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IZA DP No. 15267

Stable Income, Stable Family

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ABSTRACT

Stable Income, Stable Family*

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 maximum benefit levels mitigate the effects of layoffs. In particular, they mitigate increases in divorce associated with men's layoffs; increases in separations associated with women's layoffs; reductions in fertility associated with men's layoffs; and increases in fertility associated with women's layoffs.

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 among heterosexual couples.

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, Matsa, and Melzer, 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 job losses increase the risk of divorce (Charles and Stephens, Jr., 2004), UI may play a significant role in promoting family stability.[1]

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.[2] Our results routinely indicate that higher maximum UI benefits mitigate the effects of layoffs, particularly for outcomes that are most strongly affected by layoffs. Along these lines, we find that layoffs are strongly associated with divorce for men and that more generous UI benefits mitigate these apparent effects. Specifically, our estimates indicate that a $100 increase in maximum weekly UI benefits decreases their probability of divorce by a third of a percentage point, which represents approximately 14 percent of the estimated elevated risk of divorce they face after a layoff. For women, layoffs are also positively related to divorce but not as strongly as they are for men, suggesting that there is less scope for UI benefit generosity to

[1] For readability, we use "divorce" throughout this paper to refer to a divorce or separation. Along similar lines, our empirical analysis of "divorce" considers the probability of divorce or separation.

[2] Throughout most of this paper, we use the term "divorced" to refer to individuals who report that they are either divorced or separated. That said, we also discuss the results from analyses that separately consider separation and divorce.

have mitigation effects. Consistent with this notion, we do not find statistically significant effects of UI benefit generosity on divorce among laid-off women but we also cannot rule out the possibility that the mitigation effect for laid-off women is the same as it is for laid-off men. Moreover, when we focus on separating from one's spouse, our analyses of both men and women indicate that increases associated with layoffs are significantly mitigated by more generous UI benefits. Our analysis of fertility also indicates that UI benefit generosity mitigates the effects of layoffs, even though the effects of layoffs are opposite-signed for men and women. In particular, these results indicate that layoffs reduce the probability of having a new child for men while more-generous UI benefits increase their probability of having a child. For women, our results indicate that layoffs increase the probability of having a new child while more-generous UI benefits decrease their probability of having a child.

The results we find are consistent with theoretical models of marriage and fertility. In particular, in a model in which an individual values their spouse at least in part because of their ability to increase the household's financial resources (e.g., (Becker, 1973)), we would expect an unanticipated layoff to increase the probability that an individual is divorced by their spouse and we would expect more generous unemployment insurance benefits to help offset this effect. Moreover, these effects are expected to be less prominent for laid-off women—or work in the opposite direction altogether—if their spouses get disutility from their earnings (e.g., as a result of societal norms about gender roles and/or sentiments about "breadwinner status").[3] Along these lines, we find significantly elevated divorce rates following men's layoffs; more generous UI benefits reduce this additional risk; and we find weaker evidence of such effects for laid-off women. That said, we also note that the weaker evidence of effects on divorce among women could also be due to the fact that the benefit generosity measure that we consider—maximum weekly benefits—is less relevant to women than it is for men since women are less likely to qualify for maximum benefits (because they

[3] See Shenhav (2021) and Bertrand et al. (2021) for extensive discussions of how such norms can be incorporated into an economic framework.

have lower earnings).

With regards to fertility, our results are consistent with a theoretical framework that involves bargaining among men and women (e.g., (Grossbard-Shechtman, 1984; Lundberg and Pollak, 1993; Rasul, 2008; Alshaikhmubarak, Geddes, and Grossbard, 2019; Doepke and Kindermann, 2019)).[4] In this type of model, individuals may derive utility (or disutility) from time spent in labor market work, time spent working in the household (e.g., childbearing and childrearing), self-oriented time, non-market goods produced by time spent working in the household (e.g., children), and from commercial goods. In such a model, individuals would prefer that their spouse invest their time in producing non-market goods or in the labor market and transferring financial resources generated from this activity. Of course, the partner would be disinclined to do so because it would come at the expense of their self-oriented time and their own ability to purchase commercial goods. Thus, these outcomes are determined by bargaining, in addition to each partner's preferences, each partner's productivity in the production of non-market goods, each partner's ability to earn money in the labor market, and each partner's access to other financial resources. Naturally, the relationship may be dissolved (or not entered into in the first place for unmarried individuals considering marriage) if a suitable arrangement is not found. In this type of theoretical model, an individual has to compensate their partner in order for them to spend more time working in the household than they would otherwise prefer. In a "traditional household with gender-specific comparative advantages in labor market work and work in the household," this would involve a husband transferring financial resources he generates in the labor market to his wife who does a disproportionate amount of household production (e.g., childbearing and childrearing) and who would otherwise prefer to do less. This outcome is consistent with evidence that couples frequently disagree on the desirability of having another child and that women are more likely to be opposed than their spouses (Doepke and Kindermann, 2019).

The key point from this theoretical framework—as it relates to our analyses—is that

[4] Our discussion draws primarily upon Grossbard-Shechtman (1984).

each individual's ability to satisfy their own preferences depends on the financial resources they can generate or otherwise control. With lower earnings (e.g., due to a layoff), a husband is in a weaker position to transfer resources to his wife to compensate her for work in the household (e.g., childbearing and childrearing).[5] In contrast, with higher earnings (e.g., from more generous UI benefits), he is in a stronger position to compensate her. These predicted effects are of the opposite sign for women. In particular, with lower earnings (e.g., due to a layoff), a wife is in a weaker position to refuse a transfer of resources from her husband for work in the household (e.g., childbearing and childrearing). And with higher earnings (e.g., from more generous UI benefits), she is in a stronger position to refuse such offers. The estimated effects from our analyses of layoffs and UI benefit generosity are consistent with these predictions.[6]

1 Additional Background on Potential Mechanisms

As we noted above, a rich theoretical literature sheds light on various ways in which layoffs and unemployment insurance generosity may affect divorce and fertility, including the possibility that these effects may be different depending on the gender of the person losing their job. Another reason they may depend on gender is because maximum UI benefit levels are more likely to be binding for men (because they tend to have higher earnings). In terms of opposite-signed effects of men's and women's earnings, prior empirical research indicates that domestic violence, marital satisfaction, time spent on household chores, and divorce depend on men's and women's *relative* earnings (Aizer, 2010; Bertrand, Kamenica, and Pan, 2015; Autor, Dorn, and Hanson, 2019; Shenhav, 2021). Along similar lines, several studies

[5] Instead of thinking about "being in a weaker position to transfer resources," we can consider diminishing returns to financial resources. For example, a $1,000 transfer will have a greater disutility effect for men who earn $40,000 than for those who earn $50,000

[6] The estimated effects on divorce that we find are also consistent with this theoretical framework. In particular, one could imagine that individuals have certain expectations when they are married; lost resources resulting from unanticipated layoffs make agreed-upon arrangements infeasible; and this leads to divorce when couples do not arrive at suitable alternatives. Naturally, more generous UI benefits would serve to mitigate any such effects.

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, Schaller, and Simon, 2017; Lindo, Schaller, and Hansen, 2018; Schaller and Zerpa, 2019; Regmi and J. Henderson, 2019).

With respect to the effects of economic shocks on divorce, prior research shows that job loss increases the risk of divorce (Charles and Stephens, Jr., 2004; Doiron and Mendolia, 2012; Eliason, 2012).[7] Though emphasizing changes in men's and women's relative wages, Shenhav (2021) also presents evidence that both men's and women's wages are negatively related to divorce, with larger effects arising from changes in men's wages.[8] This evidence suggests that UI may affect divorce by mitigating the income shock associated with job loss, particularly for men.[9]

There are a number of additional 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, Glymour, and Avendano (2014) find that higher UI generosity reduces suicide rates and Kuka (2020) shows that higher UI generosity increases health insurance coverage and self-reported health. 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.[10]

[7] Research also indicates that new marriages and divorces are positively associated with aggregate measures of economic conditions (Schaller, 2013)

[8] Specifically, the estimated effects of a 10 percent increase in wages on divorce is negative for both men and women, though the estimated effect for men's wages is larger in magnitude (0.39 percentage points) and the estimated effect for women's wages (0.4 percentage points) is not statistically significant. See Column 3, Table A.13.

[9] With regard to income shocks generated by social safety nets, existing evidence suggests that the 1996 welfare reforms led to fewer marriages and divorces (Bitler et al., 2004) but the earned income tax credit (EITC) has little to no effect on marriage decisions (Dickert-Conlin and Houser, 2002; Herbst, 2011).

[10] 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, Mellor, and Nicholas, 2013; Cotti, Dunn, and Tefft, 2015; Cotti and Simon, 2017; Schwandt,

In addition, UI benefit generosity affects time use. More generous benefits 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 decreases the labor supply of spouses (Cullen and Gruber, 2000). These effects have the potential to promote or detract from family stability.

Prior empirical research on the fertility effects shows that it is procyclical and positively affected by changes in household wealth (Lindo, 2015; Schaller, 2016; Schaller, Fishback, and Marquardt, 2020; Lovenheim and Mumford, 2013; Dettling and Kearney, 2014).[11] Moreover, empirical studies of fertility have found that positive shocks to men's earnings increase fertility and negative shocks to men's earnings decrease fertility (Lindo, 2010; Black et al., 2013; Kearney and Wilson, 2018), while opposite-signed effects have been documented for changes in women's labor market conditions (Lundberg and Pollak, 1993; Schaller, 2016).[12] Given this evidence, we may anticipate that the effects of UI on fertility mitigate the effects of a job loss, but in a similarly nuanced pattern for males and females.

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.[13] Our analysis uses the 1990, 1991,

2018).

[11] Interestingly, large income transfers induced by the EITC have been shown to have economically insignificant effects on fertility outcomes (Baughman and Dickert-Conlin, 2003, 2009). It is important to note, however, that the EITC also provides an incentive to work, which could offset (or more than offset) income effects.

[12] In contrast, we note that researchers have found that women's job losses decrease fertility in Finland and Austria (Huttunen and Kellokumpu, 2016; Del Bono, Weber, and Winter-Ebmer, 2012), which may be related to the relative generosity of UI and parental leave policies in those countries.

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

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 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.[14] Note that while we refer to "divorce" throughout the paper, our empirical analyses evaluate whether an individual reports being separated or divorced at a given point in time except where we mention otherwise.[15,16]

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 an effort to better capture who is eligible for UI benefits. That said, we note that the broad definition of layoff that we use does include individuals who are temporarily laid off.[17] 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 investigation of the SIPP data which confirmed

[14] 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, and South Dakota. We omit these observations from our analysis.

[15] To be clear, this definition of the outcome variable is such that the indicator may change from zero to one and back to zero again for initially-married individuals report a separation or divorce and subsequently report being married again. An alternative approach, in which we evaluate whether an individual *has been separated or divorced after initially being observed married* generally produces estimates that are larger in magnitude, which makes sense given the way each variable is formulated.

[16] Note that SIPP differentiates between individuals who indicate that their relationship status is "separated" and individuals who indicate that their relationship status is "married" but whose spouse lives in a different location (e.g., many academic couples unable to find jobs in the same city). As such, the latter are *not* considered separated or divorced in our analyses.

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

that many of these individuals report receiving UI benefits. In addition to documenting the effects using this broad set of laid-off workers, we also examine the effects using alternative definitions based on (Hsu, Matsa, and Melzer, 2018) and (Kuka, 2020), which we discuss in greater detail below.

Our analysis also uses individual and household variables available in the SIPP data including the age, race, and educational attainment of the survey respondent as well as the number of children and ages of children. We restrict our SIPP sample to individuals that are 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 40.

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 before 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.[18]

We merge our SIPP sample with state-by-half-year schedules for unemployment insurance benefits from the U.S. Department of Labor reports published in January and July of each year.[19] 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, Matsa, and Melzer, 2018).

States have a huge amount of discretion with regards to maximum benefit levels and,

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

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

as a result, they vary substantially in levels and in changes over time. Most states increase their benefits frequently but vary in how they do so. Some states have increased maximum benefit levels to maintain roughly constant inflation-adjusted levels (e.g., Alabama, Mississippi, West Virginia, and Wisconsin) whereas many others raised levels at a rate that has outpaced inflation (e.g., Illinois, Kansas, Oregon, South Dakota, New Jersey) and others allowed real levels fall (e.g., Kansas, Arizona, Florida, Michigan). Moreover, some states vary substantially in how much they have increased benefits over time (e.g., Hawaii increased maximum benefits by \$88 from 1990 to 1995, then just \$27 from 1995 to 2000 and \$65 from 2000 to 2005, and then by \$123 from 2005 to 2010). There are also some states that change benefits very infrequently (e.g, California and New York which only increased maximum benefits six and five times, respectively, between 1990 and 2010). In Figure 1, we show states' maximum benefit levels in January 1991, maximum benefit levels in July 2010, changes in maximum benefit levels from January 1991 to July 2010, and annual benefit growth average from January 1991 to July 2010. Based on these maps, it is evident that there are some states with persistently high levels of maximum benefits (primarily in the Northeast) and some with persistently low levels (particularly in the Southeast), but it is also clear that there is quite a bit of variation. For example, some states that changed maximum benefits the most between 1991 and 2010 had relatively low levels even in 2010 (e.g., Nebraska); some changed maximum benefits so much over this period of time that they went from being among the least generous to being among the most generous (e.g., New Mexico); some states that changed maximum benefits the least continued to have relatively high levels in 2010 (e.g., Ohio); and some states increased maximum benefits the least already had very low levels in 1991 (e.g., Arizona).

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.[20] Though not particu-

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

larly stark, similar patterns appear across the panels when comparing those that experience a layoff to those that do not. The statistics indicate workers that 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.[21] Moreover, the probability of divorce is higher for both men and women after a layoff (relative to before), and the probability of having a new child is lower after a layoff for men and higher after a layoff for women.

3 Empirical Strategy

Though we also show results from more parsimonious models, our preferred estimates are based on a design that 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.[22] The inclusion of non-laid-off workers in the analysis 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-quarter-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:

$$y_{igsmqy} = \beta_1 MaxUI_{sqy} \times \mathbb{1}[AfterLayoff_{igsmqy}] + \beta_2 \mathbb{1}[AfterLayoff_{igsmqy}] + \lambda_{sqy} + \psi_{gs} + \epsilon_{igsmqy}, \tag{1}$$

where y_{igsmqy} is an outcome observed for individual i from group g residing in state s in month m, quarter q, and year y; $MaxUI_{sqy}$ is the maximum amount of weekly UI benefits in state s in quarter q and year y measured in hundreds of dollars; $\mathbb{1}[AfterLayoff_{igsmqy}]$ is an indicator variable that takes the value of one following an individual's layoff; λ_{sqy} are

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

[22]Our approach closely parallels Hsu, Matsa, and Melzer (2018) and is also similar to Kuka (2020).

state-by-quarter-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_{igsmqy} 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 clustering at the state level.

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 estimates that control for individual fixed effects, which will address any systematic differences between laid-off and non-laid-off workers that might vary with UI generosity.[23] Additionally, we report the results from a large number of specification checks, including those that use an alternative definition of layoffs, those that use different approaches to controlling for state-specific trends and other factors, and those that confirm that we do not see similar evidence of effects if we consider individuals who *quit* their jobs (who would thus be ineligible for UI benefits).

[23]For example, such fixed effects would address the possibility that the underlying divorce propensities may differ across the types of individuals who are laid off when UI benefits are relatively generous versus when they are not.

4 Results

4.1 Estimated Effects on Divorce

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, quarter-by-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 laid-off men (Panel A), indicating that UI generosity reduces divorce for these men. Though the point estimate for women is also negative, it is much smaller in magnitude and not close to statistical significance (Panel B).

The coefficients on the other variables reported in the table have meaningful interpretations and provide context for our estimated effects of UI benefit generosity for workers who 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. Specifically, the coefficient estimates indicate an elevated divorce risk of 2.6 percentage points for laid-off men and an elevated divorce risk of 1.3 percentage points for laid-off women. Thus, the interacted effect of UI generosity on these individuals (discussed above) can be viewed as mitigating these elevated risks. Indeed, that the elevated risk for men is greater than the elevated risk for women may in part explain why we find statistically significant effects of maximum UI benefits for laid-off men but not for laid-off women (i.e., there is less additional risk to be mitigated for laid-off women). 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 includes state-by-quarter-year fixed effects to control flexibly for changes in divorce probabilities across states and over time and state-by-group fixed effects to control for any differences in divorce probabilities across these groups that are constant over time within states.[24] Finally, in Column (3) we report estimates from our preferred model, which is similar but also controls for demographics and levels of education.[25] The results from these models are similar to those reported in Column (1). They indicate that men are 2.4 percentage points more likely to divorce after a layoff, and that UI benefit generosity mitigates this elevated risk. They indicate that women are 1.2 percentage points more likely to divorce after a layoff, but there is no evidence of detectable effects of UI benefit generosity on this elevated risk.

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 approximately 14 percent of the estimated elevated risk of divorce that men face after a layoff. Though not statistically significant, the negative estimate for women would indicate a reduction of 5 percent of the estimated elevated risk of divorce following a layoff for the same $100 increase in maximum weekly UI benefits. Moreover, we cannot rule out at conventional levels of statistical significance that the this mitigation effect is the same for women as it is for men.

In Figure 2 we present estimated effects over time. These estimates are based on a 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

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

[25] 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.

the layoff, rather than a single interaction term that captures the average effect of UI benefit generosity across all periods following a layoff.[26,27] 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 there is little evidence of effects on laid-off women (Panel B).

There is also some evidence of effects one—and perhaps two—quarters before men's layoffs. This may be a result of recall error with regard to the timing of job losses. That said, it is also consistent with the fact that a significant share of workers anticipate layoffs before they happen (Stephens, 2004; Hendren, 2017; Pettinicchi, Vellekoop et al., 2019), 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, LaLonde, and Sullivan (1993).[28] Importantly, prior work has demonstrated that individuals are sufficiently aware of unemployment insurance rules to modify their behavior in advance of any potential layoffs.[29] Either of these scenarios—recall error and/or anticipatory effects—

[26]The model also includes indicators for quarters before and after the layoff that are not interacted with the measure of UI benefits. As such, the regression equation is:

$$y_{ik} = \sum_{j=-4}^{7} \beta_j MaxUI_{sy} \times 1\{k=j\} + \sum_{\substack{j=-4 \\ j\neq -1}}^{7} \gamma_j 1\{k=j\} + \lambda_{sy} + \psi_{gs} + \epsilon_{ik}.$$

[27]In Appendix Figure B1, we report event-study estimates that are instead based on a similarly modified version of the approach used to produce the estimate from Column (2) of Table 1. It is visually indistinguishable from Figure 2.

[28]Specifically, Jacobson, LaLonde, and Sullivan (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 before separation and that the divergence accelerated during the quarters immediately before 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. For examples beyond Jacobson, LaLonde, and Sullivan (1993), see Sullivan and von Wachter (2009), Lindo (2010), and Couch and Placzek (2010). Along similar lines, Hendren (2017) finds that consumption decreases and spousal labor supply increases in anticipation of job losses, and Pettinicchi, Vellekoop et al. (2019) finds similar effects on consumption.

[29]Light and Omori (2004) and Britto (2016) document reductions in the probability of quitting in response to exogenous increase in UI benefit levels whereas Lusher, Schnorr, and Taylor (2022) finds evidence that workers are increasingly likely to shirk when potential benefits are more generous (presumably because they anticipate being able to collect benefits even if they are fired). Researchers have also documented responses

would suggest that the main results (in Table 1) are relatively conservative since those estimates only capture the effects in the period of time after an individual's reported month of layoff.[30]

To verify the robustness of the effects we find for laid-off men, we have also estimated these effects with different combinations of state-time adjustments, including models with state fixed effects, year fixed effects, state-linear trends, state-quadratic trends, state-by-quarter-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. Moreover, we have estimated models with UI benefits measured in real (2010) dollars.

In Appendix Figure A1 we report 48 estimates—ordered by magnitude—for all of these possible combinations of the different approaches to controlling for state-year changes over time, individual characteristics, and measuring UI benefits. These estimates are always negative and they are almost always statistically significant.[31] Along similar lines, the same exercise for women (the results of which are shown in Figure A4) also consistently yields negative point estimates that are not statistically significant, which is consistent with the results for women described above.

In Appendix figures A2 through A6 we show similar specification charts, but using alternative ways of identifying relevant laid-off workers who would likely qualify for UI benefits. Specifically, in figure A2 we report the results for laid-off men based on the approach

to rules regarding the minimum length of employment spells that are required in order for an individual to collect UI benefits (Christofides and McKenna, 1996; Baker and Rea, 1998).

[30] Along similar lines, our estimated effects will be conservative if there are effects on individuals who are not laid off but were anticipating the possibility.

[31] While we do not show these results in this specification chart, we have also investigated the degree to which the Great Recession may be driving our results in some way. Notably, our point estimates are extremely similar for men when we exclude the 2008 wave from our analysis. In particular, the coefficients on MaxUI$\times\mathbb{1}$[AfterLayoff] reported in Panel A of Table 1 are -0.0040, -0.0035, and -0.0034 whereas estimates excluding the 2008 wave from the analysis are instead -0.0037, -0.0038, and -0.0036. These estimates are statistically significant but slightly less precise, which is expected to result from the reduction in the sample size. For women (Panel B), the estimates are a bit larger in magnitude if the 2008 wave is omitted but they are still not statistically significant.

used in Hsu, Matsa, and Melzer (2018), who do not restrict attention to those with three consecutive months of employment before a layoff while considering a narrower set of individuals with respect to "current employment status" variable.[32] This alternative approach leads to estimated effects that are a bit more variable and less precise than those based on our preferred approach, but the estimates are otherwise quite similar. In Figure A3 we report the results for laid-off men based on the approach used in Kuka (2020), who restricts attention to individuals with three consecutive months of employment before reporting being laid off for a specific set of reasons.[33] This alternative approach leads to estimates that are even more variable and less precise, but which are still generally similar to those based on our preferred approach.[34] In figures A5 and A6, we show that the lack of evidence of effects of benefit generosity on divorce among women is also present if we define layoffs in these alternative ways.

We next unpack our measure of marital instability by separately estimating effects on divorce and separation. This is interesting for several reasons relating to both the expected timing of effects and the nature of the relationship transition. Separations are an informal arrangement between partners that often precede or substitute for a legal divorce. They

[32]Like us, Hsu, Matsa, and Melzer (2018) use the SIPP's RMSER variable (which describes individuals' employment circumstances) to identify potential UI recipients but they only consider individuals in category 6. Those in category 6 report having no job in the prior month while being on layoff or looking for work all weeks. Our preferred definition includes a broader set of individuals who are likely to be eligible for UI benefits, and who frequently *do* receive UI benefits based on reports of receipt in the SIPP data used for our analyses. In particular, we also include individuals in category 5, who report having a job at least 1 but not all weeks of the prior month while spending the remaining weeks on layoff or looking for work. We also include individuals in category 3, who report having a job the entire prior month but having been laid off without pay for one or more weeks of that month. We also include individuals in category 7, who report not having had a job in any week of the prior month but having been on layoff or looking for work in all weeks of the prior month. We also include individuals in category 4, who do not report being laid off but report having had a job at least one but not all prior weeks (after having reported being employed in the three prior months) and thus may be furloughed or expecting a recall.

[33]Specifically, Kuka (2020) 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.

[34]Both alternative ways of identifying layoffs lead yield weaker estimated effects layoffs on divorce. This may explain why they similarly produce weaker evidence of mitigation effects of benefit generosity.

can be considered a less formal and potentially less permanent relationship transition. Legal divorce is a much more permanent process that often involves formally navigating complex financial and custodial hurdles. As such, we may expect to see effects on separations before effects on divorce become apparent. For the same reason, we may expect to see more prominent effects on separations than on divorce given the relatively short nature of the panel data we are analyzing.

Consistent with these expectations, the results in Panel A of Table 2 demonstrate that the effects we previously found for laid-off men are driven primarily by separations. In particular, we find that layoffs are significantly (positively) related to both divorce and separation, though the magnitude of the estimated effect is larger for separation (at 1.5 percentage points vs 1.0 percentage points). While the estimated effect of maximum UI benefits on divorce among laid-off men suggests that benefit generosity helps to mitigate the effects of layoffs, this estimate is not statistically significant. The estimated effect of maximum UI benefits on separation among laid-off men is larger in magnitude and statistically significant, also indicating that benefit generosity helps to mitigate the effects of layoffs on this outcome. The estimates from Column (6) indicate that a $100 increase in maximum weekly UI benefits mitigates the 1.5 percentage point increase in the probability of divorce by 0.2 percentage points (13 percent). The estimated effects over time, shown in Appendix Figure A7, are also consistent with the notion that the effects of benefit generosity are more readily apparent than effects on divorce.

In Panel B of Table 2 and in Appendix Figure A8, we show that there is stronger evidence of effects on women when we focus on separations. Along these lines, we find that their layoffs are not significantly related to divorce but they are significantly related to separation, increasing that risk by 0.9 percentage points. Moreover, the estimated effect of maximum UI benefits for laid off women is negative and statistically significant, indicating that more generous benefits mitigate this additional risk. The estimates from Column (6) indicate that a \$100 increase in maximum weekly UI benefits reduces the layoff-induced increase in divorce by 16 percent. We hope that future work, perhaps with data that follows individuals for a longer period of time, will be able to shed light on whether these effects on separation largely result in divorce or reconciliation.[35]

4.2 Additional Validity Tests

To further assess the validity of our analyses, 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 could have been evident in the results presented in Table 1 if 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. Along similar lines, we have investigated if there is any evidence of "placebo effects" if we evaluate individuals who quit their jobs (who thus should be ineligible for UI benefits) instead of those who have been laid off.[36] The results of this analysis—shown in Appendix Table A2—indicate no significant effect of UI generosity in mitigating the risk of divorce for individuals who have quit their jobs, thus providing

[35]In ancillary analyses, we also considered how the effects might relate to spousal earnings capacity by analyzing the effects of layoffs separately for individuals with consistently employed spouses and those with non-working (or inconsistently employed) spouses. Analyses of men's layoffs indicate larger effects of layoffs and larger mitigation effects of UI benefit generosity on divorce those with non-working wives. That said, these estimates are not precise enough for us to reject that the effects are the same at conventional levels of statistical significance. Analyses of women's layoffs indicate larger effects of layoffs and larger mitigation effects of UI benefit generosity on divorce for those with working husbands. Indeed, while the point estimates are not close to being statistically significant, they are opposite-signed for women with non-working husbands. As a whole, these analyses are consistent with the idea that women value their husbands' earnings capacity and men with stable employment value their wives earnings capacity, but non-employed (or inconsistently employed) men do not get additional utility from their wives earnings capacity.

[36]As in with our analysis of laid-off workers, here we also focus on unemployed individuals who had three consecutive months of employment before the separation. For SIPP panels after 1996, we define quitters as individuals reporting they quit to take another job, because of unsatisfactory work arrangements (hours, pay, etc), or "for some other reason" based on the variable ERSEND1. For prior SIPP panels, we define as quitters individuals reporting either that they quit to take another job or "for some other reason" based on the variable WS12024.

evidence in support of the validity of our research design.[37] We have also examined the effects using a sample comprised solely of individuals who become laid off. The results of this analysis (shown in Appendix Table A3) are very similar to our main results (Table 1).

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).[38] The results of these analyses, shown in Appendix Table A4, are reassuring. They indicate that our UI benefit generosity measure is not significantly related to these other measures.[39]

As a final way to assess the validity of our empirical approach, we have evaluated the degree to which our UI benefit generosity measure captures changes in UI benefits received by laid-off individuals. To do so, we use the same strategy we used to evaluate the effects on state economic conditions and "other program generosity"—controlling for year fixed effects and

[37] Also note that the coefficient estimates on $\mathbb{1}$[After Quit] are generally positive, indicating a heightened risk of divorce for individuals following a quit just as there was a heightened risk for individuals following a layoff.

[38] 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, Macpherson, and Vroman (2001), and average income is from the Quarterly Census of Employment and Wages (QCEW) program data.

[39] We have also examined the degree to which our measure of unemployment insurance generosity relates to potential benefit duration during the Great Recession when potential duration was expanded from 26 weeks up to 99 weeks. Benefit duration has been shown to have important effects on unemployment duration (Katz and Meyer, 1990; Meyer, 2002; Schmieder, Von Wachter, and Bender, 2012), job search activity amongst unemployed individuals (Marinescu, 2017), and employee effort (Lusher, Schnorr, and Taylor, 2022). The estimated coefficient of potential benefit duration on unemployment insurance generosity from 2008-2013 is very small in magnitude (e.g. a one-week increase in potential duration increases generosity by 9 cents) and not close to statistical significance at conventional levels. In addition, we have also examined whether having a Democratic governor relates to unemployment insurance generosity. The coefficient estimate was not close statistical significance at conventional levels and very small in magnitude (indicating more generous maximum benefits of just 5 dollars per week.

state fixed effects—but we instead evaluate individual-level data on the amount of monthly UI benefits received by laid-off individuals in our SIPP analysis samples.[40] Specifically, Column (1) of Table A5 reports estimates for all laid-off individuals while Column (2) reports estimates for laid-off individuals who report receiving some UI benefits. These estimates confirm a strong relationship between our generosity measure and the amount of benefits received, and they also illustrate that this relationship is much stronger for men than women which is unsurprising given that men's benefits are more likely to be bound by the maximum than women's. Specifically, these estimates indicate that an additional $100 of maximum weekly benefits corresponds to an additional $28 in monthly UI benefits for the full set of laid-off men we consider and that they correspond to an additional $149 in monthly UI benefits for the subset receiving any benefits. For women, these estimates indicate that an additional $100 of maximum weekly benefits corresponds to an additional $11 in monthly UI benefits for the full set of laid-off women we consider and that they correspond to an additional $78 in monthly UI benefits for the subset receiving any benefits. Naturally, these numbers mask substantial heterogeneity because a large share of UI recipients will not be affected by maximum weekly benefit levels.

4.3 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.[41]

[40]The SIPP asks individuals about receipt of received state, supplemental, or other unemployment insurance benefits

[41]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."

The results of this analysis for men, shown in Panel A of Table 3, indicate that men who have been laid off are significantly more likely to 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 men without children (4.7 percentage points) and it is lowest for men with children under age 18 (0.5 percentage points and 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 men without children or with older children and there is the smallest scope for such benefits to reduce divorce for men with young children.

Along these lines, the estimated effects of maximum UI benefit benefits do indicate that benefit generosity reduces divorce most among laid-off men without children (Column 1). However, relative to the heightened risk of divorce following a layoff, the percent effect is slightly larger for those with children (Column 2). Specifically, these estimates suggest that a $100 increase in maximum weekly UI benefits leads to 14 percent and 17 percent reductions in the heightened risk of divorce associated with layoffs for these groups, respectively. The estimated effects are not statistically significant for individuals with children under age 18.

Panel B of Table 3 shows results of similar analyses focused on women. Interestingly, these estimates indicate that women without children are not at heightened risk of divorce following a layoff whereas women with children and women with children under the age of eighteen have a heightened risk of 1.7 and 1.5 percentage points, respectively. The estimated effects of UI benefit generosity on divorce among these women are not statistically significant. That said, the point estimates for these groups of women (-0.0023 and -0.0021) are not much smaller than the point estimates for men with children (-0.0026), which is notable in light of the fact that layoffs are associated with a similarly heightened risk of divorce for these men (1.5 percentage points).[42]

[42]We find qualitatively similar estimates in analyses that instead focus solely on separation.

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 20–40.[43,44]

In Panel A of Table 4 we show estimated effects on fertility based on the sample of men. The estimate from our preferred model indicates that men being laid off is negatively related to the probability of having a new child, and that this apparent impact of being laid off is significantly mitigated by generous UI benefits. Specifically, our estimates indicate that increasing maximum weekly benefits by $100 increases the probability that laid-off men have a child by 0.67 percentage points, which offsets 23 percent of the 2.9 percentage-point increase associated with a layoff.[45]

In Panel B of Table 4 we report estimated effects based on the sample of women. These estimates are consistent with earlier work showing that economic shocks affecting men and women have opposite-signed effects on fertility (e.g., Schaller (2016)). This is the case for the estimated effect of being laid off and also the estimated effect of maximum UI benefits. Specifically, these estimates indicate that being laid off is *positively* related to the probability of having a new child (unlike the relationship observed for laid-off men), and that generous UI benefits significantly mitigate this apparent impact of being laid off just as they appear to mitigate the (opposite-signed) effects for laid-off men. The estimates suggest that a $100 increase in maximum weekly benefits reduces the probability that laid-off women

[43] We define "having a new child in the household" based on whether a child's reported age is less than one.

[44] We have also analyzed the effects of maximum UI benefit generosity on divorce for laid-off individuals using this age range. Compared to the estimated effect based on our full sample of men, the coefficient estimate is somewhat smaller in magnitude for men in this age group (-0.0023 vs -0.0034). And compared to the estimated effect based on the full sample of women, the coefficient estimate is somewhat larger in magnitude for women in this age group (-0.0015 vs -0.006). That said, we cannot reject that the effects are the same for the full samples and age-restricted limited samples.

[45] If we instead evaluate fertility using a sample that is up to 45 years old, the estimated effect of UI benefits on laid-off men falls from 0.0067 (standard error = 0.0023) to 0.0052 (standard error = 0.0019), which is consistent with lower baseline fertility rates at older ages.

have a child by 0.5 percentage points, which offsets 22 percent of the 2.3 percentage point increase associated with a layoff.[46]

To explore the timing of these effects, we conduct an event study similar to the one described above for divorce but instead focusing on the a time window for laid-off individuals from 3 months before to 33 months after their layoffs. The results of these analyses, shown in Figure 3), offer some suggestive evidence that the aforementioned effects might begin to appear as soon as two quarters after layoffs before they become more clearly evident in the subsequent quarters.

We note that the estimated fertility effect of maximum UI benefits for laid-off men from our preferred model is at the very upper end of the estimated effects that we report in the specification chart showing the sensitivity of the estimates to alternative modeling choices (Appendix Figure A9) and that most estimates in this chart are not statistically significant. That said, the vast majority of specifications yield a positive coefficient estimate (with differing magnitudes and precision), including those that use alternative ways of defining laid off workers (shown in Appendix figures A10 and A11) which tend to be less precise. Along similar lines, the estimated effect for laid-off women from our preferred model is large in magnitude relative to the full set shown in a similar specification chart (Figure A12), but all specifications yield negative estimates (with differing magnitudes and precision). As before we get qualitatively similar but less precise estimates when we identify laid-off workers using the same approach as Kuka (2020). That said, the results are quite different (opposite in sign) if we instead use the same approach as Hsu, Matsa, and Melzer (2018). We believe this is because their approach only identifies laid-off individuals who report that they are looking for work. As such, it will not capture laid-off women who decide not to return to work because they intend to have children. Along these lines, we find that women's layoffs defined in such a manner are negatively related to having children, which

[46] If we instead evaluate fertility using a sample that is up to 45 years old, the estimated effect of UI benefits on laid-off women falls from -0.0050 (standard error = 0.0021) to -0.0036 (standard error = 0.0014), which is consistent with lower baseline fertility rates at older ages.

is the opposite of what we find using our preferred approach or using the same approach as Kuka (2020).[47] As such, we think the approach to identifying laid-off workers used in Hsu, Matsa, and Melzer (2018) may be useful in certain contexts but it is problematic for analyses of women's fertility.

Naturally, our analyses of both divorce and fertility raise the question: To what degree might the estimated effects on divorce explain the effects we find regarding fertility, particularly for men's layoffs which are more clearly linked to divorce? We approach this question by estimating the effects of layoffs and UI benefits on marital-status-predicted fertility rates, an outcome variable that is constructed to capture changes in fertility that are expected to result from changes in marital status (allowing for heterogeneity by age). To construct the marital-status-predicted fertility rate variable, we: (1) calculate age-specific fertility rate for married individuals in our sample; (2) assign the relevant value from this calculation as the marital-status-predicted fertility rate for individuals who are married; and (3) assign a marital-status-predicted fertility rate equal zero to individuals who are not married. We then estimate the effect of layoffs and maximum UI benefits on this outcome variable, which can be interpreted as capturing the effects on fertility that are expected based on changes in individuals marital status caused by layoffs and UI benefits.[48] The results from this analyses indicate that only a small share of the effects on fertility that we find can be attributed to divorce. Specifically, we estimate that layoffs are associated with a 0.36 percentage-point decline in marital-status-predicted fertility (versus a 2.92 percentage point decline in actual fertility) and that an additional 100 dollars in maximum UI benefits are associated with a 0.08 percentage-point increase in marital-status-predicted fertility (versus a 0.67 percentage point increase in actual fertility). For women, estimated effects on marital-status-predicted fertility are negligible, which is expected since we find only weak evidence of effects on their marital status.

[47] Results not shown but available upon request.

[48] Note that this approach leads to more conservative estimates of the effects than an alternative in which positive predicted fertility values are assigned to unmarried individuals.

5 Discussion and Conclusion

As a whole, the results of our analyses indicate that UI generosity plays a significant role in mitigating the effects of job loss on family stability. In particular, we find that higher maximum weekly UI benefits reduce the incidence of divorce for laid-off men and they reduce the incidence of separation for laid-off women. In terms of the magnitude of our estimated effects on divorce, they indicate that a 100 dollar increase in UI mitigates 14 percent (0.3 percentage points) of the elevated risk of divorce following a husband's layoff. For women, where the effect is only apparent for separations, our estimate suggests that a 100 dollar increase in UI mitigates 15 percent (0.15 percentage points) of the elevated risk of divorce following a wife's layoff.[49]

We also find that more generous UI benefits mitigate changes in fertility associated with layoffs. In particular, the reduction in fertility associated with a husband's layoff is mitigated by UI benefit generosity and the increase in fertility associated with a wife's layoff is also mitigated by UI benefit generosity. These opposite-signed effects are consistent with the theoretical bargaining framework outlined in the introduction. They are also consistent with prior empirical research on fertility. The results for men are consistent with existing evidence that increases in men's income and/or household wealth increase in fertility. For women, we find that being laid off increases fertility, which is consistent with prior research examining the reduced-form effects of aggregate shocks that are expected to disproportionately affect women (Schaller, 2016). This effect we find for women is also mitigated by UI generosity. Though opposite in sign for men and women, the mitigation effect corresponding to a $100 increase is very similar for men and women, at 23 percent for men and 22 percent for women. These opposite-signed effects we find for men and women are also consistent with studies documenting the effects of men's and women's *relative* earnings on domestic violence, marital satisfaction, time spent on household chores, and divorce (Aizer, 2010; Bertrand, Kamenica,

[49]The mitigation effect on separations following a husband's layoff is 17 percent (0.25 percentage points).

and Pan, 2015; Autor, Dorn, and Hanson, 2019; Shenhav, 2021). They are also consistent with several studies examining children's outcomes that have found evidence of detrimental effects of men's job losses and positive (or null) effects of women's job losses (Page, Schaller, and Simon, 2017; Lindo, Schaller, and Hansen, 2018; Schaller and Zerpa, 2019; Regmi and J. Henderson, 2019).

We think it is illuminating that the effects of UI benefits appear to mitigate the effects of layoffs wherever we find significant effects (and whether those effects are positive or negative). This supports the notion that the "protective effects" of generous UI benefits go beyond consumption benefits; they also help (at least some) families from dissolving and from changes in childbearing. As such, we think our results can be useful to policy-makers who wish to have a more complete understanding of the ways in which income support mitigates the effects of job loss.

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 evaluate the effects over a longer time horizon than we are able to observe with the data used in this study. We think it will be particularly important for future work to consider whether the effects on separation among laid-off women translate into effects on divorce and whether the effects on childbearing we observe translate into impacts on completed fertility. That said, it will be similarly important to consider remarriage and living arrangements more broadly. We also hope that future work will shed light on the effects on other measures of family distress, including domestic violence and child maltreatment.

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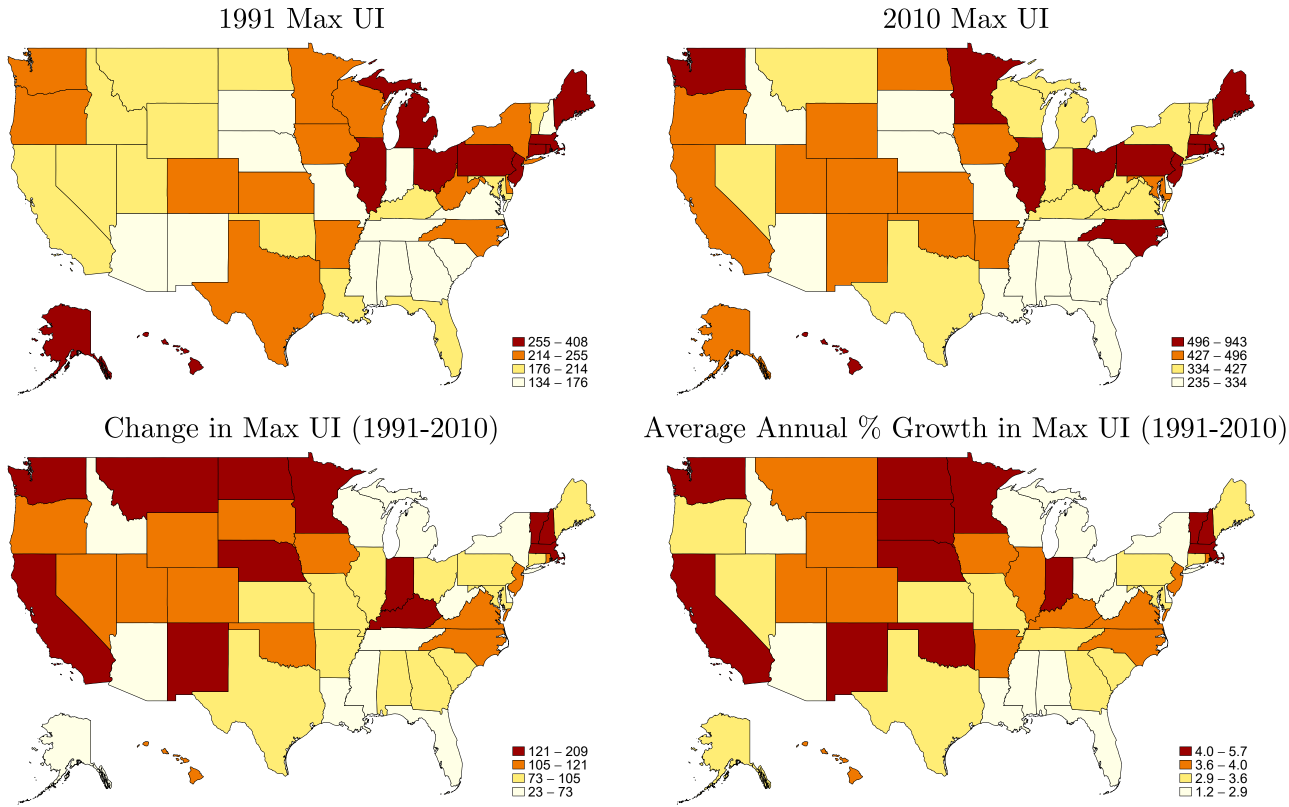
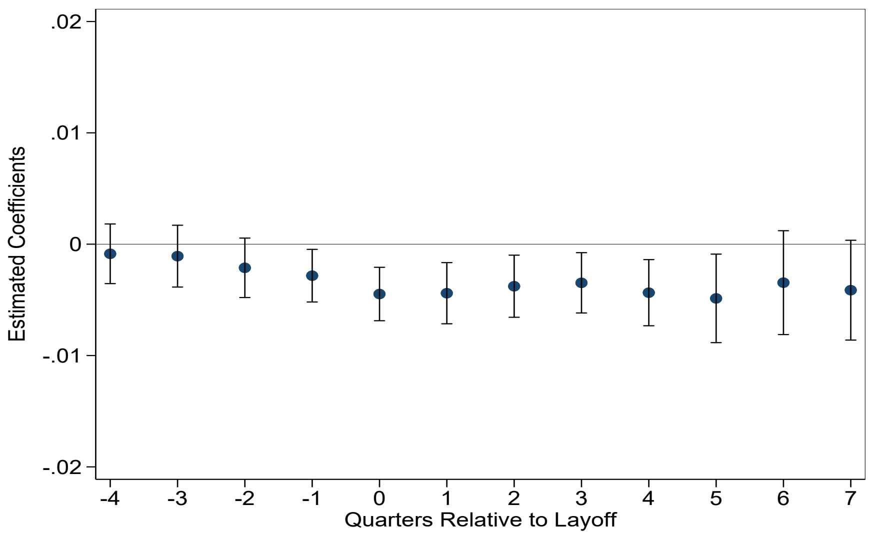
Figure 1
Maximum UI Benefits across States



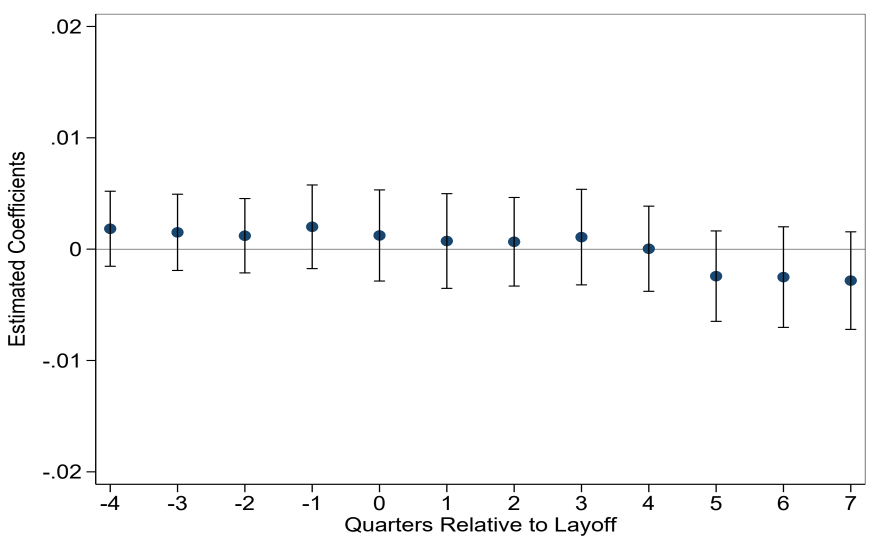
Notes: The figures plot maximum unemployment insurance benefit levels, changes, and growth corresponding to each subtitle. The shading corresponds to quartiles for each measurement.

Figure 2
Estimated effects of UI generosity on divorce over time

Panel A: Men



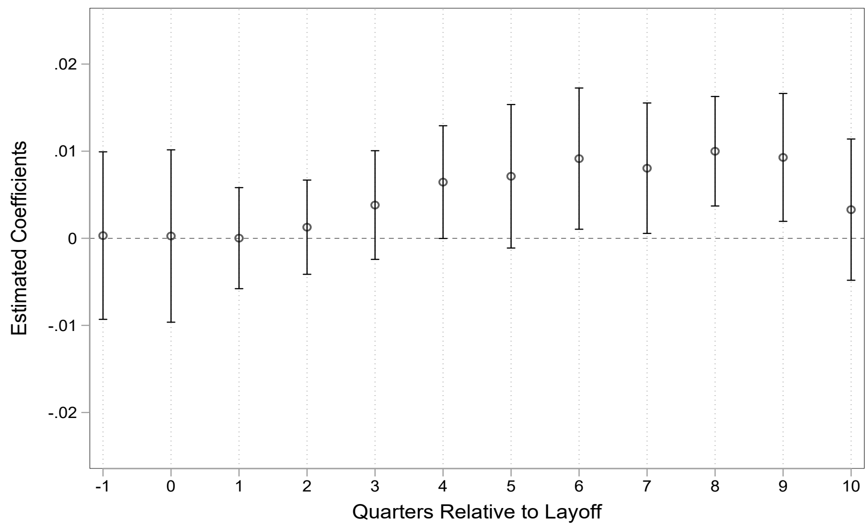
Panel B: Women



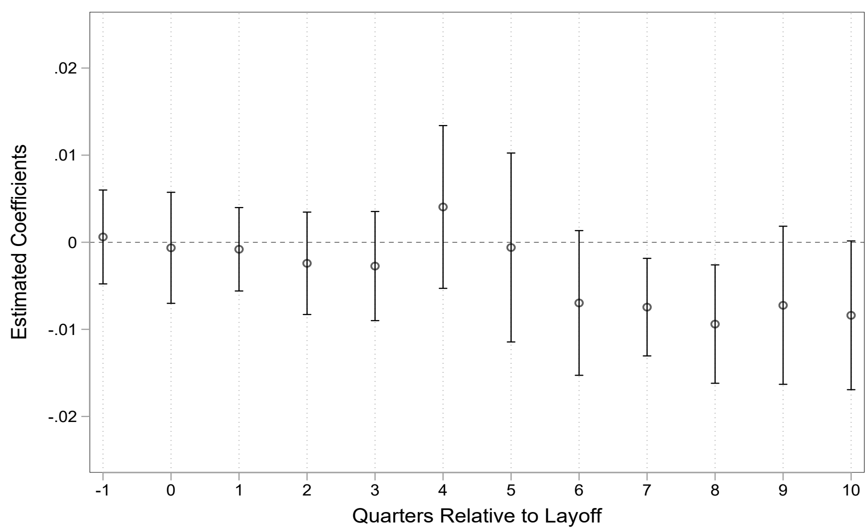
Notes: The dependent variable is an indicator variable for divorce or separation in each survey month. This figure reports estimated coefficients and 95 percent confidence intervals for interactions between indicator variables for quarters relative to layoff and the variable for maximum weekly UI benefits in hundreds of dollars (MaxUI). The regression model additionally includes individual demographic and education controls (age, race, and educational attainment), state-by-quarter-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.

Figure 3
Effects of UI generosity over time for laid-off men on fertility

Panel A: Men



Panel B: Women



Notes: The dependent variable is whether an individual ages 20 to 40 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-quarter-year 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.

Table 1
Estimated Effects on Divorce

	(1)	(2)	(3)
Panel A: Men			
MaxUI×$\mathbb{1}$[After Layoff]	-0.0040***	-0.0035***	-0.0034***
	(0.0010)	(0.0010)	(0.0010)
$\mathbb{1}$[After Layoff]	0.0255***	0.0243***	0.0238***
	(0.0036)	(0.0036)	(0.0036)
MaxUI	-0.0012		
	(0.0015)		
Panel B: Women			
MaxUI×$\mathbb{1}$[After Layoff]	-0.0009	-0.0006	-0.0006
	(0.0013)	(0.0014)	(0.0015)
$\mathbb{1}$[After Layoff]	0.0127**	0.0121**	0.0121**
	(0.0048)	(0.0052)	(0.0052)
MaxUI	-0.0014		
	(0.0013)		
Quarter-Year Fixed Effects	Y	-	-
State Fixed Effects	Y	-	-
Group Fixed Effects	Y	-	-
State-by-Quarter-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 $\mathbb{1}$[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. The number of observations is 2,421,088 in Panel A and 1,650,473 in Panel B.
*, **, and ***, indicate statistical significance at the ten-, five-, and one-percent levels, respectively.

Table 2
Estimated Effects Distinguishing between Divorce and Separation

	Divorce			Separation		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Men						
MaxUI×𝟙[After Layoff]	-0.0017**	-0.0011	-0.0011	-0.0023***	-0.0025***	-0.0025***
	(0.0009)	(0.0008)	(0.0008)	(0.0007)	(0.0008)	(0.0008)
𝟙[After Layoff]	0.0124***	0.0103***	0.0102***	0.0140***	0.0147***	0.0145***
	(0.0036)	(0.0033)	(0.0033)	(0.0025)	(0.0027)	(0.0027)
MaxUI	-0.0006			-0.0006		
	(0.0011)			(0.0008)		
Panel B: Women						
MaxUI×𝟙[After Layoff]	0.0005	0.0009	0.0009	-0.0014*	-0.0015**	-0.0015**
	(0.0011)	(0.0011)	(0.0011)	(0.0008)	(0.0007)	(0.0008)
𝟙[After Layoff]	0.0046	0.0035	0.0034	0.0086***	0.0091***	0.0092***
	(0.0039)	(0.0040)	(0.0040)	(0.0026)	(0.0025)	(0.0025)
MaxUI	-0.0013			-0.0001		
	(0.0011)			(0.0010)		

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 either being separated or divorced corresponding to the column header. 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. The number of observations is 2,402,250 in Columns 1-3 and 2,396,969 in Columns 4-6 in Panel A and 1,632,260 and 1,629,513 in corresponding columns in Panel B.
*, **, and ***, indicate statistical significance at the ten-, five-, and one-percent levels, respectively.

Table 3
Effects on divorce for those with and without children

	(1) No Children	(2) Children	(3) Children < age 18
Panel A: Men			
MaxUI×𝟙[After Layoff]	-0.0068**	-0.0026***	-0.0003
	(0.0027)	(0.0008)	(0.0009)
𝟙[After Layoff]	0.0469***	0.0150***	0.0048*
	(0.0097)	(0.0023)	(0.0028)
Panel B: Women			
MaxUI×𝟙[After Layoff]	0.0031	-0.0023	-0.0021
	(0.0022)	(0.0019)	(0.0022)
𝟙[After Layoff]	0.0025	0.0167**	0.0153*
	(0.0081)	(0.0072)	(0.0082)

Notes: The table presents the heterogenous effects of maximum weekly unemployment benefits (in 100s of dollars) 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-quarter-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. The number of observations is 685,783, 1,735,305, and 1,422,371 in Columns 1-3, respectively, in Panel A and 554,364, 1,096,109, and 854,804 in corresponding columns in Panel B.
*, **, and ***, indicate statistical significance at the ten-, five-, and one-percent levels, respectively

Table 4
Estimated Effects on fertility

	(1)	(2)	(3)
Panel A: Men			
MaxUI×𝟙[9+ Months After Layoff]	0.0019	0.0053**	0.0067***
	(0.0029)	(0.0026)	(0.0023)
𝟙[9+ Months After Layoff]	-0.0168	-0.0276***	-0.0292***
	(0.0103)	(0.0092)	(0.0085)
MaxUI	0.0004		
	(0.0025)		
Panel B: Women			
MaxUI×𝟙[9+ Months After Layoff]	-0.0031	-0.0055**	-0.0050**
	(0.0019)	(0.0021)	(0.0021)
𝟙[9+ Months After Layoff]	0.0152**	0.0238***	0.0233***
	(0.0065)	(0.0073)	(0.0074)
MaxUI	0.0028		
	(0.0021)		
Quarter-Year Fixed Effects	Y	-	-
State Fixed Effects	Y	-	-
Group Fixed Effects	Y	-	-
State-by-Quarter-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 40 has a child less than one year old in the survey month. 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. The number of observations is 1,116,691 in Panel A and 764,049 in Panel B.
*, **, and ***, indicate statistical significance at the ten-, five-, and one-percent levels, respectively

Appendix A

Table A1
Summary Statistics

	Before Layoff	After Layoff	Never Laid Off
Panel A: Men			
Divorced (including separated)	0.020	0.039	0.017
Divorced (not including separated)	0.009	0.020	0.010
Separated (not including divorce)	0.011	0.019	0.007
Child < 1 yr old	0.106	0.078	0.090
Age	41.38	42.23	43.00
White	0.86	0.85	0.88
Black	0.09	0.09	0.07
Other	0.06	0.06	0.05
Advanced Degree	0.07	0.07	0.14
Bachelor's Degree	0.15	0.14	0.22
Some College	0.27	0.28	0.29
High School	0.50	0.50	0.35
Max UI	317	334	320
Observations	182,010	310,396	1,928,613
Panel B: Women			
Divorced (including separated)	0.024	0.042	0.021
Divorced (not including separated)	0.011	0.022	0.012
Separated (not including divorce)	0.013	0.020	0.009
Child < 1 yr old	0.068	0.079	0.048
Age	39.93	40.83	42.98
White	0.87	0.87	0.86
Black	0.08	0.08	0.08
Other	0.06	0.05	0.05
Advanced Degree	0.07	0.07	0.12
Bachelor's Degree	0.18	0.18	0.21
Some College	0.31	0.32	0.32
High School	0.44	0.43	0.35
Max UI	319	332	324
Observations	169,951	287,134	1,193,323

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 40. 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

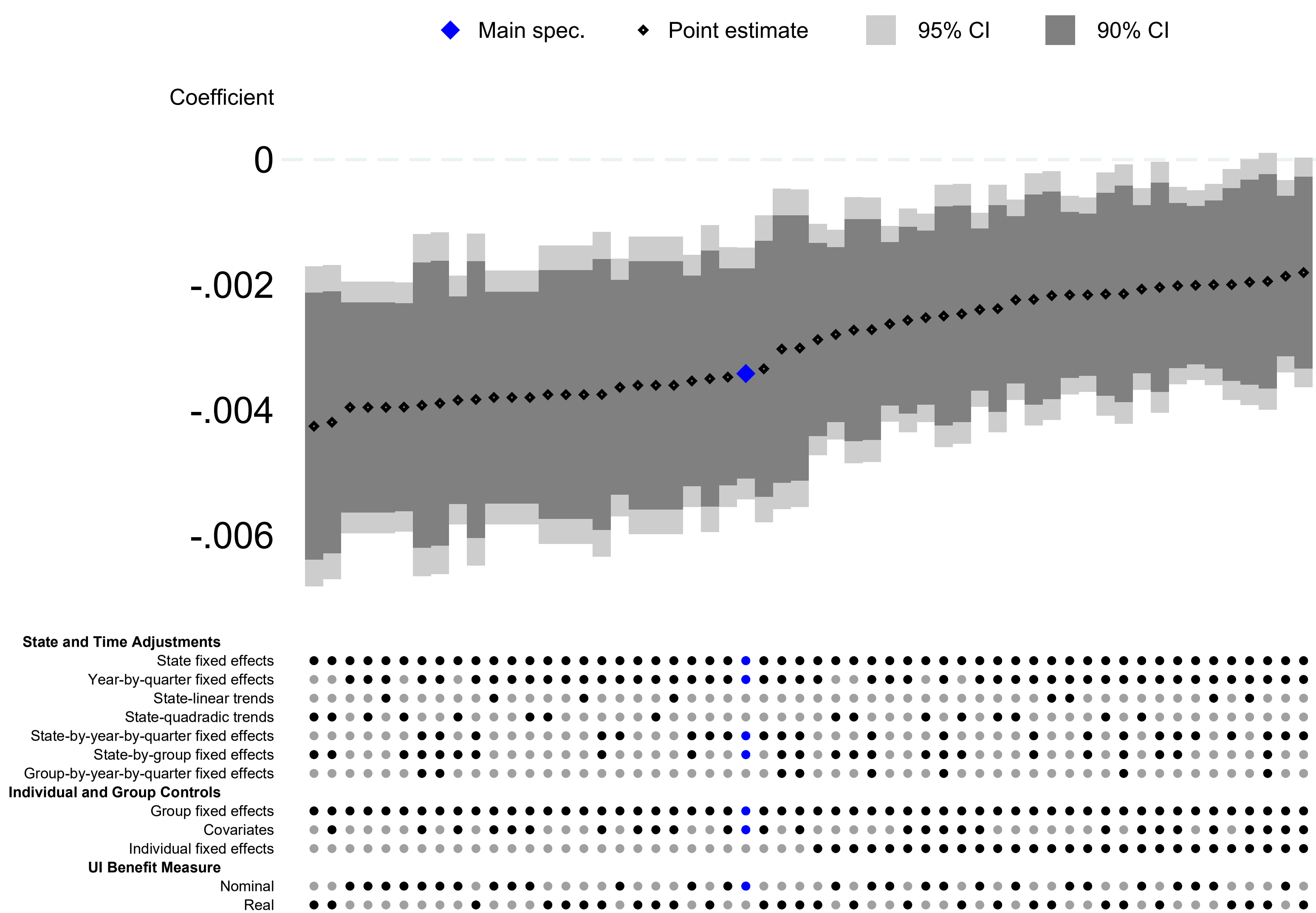


Figure A2

Estimated effects of maximum UI benefits on divorce among laid-off men using Hsu, Matsa, and Melzer (2018) approach to identifying relevant laid-off workers (compare to Figure A1)

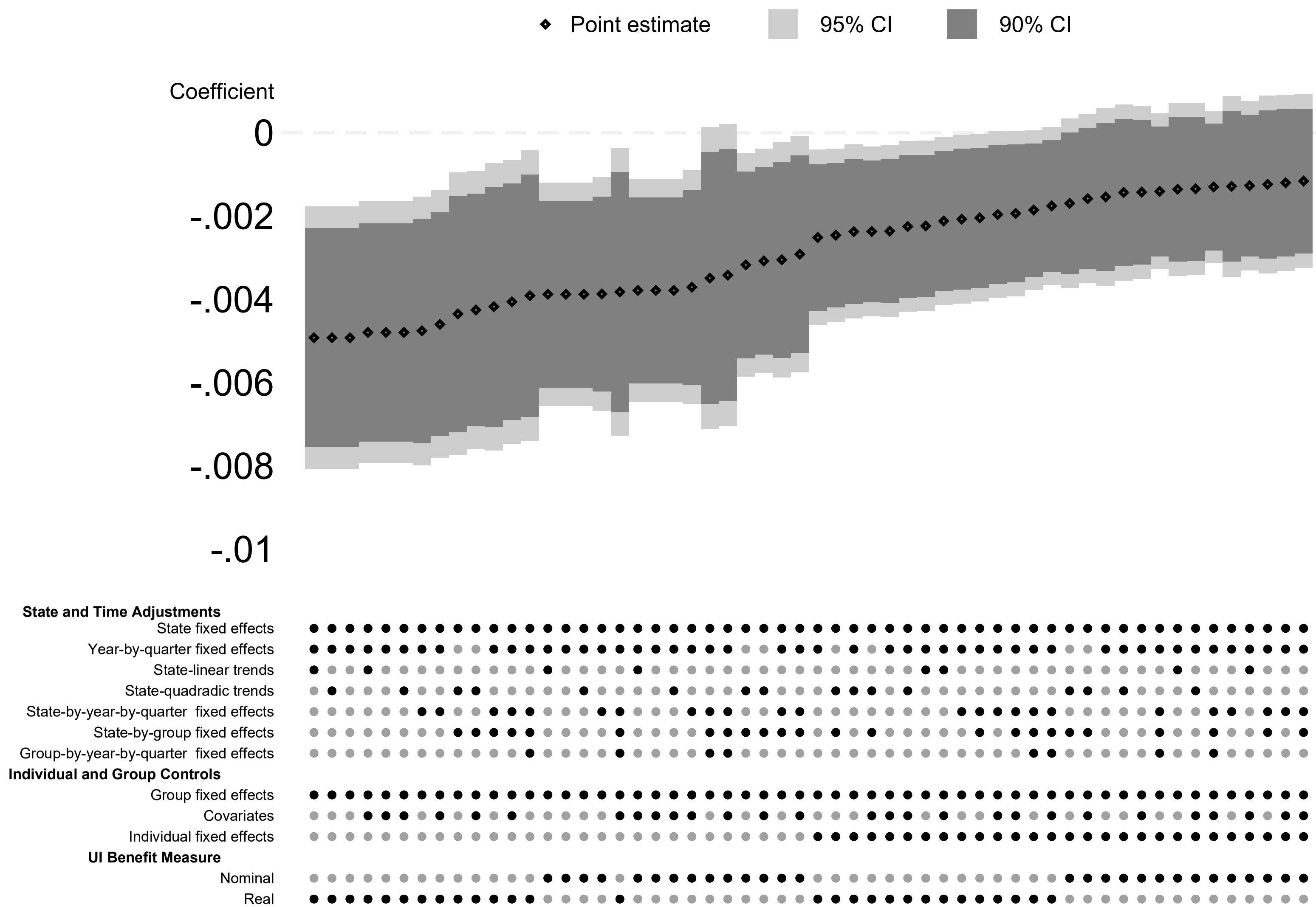


Figure A3

Estimated effects of maximum UI benefits on divorce among laid-off men using Kuka (2020) approach to identifying relevant laid-off workers (compare to Figure A1)

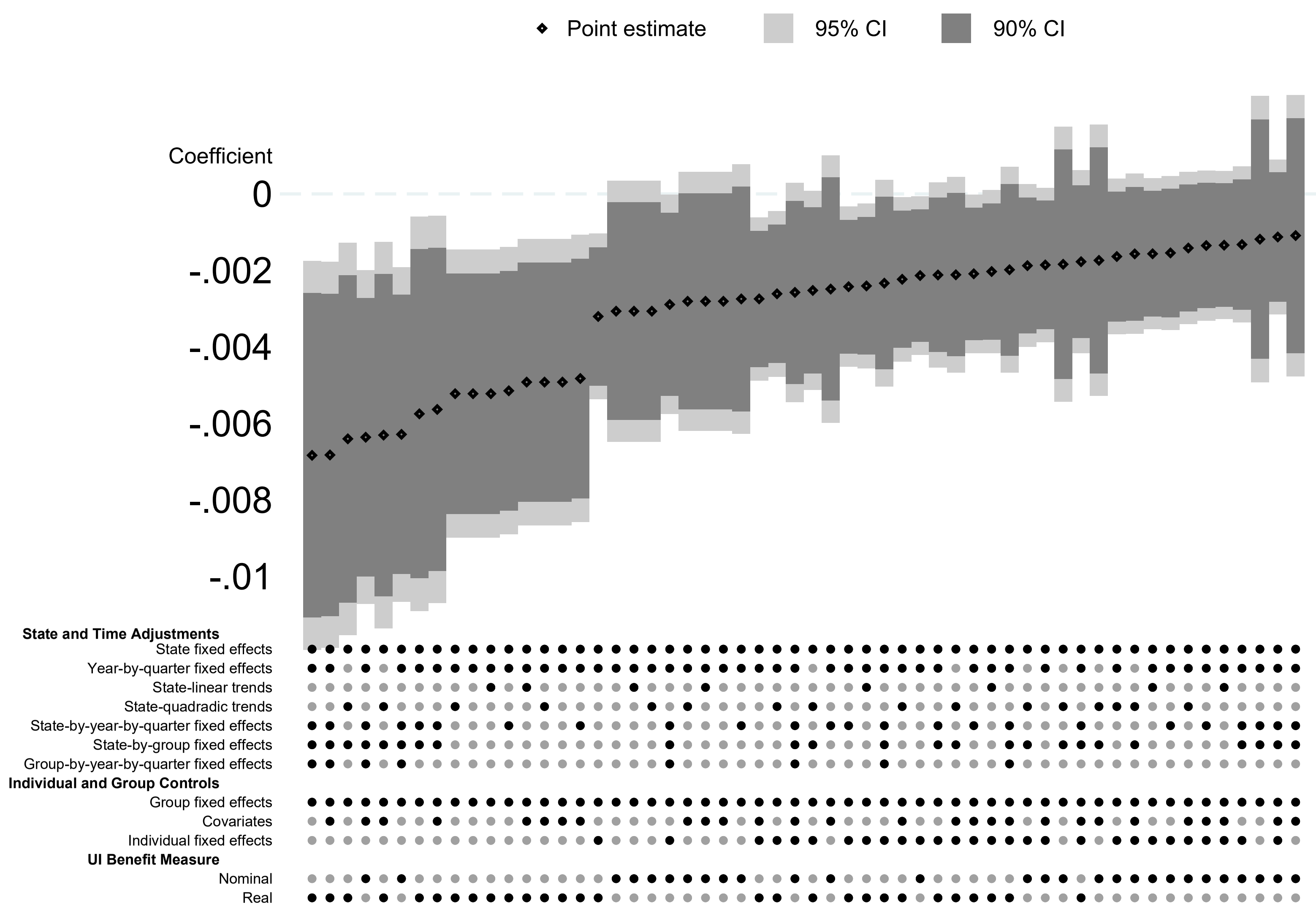


Figure A4
Specification Chart for Effects of UI Generosity on Divorce for Laid-off Women

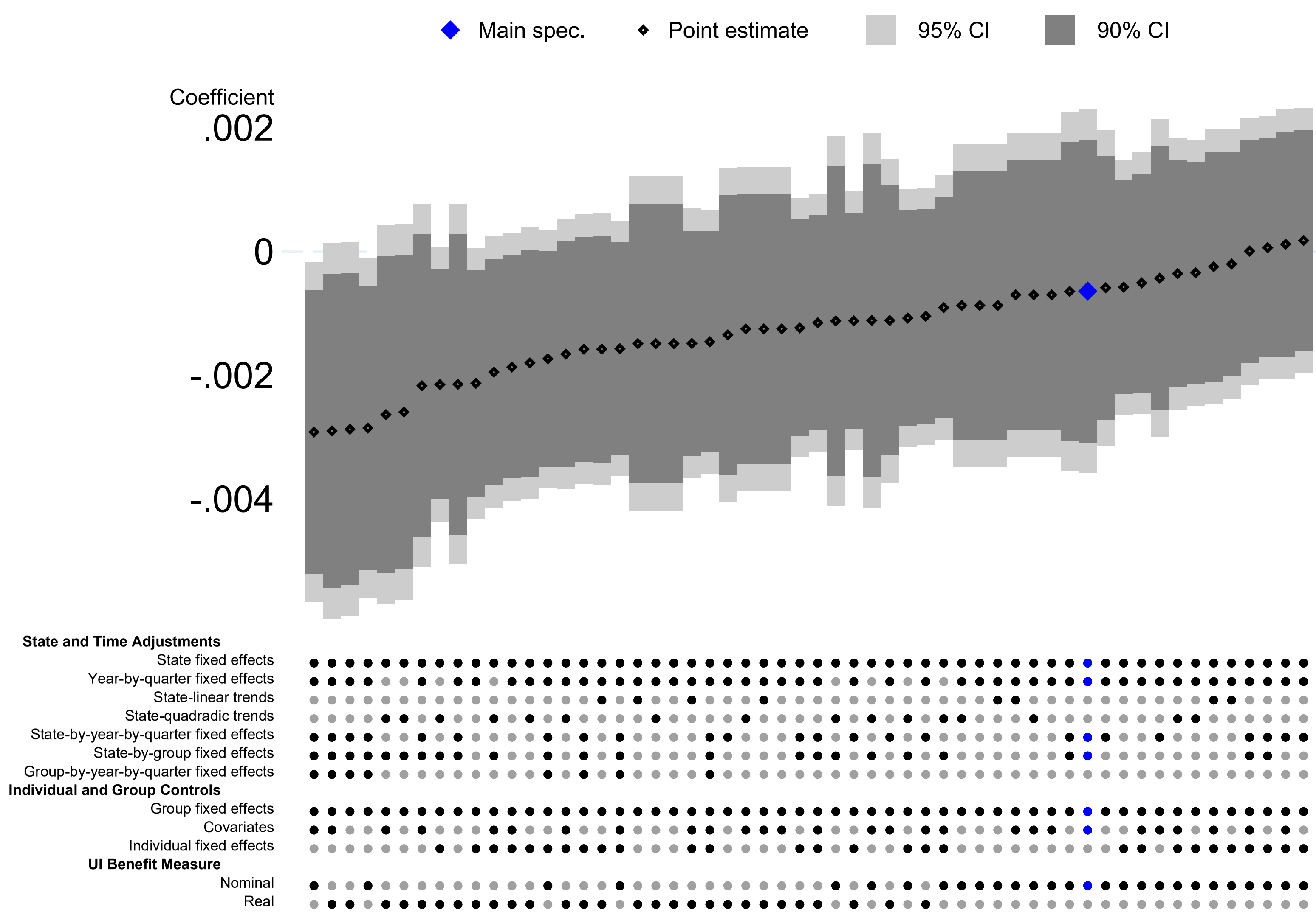


Figure A5

Estimated effects of maximum UI benefits on divorce among laid-off women using
Hsu, Matsa, and Melzer (2018) approach to identifying relevant laid-off workers (compare to Figure A4)

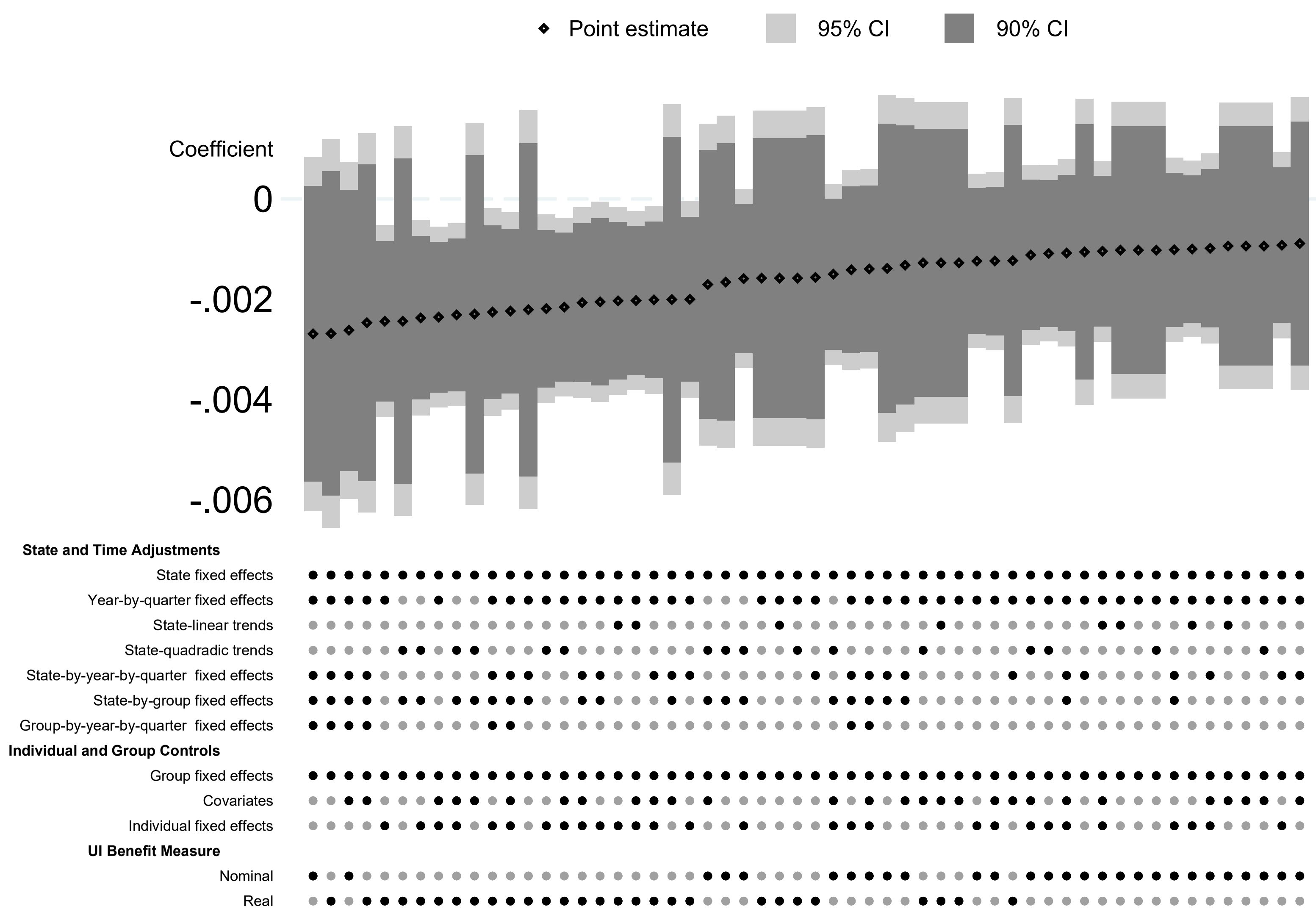


Figure A6

Estimated effects of maximum UI benefits on divorce among laid-off women using Kuka (2020) approach to identifying relevant laid-off workers (compare to Figure A4)

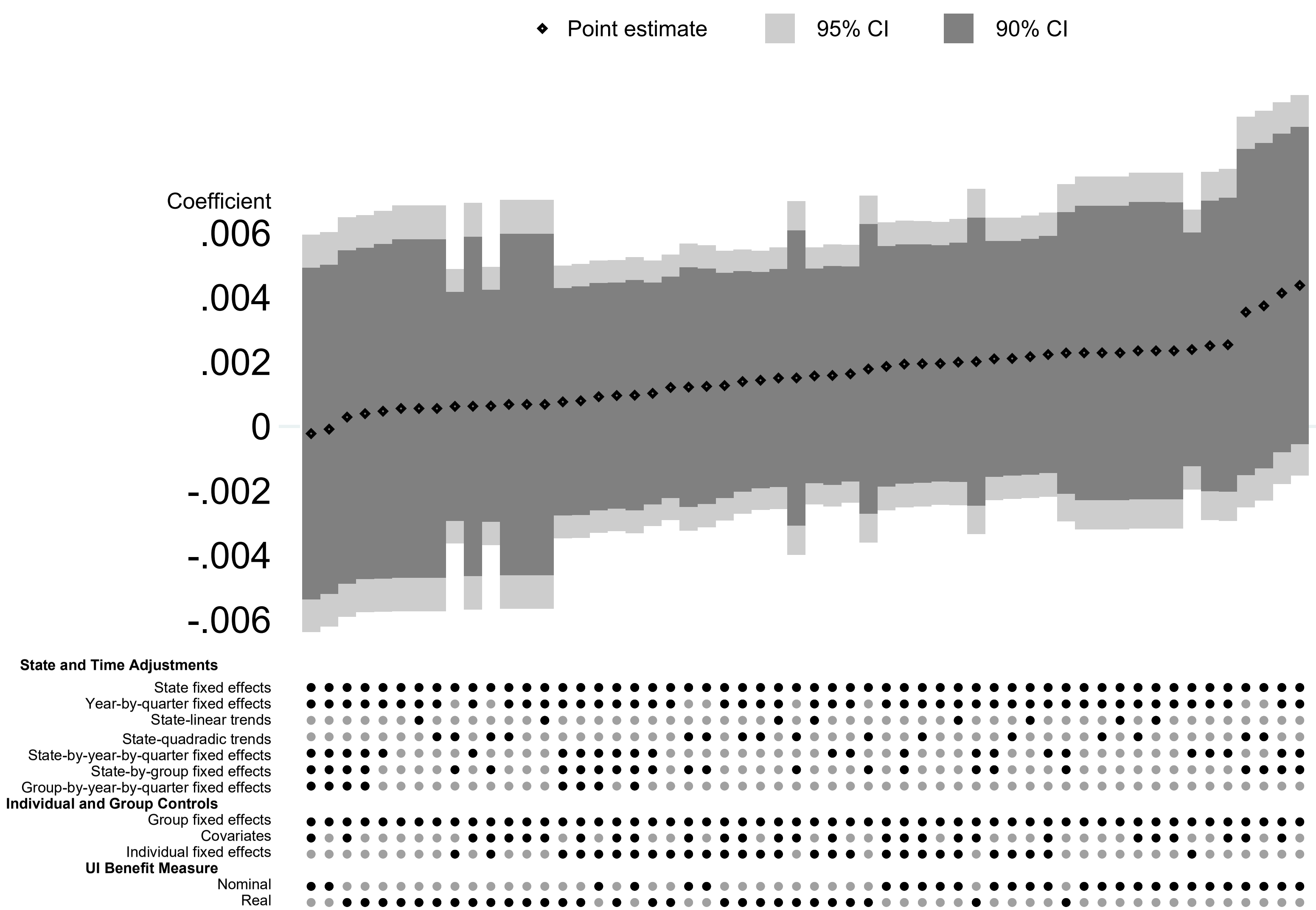


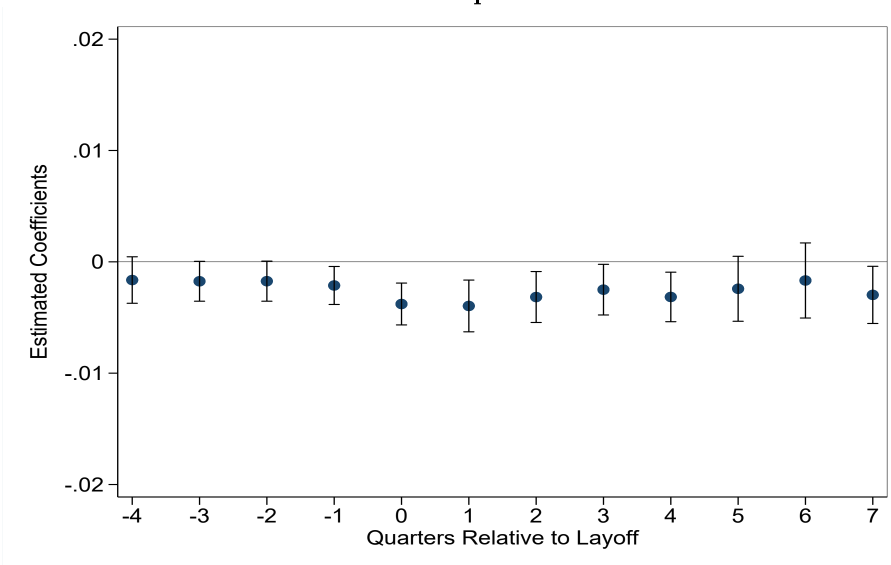
Table A2
Placebo tests evaluating those quitting jobs instead of those laid off
(Compare to Table 1)

	(1)	(2)	(3)
Panel A: Men			
MaxUI×𝟙[After Quit]	-0.0015	-0.0018	-0.0015
	(0.0014)	(0.0016)	(0.0015)
𝟙[After Quit]	0.0194***	0.0207***	0.0198***
	(0.0050)	(0.0053)	(0.0053)
MaxUI	-0.0006		
	(0.0012)		
Panel B: Women			
MaxUI×𝟙[After Quit]	-0.0025	-0.0025	-0.0026
	(0.0019)	(0.0026)	(0.0025)
𝟙[After Quit]	0.0178***	0.0182**	0.0185**
	(0.0063)	(0.0081)	(0.0080)
MaxUI	-0.0016		
	(0.0015)		
Quarter-by-Year Fixed Effects	Y	-	-
State Fixed Effects	Y	-	-
Group Fixed Effects	Y	-	-
State-by-Quarter-Year Fixed Effects	N	Y	Y
State-Group Fixed Effects	N	Y	Y
Individual Controls	N	N	Y

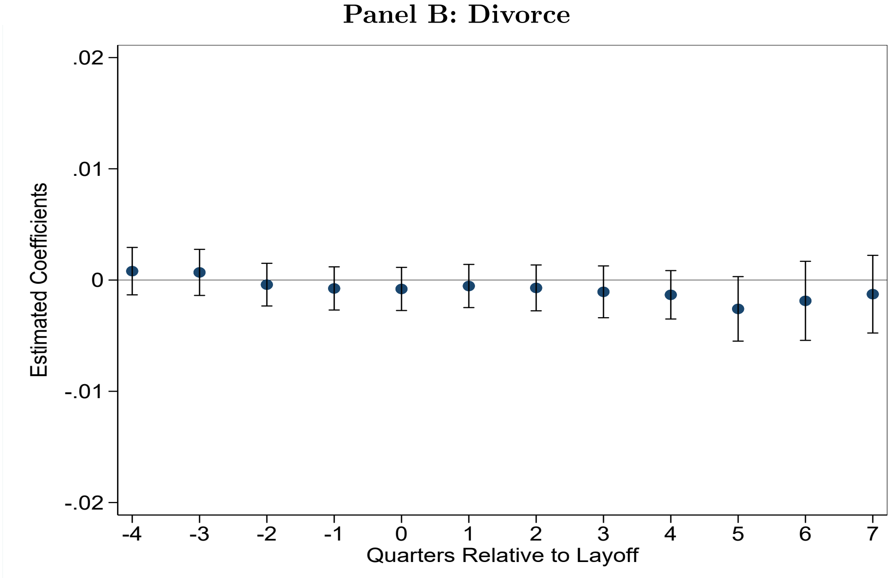
Notes: Estimates are based on the 1990, 1991, 1992, 1993, 1996, 2001, 2004, and 2008 panels of the Survey of Income and Program Participation. The dependent variable is an indicator variable for being separated or divorced. The variable 𝟙[After Quit] is an indicator that takes the value of one following a job separation due to quitting after three consecutive months of employment 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. The number of observations is 2,064,675 in Panel A and 1,398,737 in Panel B.
*, **, and ***, indicate statistical significance at the ten-, five-, and one-percent levels, respectively.

Figure A7
Estimated effects of UI generosity on laid-off men over time, distinguishing divorce and separations

Panel A: Separations



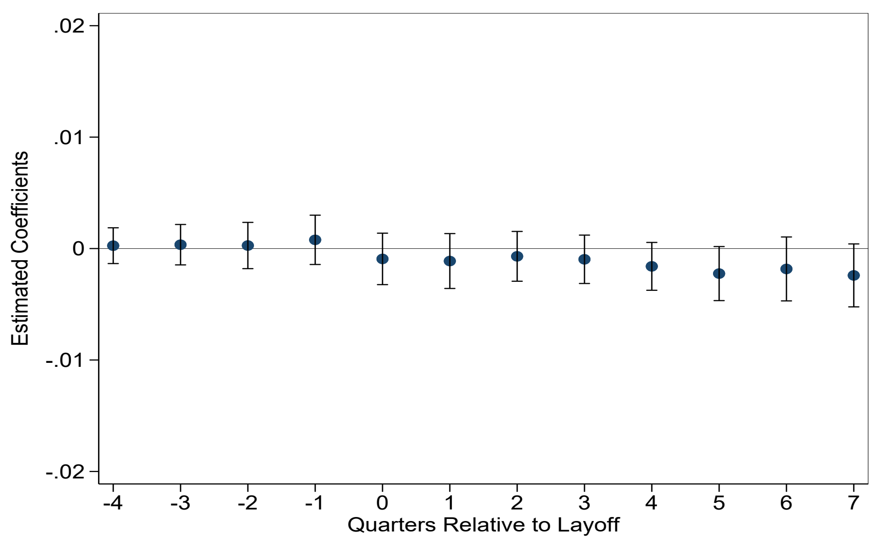
Panel B: Divorce



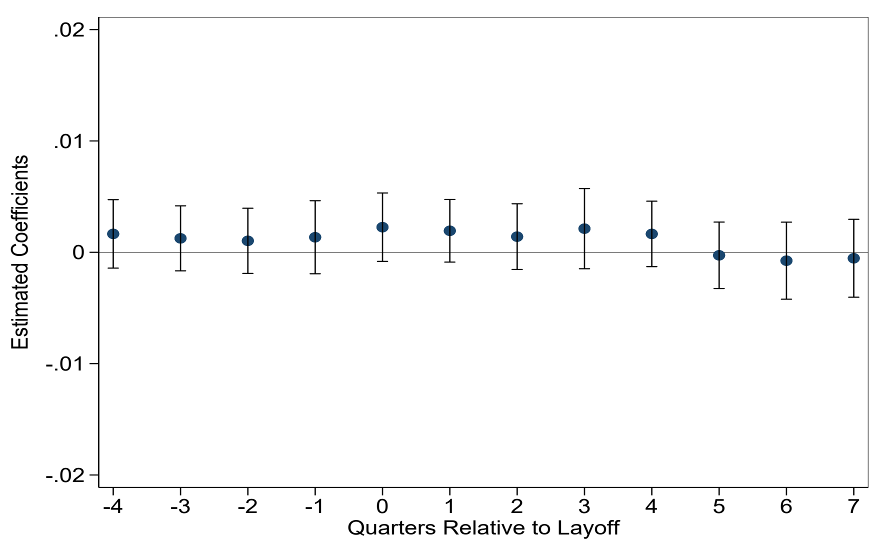
Notes: The dependent variable is an indicator variable for divorce or separation in each survey month. This figure reports estimated coefficients and 95 percent confidence intervals for interactions between indicator variables for quarters relative to layoff and the variable for maximum weekly UI benefits in hundreds of dollars (MaxUI). The regression model additionally includes individual demographic and education controls (age, race, and educational attainment), state-by-quarter-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.

Figure A8
Estimated effects of UI generosity on laid-off women over time, distinguishing divorce and separations

Panel A: Separations



Panel B: Divorce



Notes: The dependent variable is an indicator variable for either 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-quarter-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.

Table A3
Estimated effects on divorce with sample restricted to individuals experiencing a layoff
(Compare to Table 1)

	(1)	(2)	(3)
Panel A: Men			
MaxUI×𝟙[After Layoff]	-0.0027**	-0.0025*	-0.0029**
	(0.0011)	(0.0013)	(0.0013)
𝟙[After Layoff]	0.0188***	0.0185***	0.0192***
	(0.0044)	(0.0048)	(0.0048)
MaxUI	-0.0063		
	(0.0039)		
Panel B: Women			
MaxUI×𝟙[After Layoff]	-0.0025	-0.0023	-0.0024
	(0.0015)	(0.0015)	(0.0015)
𝟙[After Layoff]	0.0164***	0.0158***	0.0160***
	(0.0050)	(0.0052)	(0.0052)
MaxUI	-0.0031		
	(0.0031)		
Quarter-by-Year Fixed Effects	Y	-	-
State Fixed Effects	Y	-	-
State-by-Quarter-Year 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. The number of observations is 492,427 in Panel A and 457,100 in Panel B.
*, **, and ***, indicate statistical significance at the ten-, five-, and one-percent levels, respectively.

Table A4
UI benefit generosity and measures of economic conditions and other social programs

	(1)	(2)	(3)	(4)	(5)
Panel A: Relationship with State Economic Conditions					
StateGDPGrowthRate	0.0081				-0.3180
	(0.5020)				(0.4448)
UnemploymentRate		-1.4872			-0.7666
		(2.5334)			(2.1691)
AvgStateIncome			2.4657		2.4647
			(3.8442)		(3.8390)
UnionCoverage				0.1832	0.1753
				(2.0675)	(2.0056)
N	2142	2142	2142	2142	2142
Panel B: Relationship with Other Social Programs					
WorkersComp	0.3884				0.3801
	(0.3149)				(0.3136)
FoodStamps		-2.9520			-3.1359
		(2.2605)			(2.2812)
SSDisabilityInsurance			6.5952		4.8212
			(21.6313)		(21.4306)
Medicaid				0.5554	0.7825
				(1.5924)	(1.6145)
N	2142	2142	2142	2142	2142

Notes: This table shows the results of regressions of state-half-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

Table A5
Measure of UI benefit generosity and monthly UI benefits received

	(1)	(2)
Panel A: Men		
MaxUI	31.3546***	161.9797***
	(7.4652)	(22.7884)
Panel B: Women		
MaxUI	10.9945*	81.2928***
	(5.5623)	(23.7360)

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 the amount of unemployment insurance benefits received. The variable MaxUI is the state maximum amount of weekly UI benefits in hundreds of dollars. The sample is limited to laid-off workers. The second column further limits the sample to laid-off workers who actually receive benefits. Regression models control for state and year fixed effects, use survey weights, and adjust the standard-error estimates to allow for clusters at the state level. The number of observations is 310,405 in Column 1 and 46,903 in Column 2 in Panel A and 287,141 and 27,842 in corresponding columns in Panel B.
*, **, and ***, indicate statistical significance at the ten-, five-, and one-percent levels, respectively.

Figure A9
Specification chart for effects of UI generosity for laid-off men on fertility

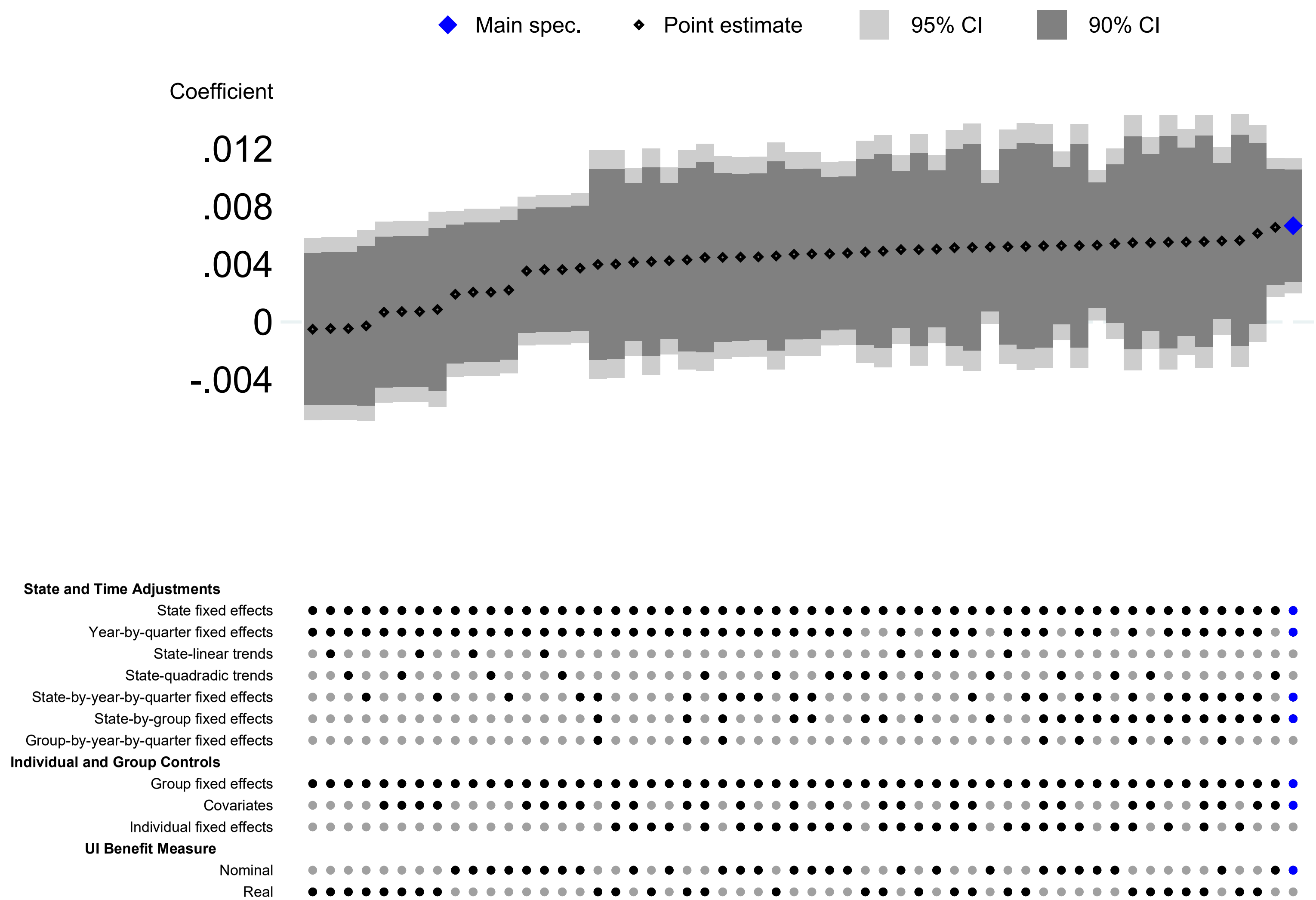


Figure A10
Estimates using Hsu, Matsa, and Melzer (2018) approach to identifying relevant laid-off workers
Effects of UI generosity for laid-off men on fertility (Compare to Figure A9)

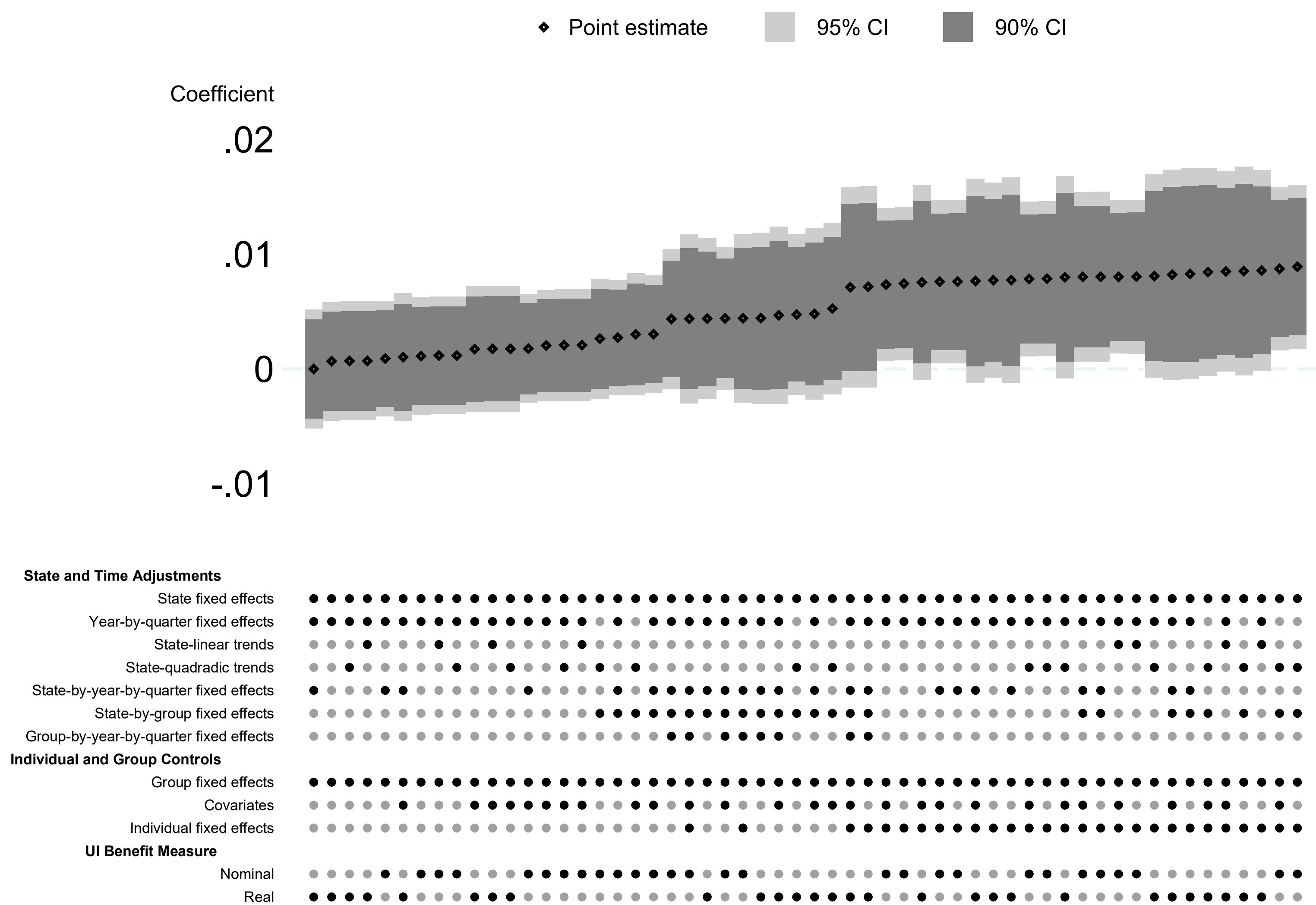


Figure A11
Estimates using Kuka (2020) approach to identifying relevant laid-off workers
Effects of UI generosity for laid-off men on fertility (Compare to Figure A9)

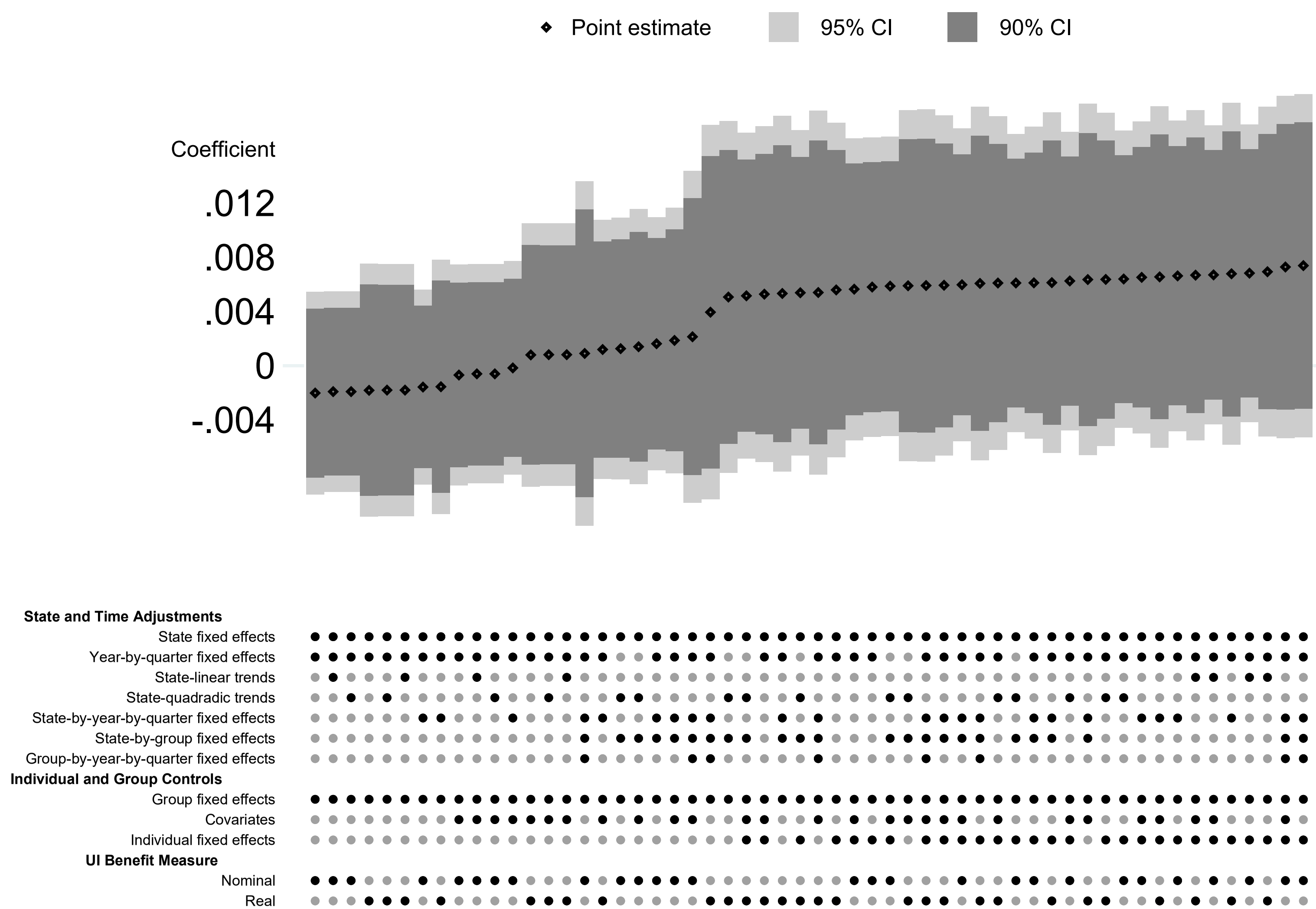


Figure A12
Specification chart for effects of UI generosity for laid-off women on fertility

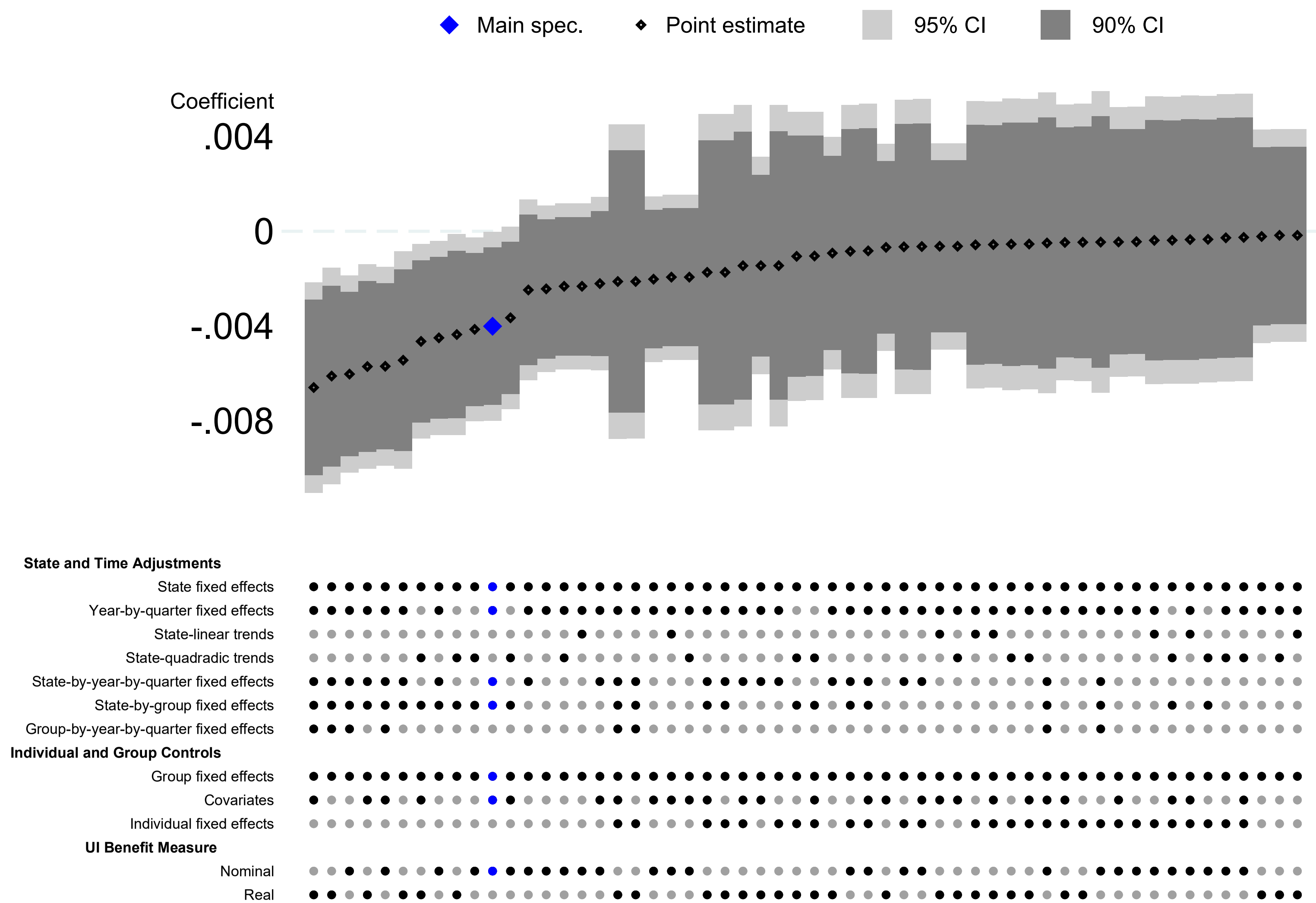


Figure A13
Estimates using Hsu, Matsa, and Melzer (2018) approach to identifying relevant laid-off workers
Effects of UI generosity for laid-off women on fertility (Compare to Figure A12)

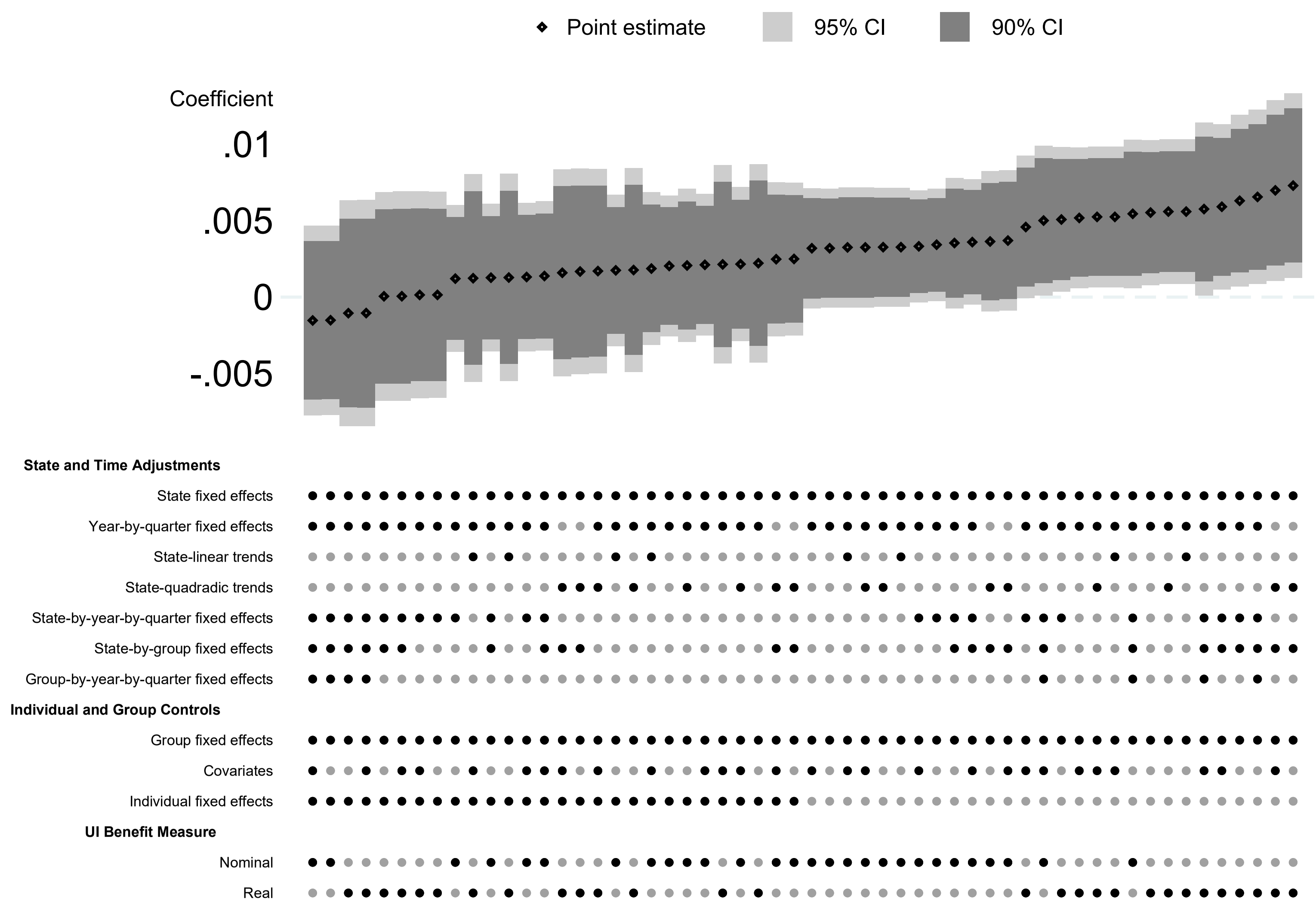
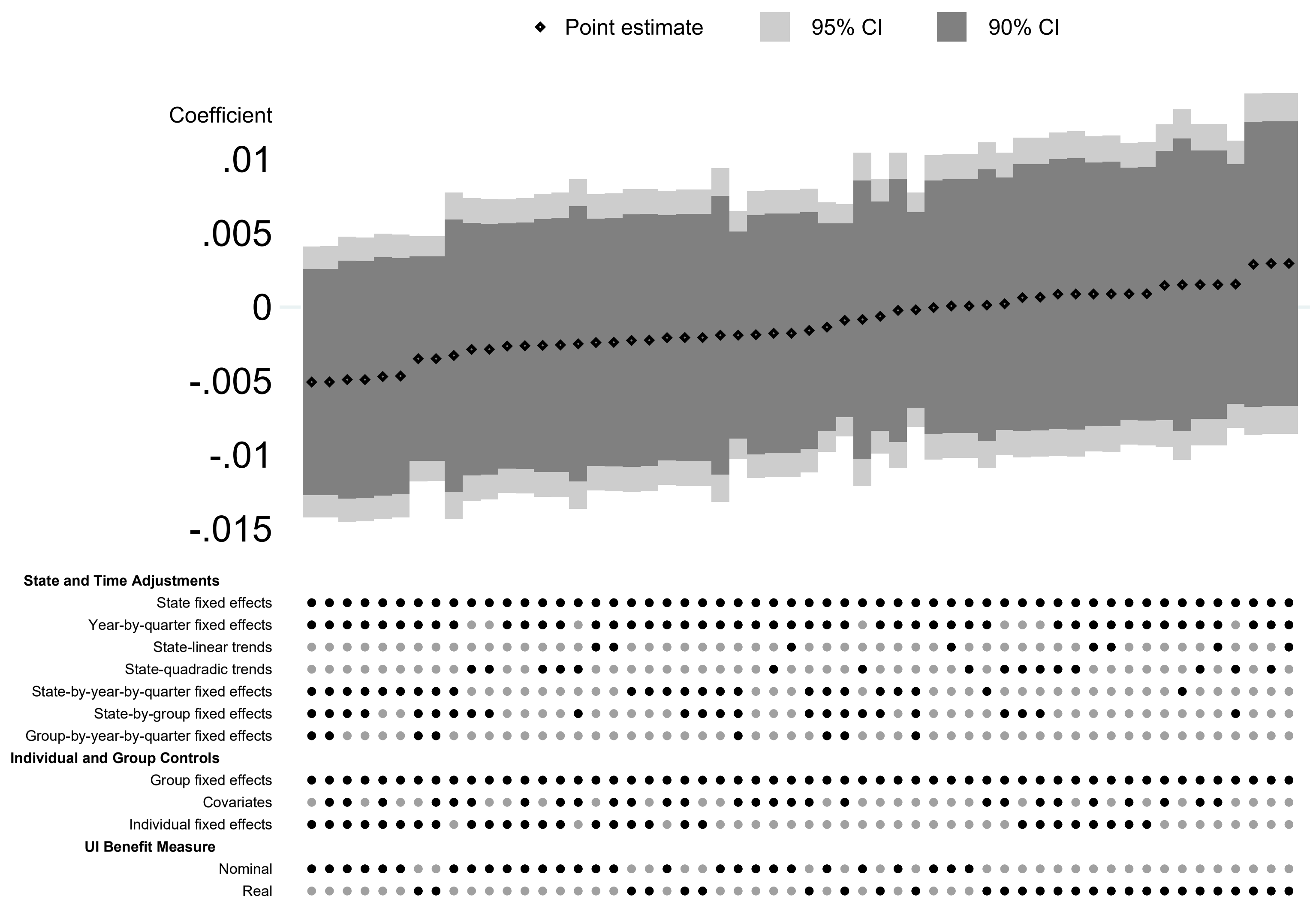


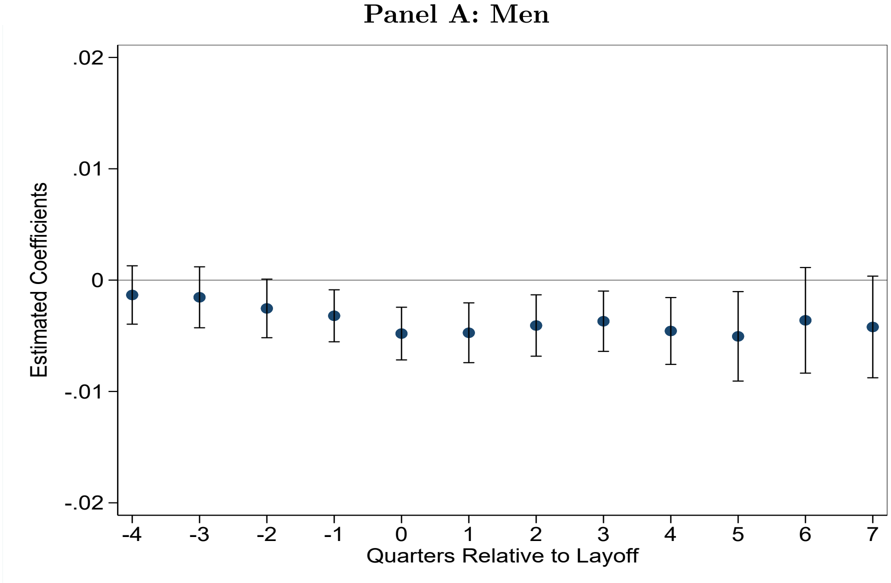
Figure A14
Estimates using Kuka (2020) approach to identifying relevant laid-off workers
Effects of UI generosity for laid-off women on fertility (Compare to Figure A12)



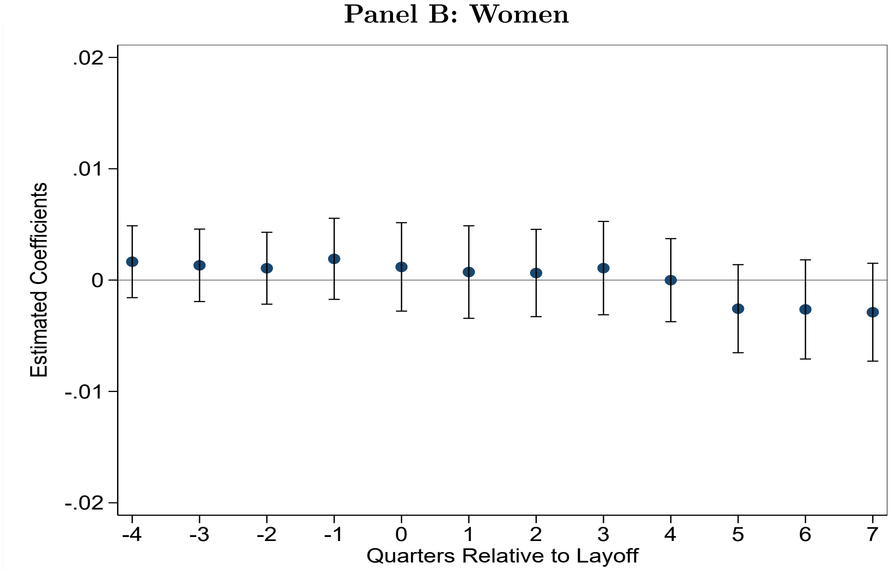
6 Appendix B (Not for Publication)

Figure B1
Event-study estimates without using individual controls

Panel A: Men



Panel B: Women



Notes: The dependent variable is an indicator variable for either 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 state fixed effects, quarter-by-year fixed effects, and group-by-state 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.