0156*
	(0.0081)	(0.0073)	(0.0082)

Notes: The table presents the heterogenous effects of maximum weekly unemployment benefits on divorce. Column 1 limits the sample to those who do not have any children. Column 2 limits the sample to those who have at least one child irrespective of age. Column 3 limits the sample to those who have at least one child under the age of 18. The regression models include individual demographic controls (age, race, and educational attainment), state-by-year fixed effects, and state-by-group fixed effects. Moreover, we use survey weights and adjust the standard-error estimates to allow for clusters at the state level.
*, **, and ***, indicate statistical significance at the ten-, five-, and one-percent levels, respectively

Panel B of Table 2. Like the results shown in Table 1, these results also indicate that UI benefit generosity does not affect divorce for laid-off women (irrespective of having children).

As we noted above, prior work has shown that men's layoffs have a significant effect on the fertility of their wives (Lindo, 2010). Naturally then, UI benefit generosity may also affect fertility, either via a direct effect or through the impacts on divorce we documented above. To investigate this question, we examine the probability of reporting a new child in the household for individuals ages 20–35.[19]

In Table 3 we show the estimated effects of UI benefit generosity for laid-off men on fertility using our most parsimonious and our preferred specifications; in Figure 2 we show how the effects evolve over time; and in Figure A2 we show the sensitivity of the estimates to alternative modeling choices. Though the estimate is not statistically significant in the most parsimonious model, it is in our preferred model. That model indicates that laid-off men are

[19]We define "having a new child in the household" based on whether a child of age zero is reported.

relatively unlikely to have children, but that this difference is significantly mitigated by generous UI benefits.

We note that the estimated effect from our preferred model is at the very upper end of the estimated effects that we report in the specification chart (Figure A2), though nearly all specifications yield a positive coefficient estimate (with differing magnitudes and precision). Moreover, the event-study estimates from our preferred model (Figure 2) support the validity of that model, as they indicate common trends before suggestive evidence of effects two quarters after the layoff and then stronger evidence of effects in the subsequent six quarters. As such, the timing of these effects line up with the estimated effects on divorce with a nine-month lag.

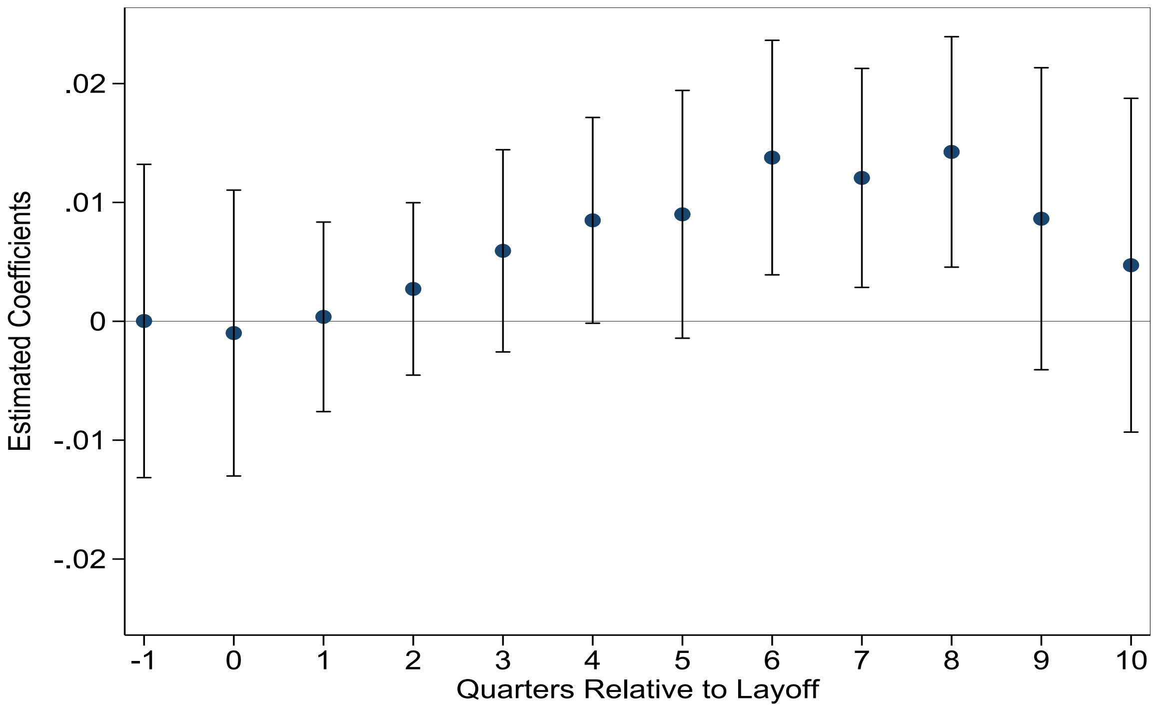
Table 3
Effect of UI benefit generosity for laid-off men on fertility

	(1)	(2)	(3)
MaxUI $\times \mathbb{1}$[9+ Months After Layoff]	0.0045	0.0082***	0.0091***
	(0.0034)	(0.0030)	(0.0028)
$\mathbb{1}$[9+ Months After Layoff]	-0.0277**	-0.0396***	-0.0397***
	(0.0128)	(0.0114)	(0.0108)
MaxUI	0.0021		
	(0.0038)		
Year Fixed Effects	Y	-	-
State Fixed Effects	Y	-	-
Group Fixed Effects	Y	-	-
State-Year Fixed Effects	N	Y	Y
State-Group Fixed Effects	N	Y	Y
Individual Controls	N	N	Y

Notes: The dependent variable is whether an individual ages 20 to 35 has a child less than one year old in the survey month. Regression models use survey weights and adjust the standard-error estimates to allow for clusters at the state level.
*, **, and ***, indicate statistical significance at the ten-, five-, and one-percent levels, respectively

We have also analyzed the effects for women experiencing layoffs. We show these results in the appendix (in Table A3 and Figure A3) because they are less conclusive. In particular, this analysis suggests some concern about the common-trends assumption such that we think caution is warranted in interpreting the estimated effects. Nonetheless, we note that these estimates provide some evidence of an effect that opposite in sign to the estimated effect for

Figure 2
Effects of UI generosity over time for laid-off men on fertility



Notes: The dependent variable is whether an individual ages 20 to 35 has a child less than one year old in the survey month. This figure reports estimated coefficients and 95 percent confidence intervals for interactions between indicator variables for quarters relative to layoff and the variable for maximum weekly UI benefits in hundreds of dollars (MaxUI). The regression model additionally includes individual demographic and education controls (age, race, and educational attainment), state-by-year fixed effects, and state-by-group fixed effects. Moreover, we use survey weights and adjust the standard-error estimates to allow for clusters at the state level.

laid-off men, such that more generous UI benefits reduce the fertility of laid-off women. As such, they are consistent with earlier work showing that economic shocks affecting men and women have opposite-signed effects, including analyses of fertility (Schaller, 2016).

6 Conclusion

As a whole, the results of our analyses indicate that UI generosity has significant effects on divorce and on childbearing. In particular, more-generous benefits reduce the incidence of divorce for laid-off men but do not appear to mitigate the elevated risk of divorce for laid-off women. We also find that UI generosity increases the probability of having children for laid-off men and suggestive evidence that it reduces this probability for laid-off women, which is consistent with a sizable literature documenting that economic shocks experienced by men and women have very different effects on families.

These results highlight how the structure of UI benefits can have profound effects on families, beyond their economic circumstances. We hope that future work will shed light on the effects on other measures of family distress, including domestic violence and child maltreatment, and on individual's long-term outcomes, including marital status and completed fertility.

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7 Appendix

Table A1
Summary Statistics

	Before Layoff	After Layoff	Never Laid Off
Panel A: Men			
Divorce	0.023	0.032	0.017
Child $<$ 1 yr old	0.131	0.097	0.117
Age	41.3	42.3	43.0
White	0.87	0.85	0.88
Black	0.08	0.09	0.07
Other	0.05	0.06	0.05
Advanced Degree	0.05	0.08	0.14
Bachelor's Degree	0.12	0.15	0.22
Some College	0.27	0.29	0.29
High School	0.56	0.49	0.35
Max UI	335	333	320
Observations	43,665	597,147	1,924,590
Panel B: Women			
Divorce	0.017	0.035	0.021
Child $<$ 1 yr old	0.088	0.079	0.080
Age	41.1	40.7	43.0
White	0.85	0.87	0.86
Black	0.09	0.08	0.08
Other	0.06	0.06	0.05
Advanced Degree	0.05	0.08	0.12
Bachelor's Degree	0.13	0.19	0.21
Some College	0.29	0.32	0.32
High School	0.53	0.42	0.35
Max UI	336	333	324
N	28,875	595,801	1,191,310

Notes: The data include the 1990, 1991, 1992, 1993, 1996, 2001, 2004, and 2008 panels of the Survey of Income and Program Participation. Columns 1 and 2 present means before and after layoff for individuals that indicate a layoff in the panel, and Column 3 provides means for individuals that do not indicate a layoff in the panel. Note that our analyses of fertility further restricts the sample to individuals that are equal to or less than age 35. These statistics and the remainder of our results use survey weights.

Figure A1

Specification chart for effects of UI generosity on divorce for laid-off men

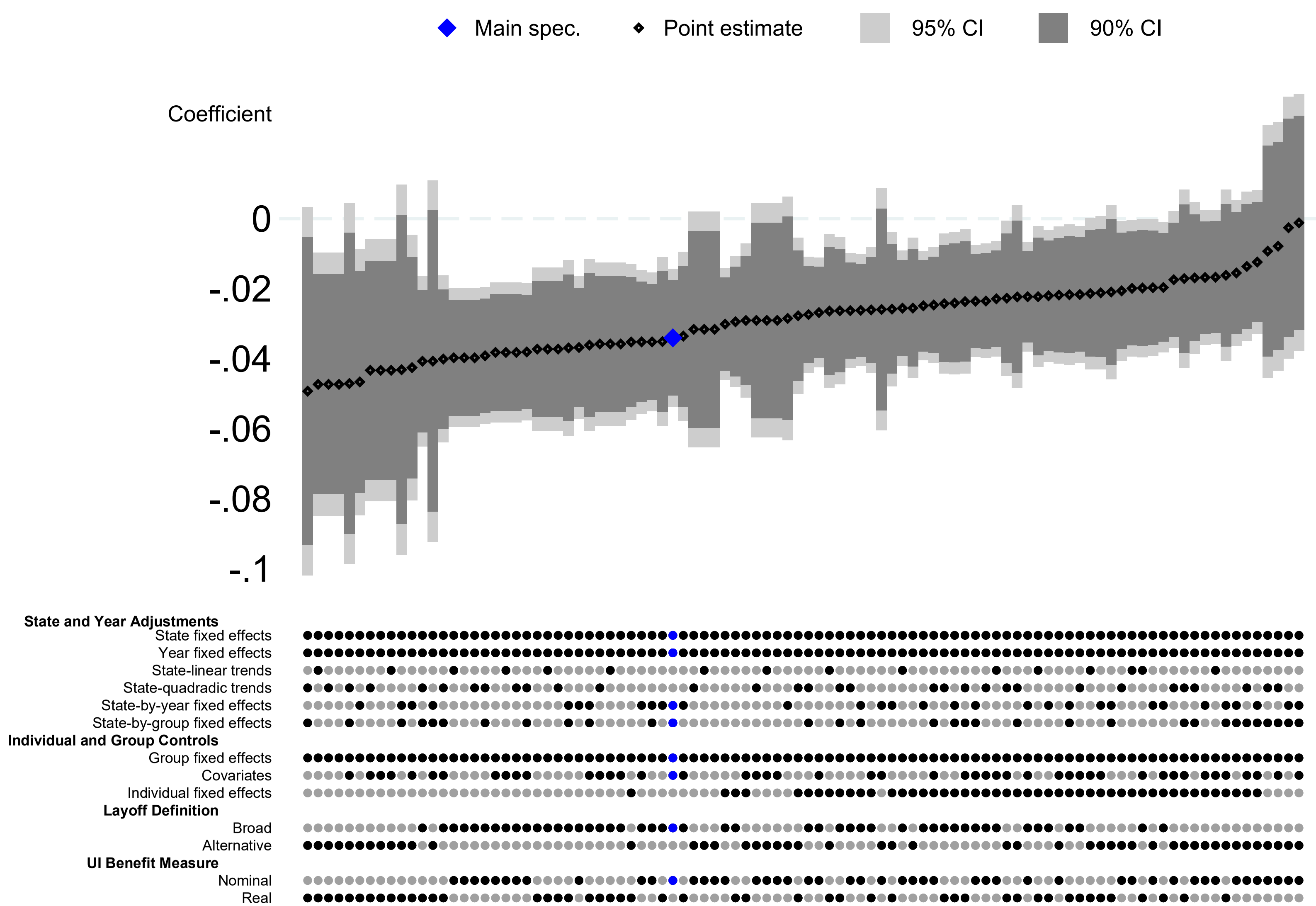


Table A2
UI benefit generosity and measures of economic conditions and other social programs

	(1)	(2)	(3)	(4)	(5)
Panel A: Relationship with State Economic Conditions					
State GDP Growth Rate	-0.0636				-0.3607
	(0.5319)				(0.4530)
Unemployment Rate		-1.1972			-0.5376
		(2.5176)			(2.1246)
Average State Income			2.3374		2.3598
			(3.8687)		(3.8587)
Union Coverage				0.2214	0.2342
				(2.0834)	(2.0297)
Panel B: Relationship with Other Social Programs					
Workers Compensation	38.8371				38.0105
	(32.0352)				(31.9336)
Food Stamps		-295.2034			-313.5927
		(229.9740)			(232.2628)
SS Disability Insurance			659.5193		482.1210
			(2200.7148)		(2181.9969)
Medicaid				55.5381	78.2481
				(162.0057)	(164.3859)

Notes: This table shows the results of regressions of state-year max UI benefits on the variables displayed in the table's rows, additionally controlling for state fixed effects and year fixed effects, using data from 1990–2010. Measures of other social programs are participation rates in each program. Each column in each panel presents the results from a separate regression.
Standard-error estimates allow for clusters at the state level.
*, **, and ***, indicate statistical significance at the ten-, five-, and one-percent levels, respectively

Figure A2
Specification chart for effects of UI generosity for laid-off men on fertility

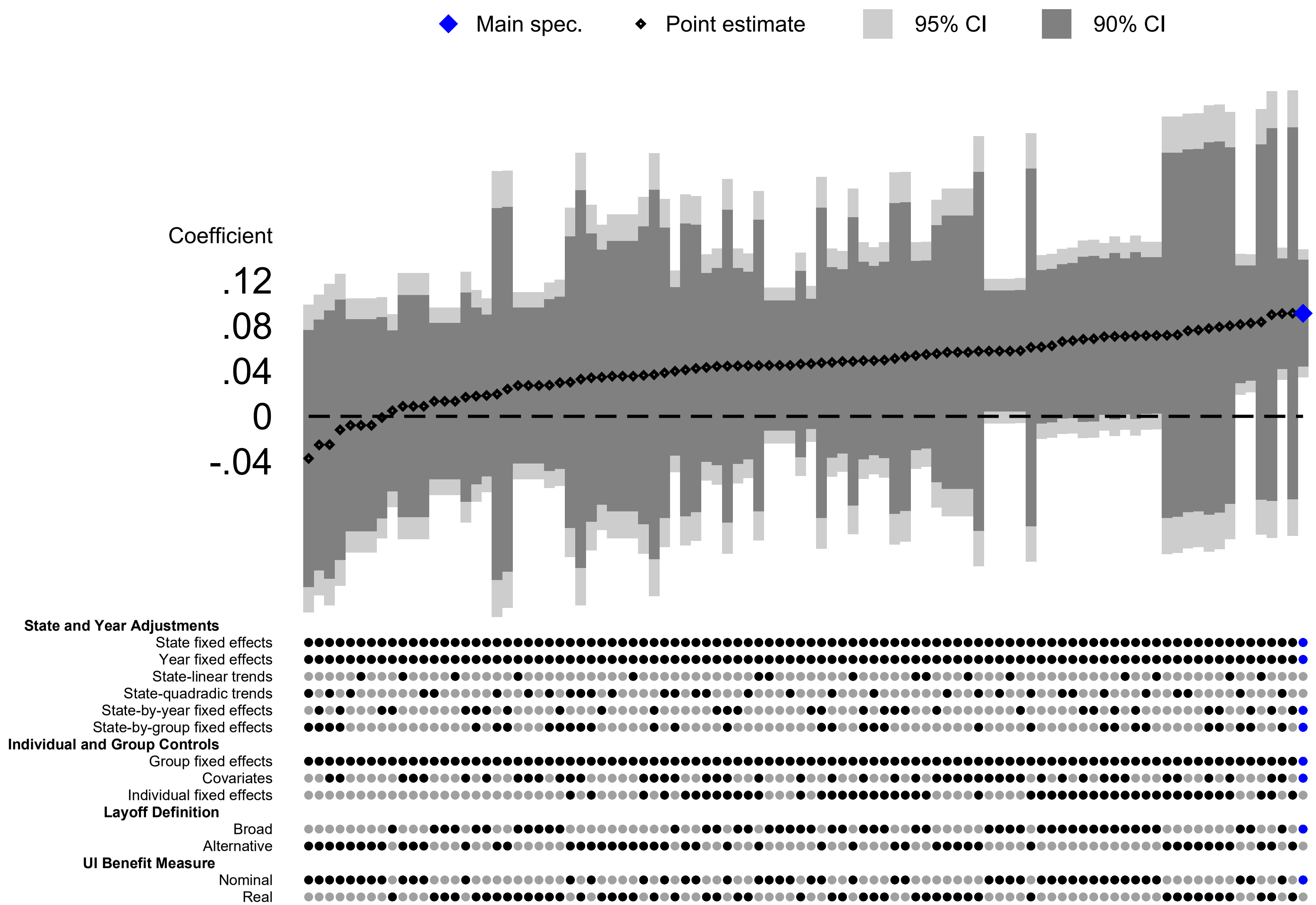
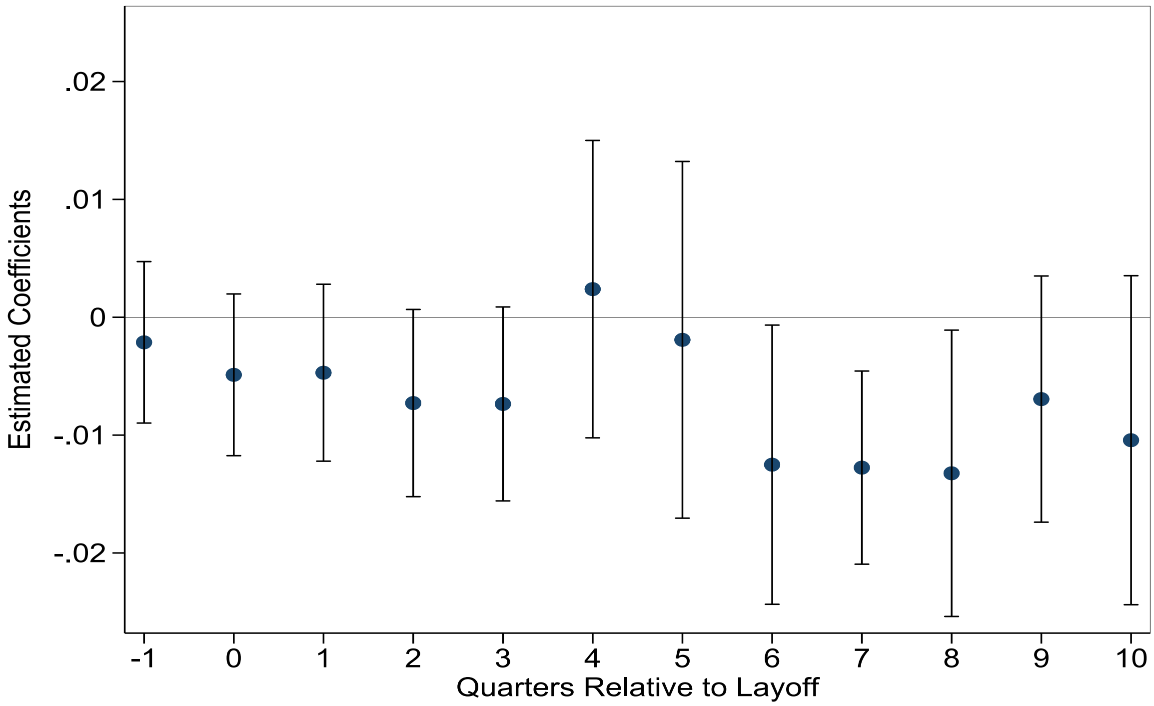


Table A3
Effect of UI benefit generosity for laid-off women on fertility

	(1)	(2)	(3)
MaxUI $\times \mathbb{1}$[9+ Months After Layoff]	-0.0028	-0.0062*	-0.0062*
	(0.0028)	(0.0033)	(0.0031)
$\mathbb{1}$[9+ Months After Layoff]	0.0138	0.0264**	0.0272**
	(0.0094)	(0.0109)	(0.0106)
MaxUI	0.0028		
	(0.0033)		
Year Fixed Effects	Y	-	-
State Fixed Effects	Y	-	-
Group Fixed Effects	Y	-	-
State-Year Fixed Effects	N	Y	Y
State-Group Fixed Effects	N	Y	Y
Individual Controls	N	N	Y

Notes: The dependent variable is whether an individual ages 20 to 35 has a child less than one year old in the survey month. Regression models use survey weights and adjust the standard-error estimates to allow for clusters at the state level.
*, **, and ***, indicate statistical significance at the ten-, five-, and one-percent levels, respectively

Figure A3
Effects of UI generosity over time for laid-off women on fertility



Notes: The dependent variable is whether an individual ages 20 to 35 has a child less than one year old in the survey month. This figure reports estimated coefficients and 95 percent confidence intervals for interactions between indicator variables for quarters relative to layoff and the variable for maximum weekly UI benefits in hundreds of dollars (MaxUI). The regression model additionally includes individual demographic and education controls (age, race, and educational attainment), state-by-year fixed effects, and state-by-group fixed effects. Moreover, we use survey weights and adjust the standard-error estimates to allow for clusters at the state level.