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DISCUSSION PAPER SERIES

IZA DP No. 13054

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ABSTRACT

Becoming Sensitive: Males' Risk and Time Preferences after the 2008 Financial Crisis*

This paper presents evidence suggesting men's (but not women's) risk and time preferences have systematically become sensitive to local economic conditions since the 2008 financial crisis. Studying longitudinal, nationally representative data for 22,579 Australian-based respondents in up to 11 surveys from 2002-2015, men respond with increased risk aversion and impatience to a rise in their region's unemployment rate – but only since 2008. We find no such relationship for women or before the crisis. This conclusion persists when accounting for individual-level fixed effects, demographics, national economic conditions, the individual's employment situation, income, wealth, as well as region- and time-specific unobservables. Exploring a potential mechanism, higher regional unemployment rates are also linked to men (but not women) being more unhappy since 2008. This 'happiness channel' only partially explains the link between the local unemployment rate and risk preferences.

JEL Classification: D81, G11, G14, G41, J16

Keywords: risk preferences, time preferences, gender differences, financial crisis

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* This study uses unit record data from the Household, Income and Labour Dynamics in Australia (HILDA) survey. The HILDA project was initiated and funded by the Australian Government Department of Families, Housing, Community Services and Indigenous Affairs (FaHCSIA) and is managed by the Melbourne Institute of Applied Economic and Social Research (MIAESR). The findings and views reported in this paper, as well as any mistakes or errors, are those of the authors, and should not be attributed to FaHCSIA or MIAESR. Declarations of interest: none.

1 Introduction

Can a major macroeconomic shock change permanently individuals' risk preferences? Classical theories and standard models in economics assume preferences to be stable over time and largely unaffected by experience (e.g., see Stigler and Becker, 1977). More recently, however, experimental evidence suggests people's willingness to take risks can be affected by traumatic events, such as natural disasters (Eckel et al., 2009; Callen, 2015; Cameron and Shah, 2015; Cassar et al., 2017; Hanaoka et al., 2018) and episodes of large-scale violence (Voors et al., 2012; Callen et al., 2014; Kim and Lee, 2014). Regarding studies on major economic shocks, Weber et al., 2013 and Guiso et al., 2018 suggest an increase of investors or bank clients risk aversion after the global financial crisis of 2008 in the United Kingdom and Italy, respectively.[1] These studies only measure the one-time impact of a major shock.

In the following pages, we show that, using longitudinal data for 22,579 Australian-based respondents from up to 11 waves (four before the crisis and seven thereafter), the *responsiveness* to economic conditions since the 2008 financial crisis has differed by gender. Specifically, an increase in the regional unemployment rate over the preceding 12 months is associated with men (but not women) reporting to be significantly less willing to take financial risks. We only identify this relationship after 2008. Our results prevail in a range of alternative estimations after accounting for a rich set of demographical characteristics, fixed effects on the individual, wave, and regional levels, as well as personal employment characteristics. More importantly, they are not driven by underlying trends in sensitivity to unemployment rates since the crisis (such as respondents becoming older between survey waves).[2]

Figure 1 presents a graphical preview of our key findings. Specifically, it shows the relationship between changes in the local unemployment rate and (within-individual) variation in the willingness to take financial risks – our main measure of risk preferences. We estimate this relationship for the full

[1] Bloom (2009) provides a structural model for uncertainty jumps after macroeconomic shocks. Analyzing decades of US survey data, Malmendier and Nagel (2011) find that "individuals who have experienced low stock market returns throughout their lives so far report lower willingness to take financial risk". Giuliano and Spilimbergo (2014) suggest growing up during a recession can systematically affect political attitudes and beliefs about redistribution. Tausch and Zumbuehl (2018) show that bad news about the economy elicit more risk aversion in survey respondents based in Germany.

[2] Dohmen et al. (2017) emphasize the importance of disentangling age, cohort, and calendar period effects when examining changes in risk attitudes over the life course. We address this identification problem by controlling for linear time trends and period effects through age (and year) dummies while using unemployment rates at the region of residence, which allows us to relate local economic conditions to risk preferences.

sample using a generalized additive model with a Gaussian process smoothing regression, but show the figures before and after the crisis by gender.

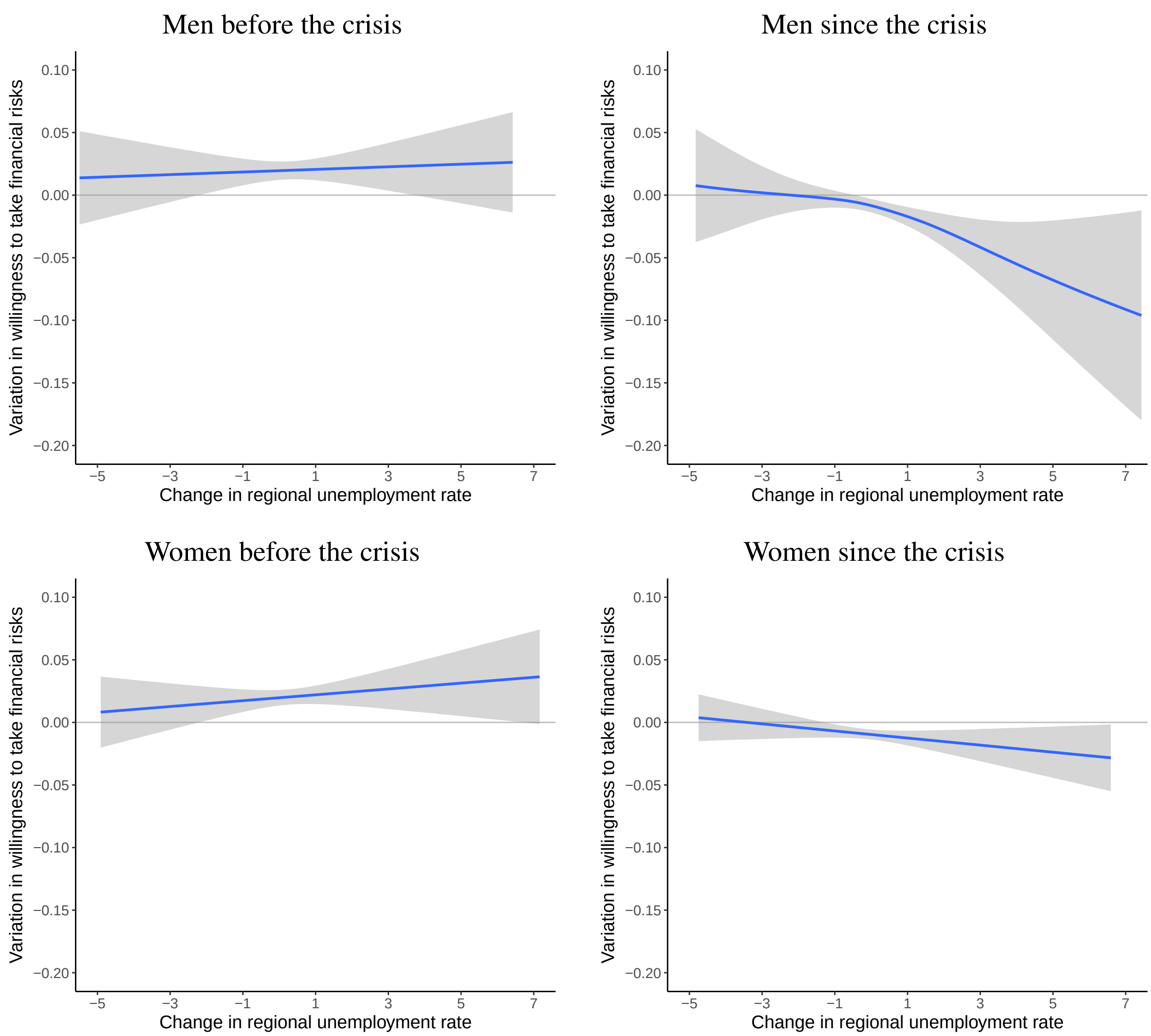

Figure 1: Relation between the variation in willingness to take financial risks (demeaned at the individual level) and changes in the regional unemployment rate

Four aspects of our findings are particularly noteworthy and, we believe, novel. First, neither the crisis itself nor the macroeconomic environment is linked to changing risk preferences in our findings. Instead, it is the *sensitivity* to local economic conditions that has changed since the crisis.

Second, throughout our estimations, this finding is driven by men, whereas we find no statistically or economically discernible relationship for women. In terms of magnitude, going from the lowest to the highest value of unemployment in our sample (from 1.5 to 12.5 percent) is associated with an increase in men's risk aversion that is equivalent to nearly 40 percent of the overall gender gap in risk preferences. Although a range of studies have identified gender differences in risk preferences *per se* (Byrnes et al., 1999; Borghans et al., 2009; Croson and Gneezy, 2009; Eckel and Füllbrunn, 2015), less is known about whether and how major universal macroeconomic event can affect the formation of risk preferences differentially for men and women.

Third, in addition to risk preferences, we examine time preferences. A closely related body of literature focuses on the temporal stability of inter-temporal decisions and their response to real world shocks (Krupka and Stephens, 2013; Chuang and Schechter, 2015; Meier and Sprenger, 2015). We find that, since 2008, men react to an increase in the regional unemployment rate by becoming more impatient, whereas women do not. This result is robust to accounting for risk preferences – a natural confounder to estimating how impatient individuals actually are (Andersen et al., 2008).

Fourth and final, we explore a potential channel to explain our findings results. A growing line of research identifies emotional well-being in general – and reported "happiness" in particular – to be sensitive to macroeconomic fluctuations (Di Tella et al., 2001, 2003). In turn, this positive affect has been shown to influence risk and time preferences (e.g., see Isen and Geva, 1987, and Ifcher and Zarghamee, 2011). Thus, local economic conditions may affect risk preferences via emotional responses. Our analysis produces evidence consistent with this idea, as exposure to higher rates of unemployment after the crisis appears to be related to lower reported "happiness" levels for men. In turn, "happiness" is positively associated with risk loving, or, "unhappiness" is positively linked to risk aversion. In line with our previous findings, we again do not observe such relationship for women.

Overall, our results contribute to our understanding of whether and how people respond to macroeconomic crises by relating risk and time preferences to local economic conditions. These findings can matter for companies and policymakers because both risk and time preferences are related to a range of important real-life outcomes, such as educational and occupational choices (DellaVigna and Paserman, 2005; Bonin et al., 2007) or investment decisions (Cardak and Wilkins, 2009). The fact that our findings emerge consistently for men but not women further highlights a particular applicability to male-dominated professions, such as those related to the finance sector (Adams et al., 2016).

Finally, our findings raise questions about *why* we identify such a notable gender gap. While we find some evidence of an emotional response, this mechanism does not fully explain how experience of the crisis alters the sensitivity of men's risk and time preferences to local economic conditions. Other psychological factors may also matter, such as fear and stress, as suggested by Cohn et al. (2015) and Guiso et al. (2018), or experiencing a stock market crash, which results in more pessimistic beliefs about the economic future, as shown by Malmendier and Nagel (2011). Although our study does not allow us to directly explore these channels, we do find suggestive evidence that men's (but not women's) risk preferences are also sensitive to heightened uncertainty – a finding consistent with Borghans et al. (2009). We also cannot discard the existence of systematic differences in responses across gender as found by Bryan and Venkatu (2001) and Ehrmann and Tzamourani (2012), when studying the behavior of men and women about inflation perceptions and experiences, and Eckel et al. (2009) and Hanaoka et al. (2018), when documenting how men's and women's risk attitudes change in the aftermath of a natural disaster.

2 Background: Australia and the 2008 Financial Crisis

2.1 Overview

Although most countries have a history of experiencing financial instabilities, the 2008 Financial Crisis was the most severe event to hit advanced and emerging markets since the Great Depression. It unfolded from a meltdown in the US subprime market in 2007, triggering a credit crunch, and eventually causing an acute shortage of liquidity in the interbank lending market. Following the collapse of Lehman Brothers on September 15, 2008, the crisis swept rapidly through the wider global financial system (Reserve Bank of Australia, 2010).

In Australia, approximately 20,000 jobs in the finance and insurance industry were lost between August 2008 and February 2009, equivalent to six percent of the entire industry (Mowbray et al., 2009). Both trade-exposed sectors and non-mining states experienced weak economic conditions (Nicholls and Rosewall, 2015). In addition, manufacturing areas, particularly those specializing in automotive production, were severely hit by accelerated structural change (Productivity Commission, 2014). Thus, economic conditions since the crisis have differed significantly, depending on both temporal and spatial dimensions.

2.2 Local Macroeconomic Conditions

As the interest of our study is to understand how risk preferences are shaped by changes in economic conditions, our explanatory variable should be one that captures the wide variation of macroeconomic experiences for individuals who suffered deep- and long-lasting downturns to those who were largely spared the negative consequences of the crisis. One conventional measure in this regard would therefore be to use annual estimates of gross domestic product at the state level (i.e., gross state product). However, this variable would likely not produce enough variation, as only two out of the eight Australian states experienced at least one year of negative growth between June 2002 and June 2015 (the period covered in our survey data).[3] Instead, the main explanatory variable we use is regional unemployment rates as a measure of local economic conditions following the crisis.

The regional unemployment rate is a key indicator of location-specific macroeconomic conditions (see Kahn, 2010, Oreopoulos et al., 2012, and Giuliano and Spilimbergo, 2014, who study labor market outcomes and political beliefs, respectively). Every month, the Australian Bureau of Statistics (ABS) publishes unemployment rates for all 87 regions, sampling approximately 26,000 dwellings. These regions represent the largest sub-state areas and are specifically designed to capture local labor market developments. In our main analysis, we calculate the average unemployment rate for the 12 months up to and including the month in which survey responses are elicited (as discussed shortly in Section 3). This assignment protocol has the advantage that it allows us to measure as accurately as possible the local economic conditions of each individual in the preceding year (e.g., see Brown et al., 2018 and Tausch and Zumbuehl, 2018), in addition to lessening concerns about sampling variability in the regional estimates.[4]

[3]The Australian states are the Australian Capital Territory, New South Wales, the Northern Territory, Queensland, South Australia, Tasmania, Victoria, and Western Australia.

[4]Sampling error remains a key concern regarding the quality of regional estimates, particularly for regions with smaller populations. In addition, the data provided remain unadjusted to seasonal factors and short-term irregular fluctuations. Thus, the ABS recommends using a smoothing filter on the original data. In fact, since July 2016 the ABS has included an adjusted series of the regional data based on annual averages over the last 12 months – the same approach used throughout our paper.

Nevertheless, our results are robust to different ways of assigning our unemployment rate measure, as well as accounting for those who moved over the preceding 12 months.

To provide a basic illustration of the geographical distribution of regions within Australia and to highlight intra-regional differences in unemployment, Figure 2 maps the average rate of unemployment for each region between June 2002 and June 2015.

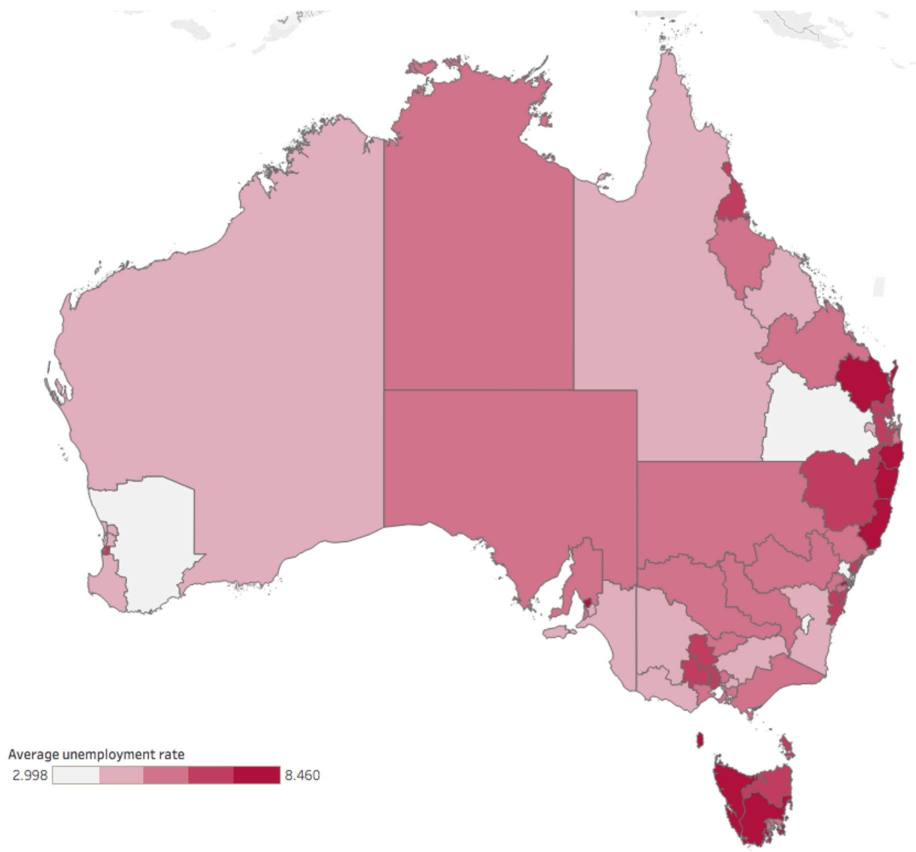

Figure 2: Average regional unemployment rates of the 87 labor market regions across Australia between June 30, 2002, and June 30, 2015.

It is interesting to see substantial variation across regions and even within the same state and between neighbouring areas. Especially the eastern states and Tasmania have seen, on average, higher rates of unemployment between June 2002 and June 2015, whereas average unemployment in Western Australia remained relatively lower over the same period. In additional estimations, we account for several measures of *national* and *state* economic conditions, but our results remain consistent in that the *regional* unemployment rate plays a central role in explaining risk preferences after the crisis (see Tables A8 and A11).

3 Data

3.1 Risk Preferences

To derive individuals' risk preferences, we access the Household, Income and Labour Dynamics in Australia (HILDA) survey – a nationally representative annual panel study of Australian households for consecutive waves since 2001. In the first wave of this longitudinal survey, the sample was stratified according to the resident population of Australia (see Wooden et al., 2002) and since then respondents have been followed with interviews conducted between August and November each year.

Most relevant for our investigation, HILDA asks respondents about their willingness to take financial risks in the context of a risk-return tradeoff in all waves until 2015 with the exception of waves 5, 7, and 9. This approach to elicit risk preferences via an attitudinal survey-based method is akin to those employed by Malmendier and Nagel (2011) and Guiso et al. (2018), for example. In fact, this question is closely designed after a popular risk tolerance measure in the US Survey of Consumer Finances (SCF). Specifically, respondents are asked:

> *Which of the following statements comes closest to describing the amount of financial risk that you are willing to take with your spare cash? That is, cash used for savings or investment.*

They can then respond on a scale from one to five, where: (1) I would take substantial financial risks expecting to earn substantial returns, (2) I would take above-average financial risks expecting to earn above-average returns, (3) I would take average financial risks expecting to earn average returns, (4) I would not be willing to take any financial risks, and (5) I never have any spare cash. If the fifth option is chosen, respondents are presented with a follow-up question asking them to choose from options (1) to (4) "assuming" they had spare cash in waves 6, 8, 10, 11, 12, 13, 14, and 15. In our main estimations, we focus on the original question and exclude those who select option five (17.8 percent), but our results are not sensitive to alternative proxies for risk (see Table A12).[5]

One potential concern regarding survey responses to non-incentivized hypothetical scenarios is whether they provide a valid measure of individuals' underlying risk preferences. Several studies find that self-reported risk measures from survey questions are indeed linked to actual risky behavior (Barsky et al., 1997; Anderson and Mellor, 2008) and provide a behaviorally valid predictor of risk attitudes typically elicited in real-stakes lottery experiments (Dohmen et al., 2011). More recently, Frey et al. (2017) show that self-reported measures outperform incentivized behavioral ones in terms of reliability in test-retest analyses (i.e., temporal stability), as well as in capturing a general factor of risk preferences across different measures and domains.

Importantly, this specific survey-based elicitation of individual risk preferences has been shown to predict a variety of financial and non-financial risky behaviors (e.g., see Brown and Van Der Pol, 2015, and Kettlewell, 2019). In particular, Kettlewell (2019) finds the risk responses elicited from the HILDA questionnaire to be predictive of risk-taking activities, such as owning dividends and being self-employed.

In order to check the validity of the risk measure in our sample, we test whether it predicts risky behavior, as well as attitudes towards risk in general (as opposed to specifically in the financial domain).[6] Table A1 in Appendix A shows significant correlations between our risk measure and risk-taking behavior measures (i.e., risk aversion is negatively related to both equity market participation and share of assets in equity). Further, our risk measure is positively correlated with a more general measure of risk attitudes. These findings are in line with Dohmen et al.'s (2011) results.

[5]We follow this approach in our main estimations because (i) it is difficult to assign a level of risk aversion (relative to the other options) to such individuals and (ii) we wish to isolate changes in risk preference from a set of risk-return choices that are consistently defined between survey waves.

[6]The question "Are you generally a person who is willing to take risks or are you unwilling to take risks?", which resembles the respective question of the German Socio-Economic Panel (SOEP), is only incorporated in wave 14 (2014) and therefore cannot be used in our main analysis.

3.2 Descriptive Statistics

We use the natural ordering of the risk-return combinations to construct a categorical variable assigning values from one to four, i.e., larger values indicate more risk aversion. In our main estimations, we exclude information from the first wave because information on the respondent's location in the previous year is not readily available, i.e., we cannot ascertain that the respondent did not move. Since we are linking the *regional* unemployment rate to an individual's responses, it is important to carefully control for those who are moving between regions.[7] Further, we exclude those observations where the respondent moved between survey waves or where the respondent reported changing their residence in the past 12 months (6.3 percent).[8] Overall, this produces a sample of 108,858 observations for 22,579 individuals across 87 regions.

Figure 3 plots gender-specific means of risk preferences across waves, where vertical lines correspond to 95 percent confidence intervals. Consistent with the bulk of the literature (Byrnes et al., 1999; Croson and Gneezy, 2009), the average woman exhibits significantly more risk aversion than the average man. In general, average risk aversion indeed appears to be slightly higher following the 2008 financial crisis. Since the onset of the crisis can be dated from 2007, we classify a post-crisis binary indicator for responses in waves 8 to 15.[9] Specifically, we merge the HILDA data with crisis severity data at the region in which the respondent resided in for the respective year. Since we have information on the date of an individual's interview, the severity measure is the average regional unemployment rate over the 12 months up to and including the month that risk preferences are measured.[10]

[7]For respondents with gaps between survey waves, we use a question asking about a change in residence in the past 12 months. Note that reporting a change in residence may also capture intra-regional moves – those in which respondents changed address but not their region. Thus, this produces a slightly stricter definition of the region of residence for respondents not directly observed in the previous survey year.

[8]As a robustness check for movers, we also estimate our main regression model including individual who moved between survey waves. The results are similar in terms of (overall) magnitude when compared to those from the sample restricted to non-movers, but they are less precisely estimated (see Table A3.

[9]In Australia, the effects of the crisis could be seen as early as August 2007 in the domestic money market (Debelle, 2009). In fact, according to local accounts some regions and sectors experienced severe contractions in credit at the beginning of 2007 (Parliament of the Commonwealth of Australia, 2009).

[10]While most interview dates are provided, some appear to be missing. In fact, before 2009 the survey did not collect the completion date for the self-completion questionnaire (SCQ), where our measure of risk preferences is elicited. Thus, in the case where the SCQ date is missing or not provided, we use the completion date of the person questionnaire (PQ). Nevertheless, assigning our severity measure to other dates, including only the PQ date or the month of June (the end of the financial year in Australia) produces consistent results (see Section A9).

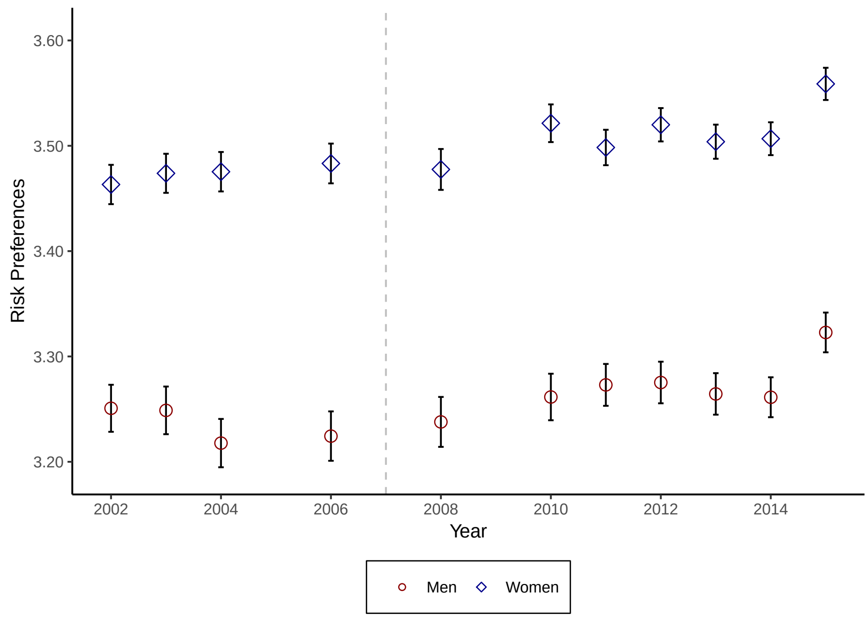

Figure 3: Average risk preferences across survey waves and by gender, where higher values indicate more risk aversion. The vertical dotted line separates the pre-crisis period (up to wave 6) from the post-crisis period (wave 8 onwards).

Table 1 presents summary statistics of the pooled sample. Reported risk preferences average a value of 3.4 on the one-to-four scale, i.e., the average respondent is somewhere between taking "average financial risks expecting to earn average returns" and "not willing to take any financial risk". Regional unemployment rates fluctuate between 1.5 and 12.5 percent with a mean of 5.6 percent.

Panel B of Table 1 documents descriptive statistics for control variables on the individual level, which will be discussed in Section 4. Other control variables included in the main analysis (but not reported in Table 1) are indicators for marital status (8 categories) and educational attainment (8 categories). Finally, additional outcome variables for time preferences and happiness – aspects we will explore in Sections 5.3 and 5.4 – as well as covariates employed in robustness checks are referred to the appendix Table A2.

Table 1: Summary statistics for the main variables.

Variables	Mean	(Std. Dev.)	Min	Max
Panel A: Main sample				
Risk preferences (increasing from 1 to 4)	3.39	(0.70)	1	4
Regional unemployment rate	5.59	(1.66)	1.52	12.48
Male	0.48	(0.50)	0	1
Panel B: Individual control variables				
Age (in years)	46.00	(18.28)	14	101
Income (in A$)	41,088	(51,010)	0	5,183,544
Number of children	0.71	(1.07)	0	11

Notes: Additional control variables included in the full sample, but not reported, are 8 categories for marital status, as well as 8 indicators for educational attainment. For marital status, these include: refused/not stated (0.0%), do not know (0.0%), legally married (54.7%), de facto (12.2%), separated (2.2%), divorced (5.4%), widowed (4.8%), and never married and not de facto (20.7%). As for educational attainment, they represent: postgraduate degree (4.7%), graduate diploma (6.0%), bachelor or honors (14.2%), advanced diploma (9.6%), Certificate III or IV (20.4%), year 12 (14.7%), year 11 or below (30.4%), and undetermined (0.1%).

4 Empirical Strategy

4.1 Main Outline

Our empirical strategy follows a conventional regression approach (akin to Hoffmann et al., 2013, Weber et al., 2013, and Guiso et al., 2018). To properly account for individual-fixed effects, we employ a linear regression model, as opposed to an ordered logit or probit framework (e.g., see Greene, 2004). Nevertheless, results using the blow up and cluster (BUC) fixed effects ordered logit model discussed in Baetschmann et al. (2015) are qualitatively comparable to the standard linear framework and exponentiated coefficients (odds ratios) from this model are reported in Table A4.

We predict individual i's reported level of risk preferences at time t (and later other outcome variables) with three main variables: A post-crisis binary variable, the unemployment rate in i's region averaged over the preceding 12 months, and an interaction term between the two. Formally, we estimate

$$
\begin{aligned}
Y_{it} = &\beta_0 + \beta_1\big(\mathrm{Post-Crisis}_t\big) + \beta_2\big(\mathrm{Unempl}_{it}\big) + \\
&\beta_3\big(\mathrm{Post-Crisis}_t \times \mathrm{Unempl}_{it}\big) + \beta_4 \mathbf{Z_{it}} + \lambda_i + \epsilon_{it},
\end{aligned}
\tag{1}
$$

where Y_{it} measures risk preferences, $\mathrm{Post-Crisis}_t$ represents a binary indicator that takes on a value of one from 2008 onwards and zero before, and Unempl_{it} constitutes the regional unemployment rate. $\mathbf{Z}_{it}$ represents a vector of time-variant personal characteristics, including measures for age (linear and squared), personal income, marriage status, the number of children, and educational attainment (see footnote of Table 1 for detailed categories). Including a binary indicator for the crisis along with age variables controls for a continuous year trend (see Dohmen et al. (2017) for a discussion of risk attitudes over the life course). An alternative approach would be to include a full set of year-fixed effects. Our results are not sensitive to these inclusions. (When both individual-level fixed effects and age variables are incorporated, a continuous year trend is automatically controlled for.) We refer to Cohen and Einav (2007), Dohmen et al. (2011), and Sahm (2012), among others, for the respective connection of these variables with risk preferences.

The parameter λ_i captures fixed effects on the individual level, accounting for any unobserved individual characteristics that remain constant over time. For example, λ_i accounts for unique experiences in one's childhood and intergenerational transmission channels in attitudes towards risk (e.g., see Hryshko et al., 2011, and Dohmen et al., 2012). It also controls for the macroeconomic environment in which each respondent grew up – factors that have been shown to explain variation in risk preferences (e.g., see Malmendier and Nagel, 2011). Finally, ϵ_{ijt} constitutes the conventional error term, clustered at the regional level to permit for arbitrary serial correlation within each region (Bertrand et al., 2004).

Equation (1) includes three coefficients of interest. First, β_1 measures whether the crisis by itself, that is, when the unemployment rate equals to zero in this regression, affected i's risk preferences. A positive coefficient (i.e., greater risk aversion) would be consistent with findings from Italian bank clients (Guiso et al., 2018) and UK online-brokerage customers (Weber et al., 2013) after the 2008 crisis.[11] Second, β_2

[11] For ease of comparison to previous studies, we calculate the effect of the crisis for the mean rate of regional unemployment and find that men, on average, report higher risk aversion since 2008 (see Table A5).

captures the link between the regional unemployment rate and risk preferences before the crisis. In this case, a positive coefficient would be consistent with findings from Germany, where bad economic news are associated with more risk aversion (Tausch and Zumbuehl, 2018). Third, β_3 constitutes our main variable of interest: If the link between local unemployment and risk preferences were systematically altered since the financial crisis, then β_3 should become statistically significant. A positive coefficient would indicate that, since the Financial Crisis, a respondent would respond to a higher unemployment rate with more risk aversion, conditional on observables.

Finally, we discuss additional covariates as they are introduced in the robustness checks and extensions. To explore potential differences across gender, we then run equation (1) separately for male and female subsamples.

4.2 Threats to Identification

An econometric concern regarding our identification strategy is the potential selective migration and settlement of particular individuals in the sample. For instance, Jaeger et al. (2010) and Bauernschuster et al. (2014) show that individuals who are less risk averse are more likely to migrate between regions. In our setting, less risk averse respondents may be more likely to leave their region of residence to seek employment opportunities elsewhere, conditional on local economic conditions. To examine this claim, we can compare the mean risk preference of respondents who move to different regions from those who do not. Indeed, we find that movers report, on average, slightly lower risk aversion (mean = 3.35) than those who stay within their region (mean = 3.39), and that this difference is statistically significant at the one percent level.[12] Thus, failing to account for the potential influence of geographical mobility and selection on risk preferences could lead to biased results.

One of the biggest advantages of our dataset is that it follows individuals over time; respondents who move to a new location are interviewed at their new residence and if the move results in a split of the household, all respondents of the original household are followed and interviewed. Thus, we can identify an individual's location in each survey year. Crucially, this allows us to allocate to each individual the

[12] We also test for potential gender differences in migration between regions and find that the null cannot be rejected with a p-value of 0.982, suggesting the migration patterns of men do not statistically differ from those of women, at least in our setting.

exposure of local economic conditions owing to the fact that their region of residence from one survey year to the next remains the same. Nonetheless, appendix Table A3 produces remarkably similar (though less precisely estimated) results when including movers.

In addition to the issue of selective migration, another econometric concern is the potential for both exposure to local economic conditions and risk preferences to be related to unobserved pre-existing individual characteristics. Past experiences of recessions can be such an example in our setting, as they may be correlated with both risk preference formation (e.g., see Malmendier and Nagel, 2011) and exposure to economic downturn post-crisis. In fact, to test this claim we can examine whether differences in the baseline levels of risk preferences are associated with differences in pre-crisis local economic conditions. Figure 4 plots the relationship between risk preferences and the regional unemployment rate before the crisis. Note that each shape in the figure represents the mean of observations within each bin of 0.2 in our regional unemployment rate measure. Further, the size of each shape reflects the number of observations within each bin. Here again, notice that we use gender-specific samples.

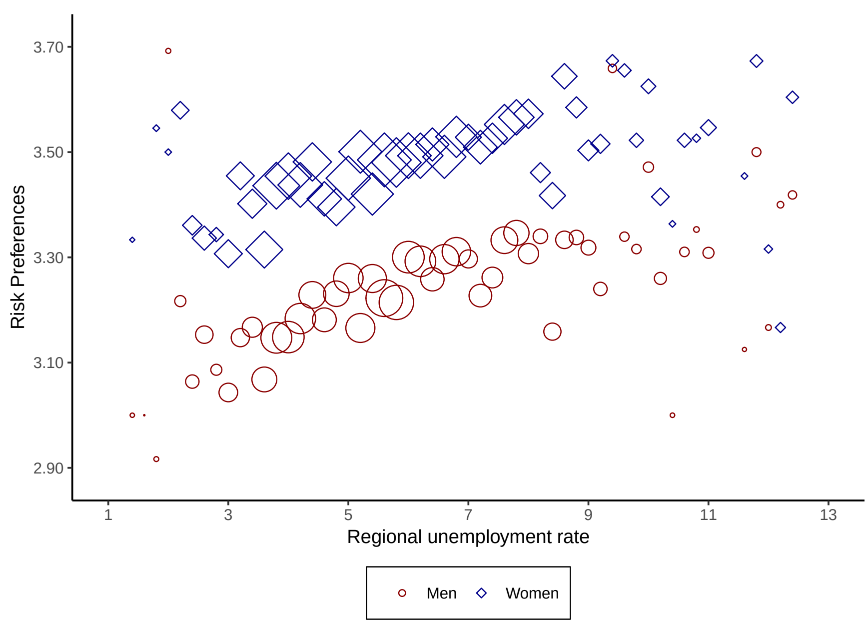

Figure 4: Risk preference levels across different regional rates of unemployment before the crisis (2002, 2003, 2004, and 2006 survey years).

Figure 4 shows that before the onset of the crisis, more risk averse individuals indeed tended to live in regional labor markets with higher unemployment rates. This pattern is observed among both men and women. Thus, to the extent that such residential sorting prior to the commencement of the survey drives differences in the baseline levels of risk preferences, the estimates based on a cross-sectional setting can be biased. Fortunately, we have panel data and can isolate unobserved individual fixed effects. In particular this allows us to control for any time-invariant pre-existing individual characteristics that could influence risk preference formation.

5 Empirical Findings

5.1 Risk Preferences

Table 2 displays our main results where columns (1)-(3) explore the full sample, (4)-(6) study the male subsample, and (7)-(9) are dedicated to women. For each sample, we begin with a specification that only includes the binary post-crisis indicator, the regional unemployment rate, and the respective interaction term. Next, we account for individual effects before displaying results from the benchmark estimations that also account for the full set of covariates discussed in Section 4.

In column (1), we find respondents who live in locations with higher unemployment rate report to be more risk averse – consistent with the visuals from Figure 4 – and that this relationship has become stronger *after* the crisis, as indicated by the positive and statistically significant coefficient on the interaction term. Columns (4) and (7) produce similar findings for the gender-specific subsamples. Magnitudes are comparable across the gender-specific subsamples.

Once individual-level fixed effects are accounted for, however, we notice two changes. First, the regional unemployment rate loses power, both in statistical and economic terms. In fact, we derive a relatively precisely estimated null effect for the general sample, as well as for the gender-specific subsamples. And second, although the interaction term retains its predictive power in the full sample, columns (5) and (8) suggest that men are driving that result. For women, on the other hand, we derive no statistically meaningful relationship.

Table 2: Main regression results, predicting risk preferences (higher values indicate more risk aversion).

Dependent variable: Risk preferences (mean = 3.39)	Full sample			Men			Women		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Post-crisis	-0.008	-0.004	-0.012	-0.011	-0.025	-0.030	-0.003	0.015	0.005
	(0.031)	(0.020)	(0.019)	(0.036)	(0.025)	(0.024)	(0.033)	(0.022)	(0.021)
Regional unemployment rate	0.028***	-0.002	-0.001	0.033***	-0.002	-0.002	0.024***	-0.001	0.000
	(0.006)	(0.002)	(0.002)	(0.006)	(0.004)	(0.004)	(0.007)	(0.003)	(0.003)
Post-crisis × regional unemployment rate	0.011**	0.009***	0.004	0.012*	0.012***	0.010**	0.010*	0.005	-0.001
	(0.005)	(0.003)	(0.004)	(0.006)	(0.004)	(0.004)	(0.006)	(0.004)	(0.004)
Individual fixed effects		×	×		×	×		×	×
Controls[a]			×			×			×
# of individuals	22,579	22,579	22,579	10,898	10,898	10,898	11,681	11,681	11,681
# of waves	11	11	11	11	11	11	11	11	11
N	108,858	108,858	108,858	52,293	52,293	52,293	56,565	56,565	56,565

Notes: Standard errors clustered at the regional level are displayed in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. [a]Includes measures for age, age squared, income, and number of children, as well as indicators for marital status (8 categories) and educational achievement (8 categories).

Finally, columns (3), (6), and (9) incorporate the comprehensive set of control variables into this fixed effects framework. For the full sample, we derive no statistically discernible relationship between regional unemployment post-crisis and risk preferences. Were we to stop here, our conclusions would indicate that the financial crisis did not affect the relationship between local unemployment and risk preferences. Nevertheless, column (6) shows that a positive relationship prevails for men and remains statistically different from zero at the five percent level. For women, we observe no such connection (column 9).[13]

It is also interesting to see that neither the post-crisis indicator alone nor the unemployment rate before the crisis emerge as meaningful predictors of risk preferences in this restrictive econometric setting where we account for fixed effects on the individual level and a host of potentially confounding factors. It is only after the crisis that men's risk preferences appear to become sensitive to the unemployment rate.

To put the respective magnitude in perspective, consider an increase in unemployment from the lowest value in our sample period (1.5 percent in Queensland-Outback in 2006) to the highest value (12.5 percent in Queensland-Outback in 2010). Such a(n admittedly dramatic) change in unemployment would be associated with a decrease in risk preferences by 0.091 index points, equivalent to nearly 40 percent of the mean gender gap in risk preferences before the crisis (0.238).

5.2 Robustness Checks and Extensions

In addition to controlling for several personal covariates in Table 2, we perform a series of robustness checks on our main results. Here, we display some of these results in more detail and summarize the additional robustness checks at the end of this Section.

5.2.1 Individual Employment and Wealth

Table 3 investigates whether our results are robust to changes in personal experiences and region-specific effects. An obvious concern about our main results is that personal conditions (e.g., one's employment

[13] We also estimate the full sample completely interacted with a gender dummy and find that the magnitude of the relationship between local unemployment and risk preferences is substantially smaller for women compared to men post-crisis, if only at p = 0.098 (see Table A6).

status) would affect individual risk preferences – presumably more so than local macroeconomic conditions. However, the results presented in Table 3 suggest that is not the case. All of the corresponding estimations build on the most complete specifications of columns (6) and (9) from Table 2.

Starting with men, column (1) adds individual i's job-related characteristics, including indicators for being unemployed, experiencing job displacement, and changing employers. For example, Sahm (2012) shows that individuals who are more risk tolerant are more likely to choose jobs with higher displacement risk. Such systematic sorting into certain risky careers could drive our results. However, the coefficient on the interaction between the crisis indicator and the regional unemployment rate remains statistically significant at the five percent level with its magnitude being virtually unchanged. In additional estimations, we also distinguish between those not in the labor force and the employed, as well as including more detail on the industry and profession of those who report being employed. The corresponding conclusions remain consistent (see Table A7).

Column (2) adds covariates related to wealth effects, including a binary indicator for home ownership, as well as the natural logarithm of the property value and stimulus payments. It is possible that individuals who were hit hardest in terms of economic conditions after the crisis also experienced substantial losses. Alternatively, individuals who received low or no fiscal stimulus payments in response to the crisis may have suffered larger psychological costs (e.g., see Di Tella et al. 2003). Thus, we control for home ownership and the value of the property, as well as stimulus payments received by respondents in 2009.[14] Here as well, the estimates barely change.

Finally, column (3) provides our most demanding specification, adding region-fixed effects. In particular, differences in economic conditions between regions are likely not only driven by macroeconomic shocks, but also region-specific factors such as cultural differences, political ideology, geographic features, remoteness, or access to labor markets. If such region-specific (level) differences relate to individuals in locations experiencing a recession to exhibit more sensitivity toward local unemployment, then our estimates should also exhibit sensitivity to the inclusion of region-fixed effects. Note that any omit-

[14]Unfortunately, the survey only collects information on other measures of wealth, including financial assets, every four years. Nevertheless, home ownership, which is available for each survey wave in our main analysis, has been shown to be positively associated with other risky asset holdings such as shares and mutual funds (Cardak and Wilkins, 2009). Therefore, controlling for home ownership could, at least partially, address wealth effects related to changes in financial wealth.

Table 3: Robustness checks, including covariates measuring labor market status, wealth, and region-fixed effects.

Dependent variable: Risk preferences (mean = 3.39)

	Men			Women		
	(1)	(2)	(3)	(4)	(5)	(6)
Post-crisis	-0.029	-0.025	-0.027	0.005	0.006	0.003
	(0.024)	(0.024)	(0.024)	(0.021)	(0.021)	(0.021)
Regional unemployment rate	-0.002	-0.001	-0.003	0.000	0.000	0.000
	(0.004)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)
Post-crisis × regional unemployment rate	0.010^{**}	0.010^{**}	0.010^{**}	-0.001	-0.000	0.000
	(0.004)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)
Individual fixed effects	×	×	×	×	×	×
Control variables[a]	×	×	×	×	×	×
Unemployed	×	×	×	×	×	×
Fired	×	×	×	×	×	×
Changed jobs	×	×	×	×	×	×
Home ownership		×	×		×	×
Property value		×	×		×	×
Stimulus payments		×	×		×	×
Region fixed effects			×			×
# of individuals	10,881	8,164	8,164	11,663	8,713	8,713
# of waves	11	11	11	11	11	11
N	52,141	43,598	43,598	56,387	46,950	46,950

Notes: Standard errors clustered at the region level are displayed in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.
[a]Includes measures for age, age squared, income, and number of children, as well as indicators for marital status (8 categories) and educational achievement (8 categories).

ted time-invariant variables accounted for by individual-level fixed effects are not necessarily collinear with those within regions. This is because while observations where the individual moves to a different location between waves are excluded, subsequent observations are not. Thus, in our final specification we also add region-fixed effects. Once again, both magnitudes and statistical significance levels of the coefficient on the interaction term remain consistent with the conclusion that unemployment rates are positively related to risk aversion post-crisis.

Turning to the results from exploring the female sample in columns (4) – (6), we again identify no discernible relationship between unemployment post-crisis and risk preferences.

5.2.2 Additional Robustness Checks

We want to briefly summarize the additional robustness checks conducted to test the validity of our main result. First, one may argue that heightened uncertainty since the onset of the crisis may be another factor that affects individual risk preferences. For instance, in a laboratory setting Cohn et al. (2015) show that individuals invest significantly less in a risky asset when the probability of success in the investment task was uncertain. In addition, Borghans et al. (2009) find that differences in the valuation of uncertain prospects by gender may explain differences in risk aversion, which coincides with our findings. In Table A8, we show that our findings are not explainable by macroeconomic conditions on the country level, such as realized volatility (calculated as the monthly standard deviation of the daily ASX S&P 200 index), implied volatility (based on the ASX S&P 200 VIX Index), or an index of economic policy uncertainty (EPU) in Australia (see Baker et al. (2016), for the construction of this measure).

Second, our results may hinge on the particular assignment of our severity measure. In particular, we measure the annual average rate of regional unemployment over the 12 months up to and including the month when risk preferences are elicited to determine the influence of local economic conditions. However, this strategy may introduce a response-time pattern that could bias our estimates. Table A9 shows that assuming alternative times for completing the questionnaire produces consistent findings.

Third, responses to local economic conditions may have changed with more time passing since the Financial Crisis, i.e., the link between unemployment rates and risk preferences could be non-linear and revert back to zero after a while. Using the simple binary indicator for the post-crisis period could mask such effects. We exploit the fact that we observe individuals multiple times following the crisis to test the sensitivity of the results to the inclusion of wave-fixed effects, as well as interacting regional unemployment rates with a crisis trend dummy, where the crisis trend is the reciprocal of years since the onset of the crisis. Table A10 shows that our results remain intact and we find no reversion to zero, at least in the seven waves since the crisis.

Fourth, we conduct a comparison between our regional unemployment rate measure and another conventional measure of economic change, i.e., state GDP growth. Note that changes in GDP only allow us to relate annual June (end of the financial year in Australia) estimates to our elicited risk preference measure, as they are provided in a yearly fashion at the state level. Table A11 presents the corresponding results. Most notably, we find that a decrease in state GDP growth relates to an increase in risk aversion for men; however, unlike the interpretation of our main variable of interest this relationship does not appear to be exclusive to the period following the crisis.[15]

Finally, Table A12 demonstrates the robustness of our results to choosing alternative measures of risk preferences when (i) excluding individuals who chose the highest risk-return combination, i.e., taking "substantial financial risks expecting to earn substantial returns", (ii) collapsing the risk-return combinations into a binary indicator for whether individuals are willing to take any risk at all, and (iii) incorporating the risk-return choices elicited from the (hypothetical) follow-up question for waves 6 onwards.

5.3 Time Preferences

In addition to risk preferences as an outcome variable, we now explore time preferences, i.e., a person's preferences of the present over the future. Since the von Neumann-Morgenstern utility theorem (Von Neumann and Morgenstern, 2007), the concepts of risk and time preferences have often been linked together, and a long line of theoretical and empirical research seeks to disentangle both concepts (e.g., see Andersen et al., 2008, and Tanaka et al., 2010, for recent empirical work). For example, Andreoni

[15]In fact, the interaction term between GDP growth and the post-crisis indicator is positive, suggesting that the link has become weaker since the onset of the crisis. A possible explanation for this contrasting result could relate to the greater precision of our main severity measure with respect to timing and spatial variation. In particular, the unemployment data allows us to match the regional average rate over the last 12 months to date of the survey interview (as opposed to the yearly measure of GDP at the state level).

and Sprenger (2012) begin their manuscript by stating that "[r]isk and time are intertwined. The present is known while the future is inherently risky." In fact, the evidence on the stability of time preferences over time is even less clear than the stability of risk preferences (e.g., see Chuang and Schechter, 2015).[16] Thus, there is little consensus on if and, if so, how a macroeconomic shock may affect time preferences.

HILDA elicits a measure of time preferences, using a question about financial planning horizons in waves 1, 2, 3, 4, 6, 8, 10, 12, and 14. The fact that responses are available before and after 2008 allows us to test whether the sensitivity of time preferences has also become more responsive to regional unemployment rates since the financial crisis. In particular, respondents are asked:

> *In planning your saving and spending, which of the following time periods is most important to you?*

Respondents are presented with six response options: (1) The next week, (2) the next few months, (3) the next year, (4) the next 2 to 4 years, (5) the next 5 to 10 years, or (6) more than 10 years ahead. For our analysis, we reverse the original ordering of these choices and construct a categorical variable assigning values from one to six. Thus, higher values indicate impatience. This approach is consistent with comparable studies, which use planning horizon as a proxy for time preferences (Cardak and Wilkins, 2009; Brown and Van Der Pol, 2015).Further, Adams and Nettle (2009) find that stated time period for financial planning is significantly correlated with other proxies used to measure time preference, including hypothetical money choice tasks typically used in experimental studies (see also Frederick et al., 2002, for an overview of measuring time discounting).

Table 4 documents our results from predicting time preferences, following the familiar regression format. Columns (1) and (2) consider the male sample, whereas columns (3) and (4) study the female sample. Column (1) shows a positive and statistically significant interaction term, indicating that men have become more impatient with higher unemployment rates since the crisis.

One interpretation of this result is that men who became more risk averse because of the crisis have come to favor the known present over the inherently uncertain future. That is, the higher rate of time preferences observed among men may simply be an artifact of an increasing preference for

[16] Notable exceptions that use longitudinal data include Krupka and Stephens (2013) and Meier and Sprenger (2015).

Table 4: Exploring the effect of the regional unemployment rate on time preferences before and after the crisis (higher values indicate more impatience).

Dependent variable: Time preferences (mean = 4.13)	Men		Women	
	(1)	(2)	(3)	(4)
Post-crisis	0.169***	0.193***	0.156***	0.162**
	(0.055)	(0.064)	(0.055)	(0.065)
Regional unemployment rate	-0.002	-0.004	0.004	-0.003
	(0.008)	(0.009)	(0.007)	(0.008)
Post-crisis × regional unemployment rate	0.020**	0.024**	0.008	0.011
	(0.010)	(0.012)	(0.010)	(0.010)
Individual fixed effects	×	×	×	×
Control variables[a]	×	×	×	×
Risk preferences		×		×
# of individuals	10,973	10,075	11,881	10,731
# of waves	8	8	8	8
N	42,426	35,842	47,987	38,660

Notes: Standard errors clustered at the region level are displayed in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.
[a] Includes measures for age, age squared, income, and number of children, as well as indicators for marital status (8 categories) and educational achievement (8 categories).

certainty following the crisis. In order to check for this hypothesis, we control for risk preferences in column (2), following Andersen et al. (2008). The estimate on our coefficient of interest remains statistically significant at the five percent level, while its magnitude becomes slightly *larger* from 0.020 to 0.024. Thus, risk preferences are unable to explain men's heightened sensitivity to the unemployment rate when it comes to time preferences. As with all our estimations, we again derive no such effects for women as the interaction term between unemployment and the post-crisis indicator remains statistically indistinguishable from zero in both columns (3) and (4).

Finally, the post-crisis period itself sees both male and female respondents more impatient than before the crisis. This result is consistent with findings by Krupka and Stephens (2013) who suggest that turbulent economic conditions lead to less patience.

5.4 Testing for a Potential Mechanism: Emotional Well-Being

Although it remains difficult to comprehensively illuminate potential mechanisms via which men's risk and time preferences have become more sensitive to regional economic conditions since the financial crisis, we now exploit the existing data in HILDA to investigate one possible avenue: Emotional well-being. This avenue is motivated by research in psychology and behavioral economics, showing self-reported emotional well-being in general, and reported happiness in particular, to be sensitive to macroeconomic movements, including unemployment rates (Di Tella et al., 2001, 2003).[17] In addition, Wolfers (2003) provides suggestive evidence that high levels of unemployment may be especially harmful to emotional well-being during business cycle busts. Finally, several studies find the link between self-reported happiness and the regional unemployment rate to be stronger for men (e.g., see Clark, 2003 and Clark et al., 2010), which coincides with our results up to this point.

At the same time, an equally rich and growing literature continues to produce evidence suggesting emotional reactions to negative events may systematically influence risk preferences (Lerner and Keltner, 2001; Loewenstein et al., 2001; Kuhnen and Knutson, 2011). Of particular interest are studies finding gender differences in the effects of emotions on risk preferences (e.g., see Lerner et al., 2003, Fessler et al., 2004, and Fehr-Duda et al., 2011). In order to explore this possibility in our sample, we access

[17]See also Frey and Stutzer (2002) for an overview of happiness research in economics.

HILDA information on the emotional well-being of respondents focusing on a question eliciting reported happiness levels. Specifically, respondents are asked:

How much of the time during the past 4 weeks have you been a happy person?

Responses range from one to six, where one corresponds to "all of the time" and six to "none of the time". Thus, a higher score indicates a respondent to be less happy and we label the corresponding variable *unhappiness*.

Table 5 summarizes the estimates from predicting unhappiness. As before, we account for the list of covariates introduced in Section 4. The results displayed in column (1) produce a positive and marginally statistically significant coefficient associated with the familiar interaction term between the post-crisis indicator and the regional unemployment rate. Thus, a higher unemployment rate appears to make men less happy – but only since the financial crisis. One explanation for this result may relate to individual unemployment – in fact, the link between an individual's labor market status and emotional well-being has been well-documented (Clark and Oswald, 1994; Winkelmann and Winkelmann, 1998). Therefore, in column (2) we include a control for men who report being unemployed. However, the estimate on our coefficient of interest remains unchanged, both in qualitative and quantitative terms. As for women, columns (3) and (4) show that the estimate on the interaction term is not statistically significant at any conventional levels.

Next, we evaluate the link between reported happiness and our preference measures. In particular, several studies find positive affect, such as happiness, to influence risk and time preferences (e.g., see Isen and Geva, 1987 and Ifcher and Zarghamee, 2011). Thus, if emotional well-being is indeed a potential channel in our setting, then unhappiness should be positively associated with risk aversion and impatience.

Tables 6 and 7 display the estimates of our baseline specifications for risk and time preferences respectively, where the main explanatory variable now is reported happiness levels. Starting with men, column (1) from the respective tables shows a positive and statistically significant relationship between unhappiness and both risk aversion and impatience. Interestingly, we also find reported happiness to be a positive and statistically significant predictor of time preferences for women, while no discernible link is observed between unhappiness and risk aversion as displayed in column (3) of Tables 6 and 7.

Table 5: Exploring the effect of the regional unemployment rate on unhappiness before and after the crisis.

Dependent variable: Unhappiness (mean = 2.53)	Men		Women	
	(1)	(2)	(3)	(4)
Post-crisis	-0.033	-0.033	-0.028	-0.028
	(0.034)	(0.034)	(0.034)	(0.034)
Regional unemployment rate	0.003	0.003	-0.002	-0.002
	(0.006)	(0.006)	(0.005)	(0.005)
Post-crisis × regional unemployment rate	0.011*	0.011*	0.003	0.003
	(0.007)	(0.007)	(0.006)	(0.006)
Individual fixed effects	×	×	×	×
Control variables[a]	×	×	×	×
Unemployed		×		×
# of individuals	10,878	10,878	11,662	11,662
# of waves	11	11	11	11
N	51,978	51,978	56,237	56,237

Notes: Standard errors clustered at the region level are displayed in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.
[a]Includes measures for age, age squared, income, and number of children, as well as indicators for marital status (8 categories) and educational achievement (8 categories).

Table 6: Exploring the link between unhappiness and risk preferences (higher values indicate more risk aversion).

Dependent variable: Risk preferences (mean = 3.39)	Men		Women	
	(1)	(2)	(3)	(4)
Unhappiness	0.012***	0.012***	0.003	0.003
	(0.004)	(0.004)	(0.003)	(0.003)
Post-crisis		-0.030		0.004
		(0.024)		(0.021)
Regional unemployment rate		-0.002		-0.000
		(0.004)		(0.003)
Post-crisis × regional unemployment rate		0.010**		-0.001
		(0.004)		(0.004)
Individual fixed effects	×	×	×	×
Control variables[a]	×	×	×	×
# of individuals	10,878	10,878	11,662	11,662
# of waves	11	11	11	11
N	51,978	51,978	56,237	56,237

Notes: Standard errors clustered at the region level are displayed in parentheses. $^{*}p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$.
[a] Includes measures for age, age squared, income, and number of children, as well as indicators for marital status (8 categories) and educational achievement (8 categories).

Finally, we determine whether happiness is a mediator that explains the underlying mechanism of the relationship between regional unemployment and our preference measures. In particular, columns (2) and (4) of the respective tables reintroduce our main variables of interest for both men and women. Surprisingly, the estimated effect of the interaction term persists for the male subsamples in Tables 6 and 7. In fact, column (2) of Table 6 reveals virtually no impact on the estimates for our main variables of interest from the baseline results (column (6) of Table 2). Overall, these findings suggest that happiness is not able to comprehensively explain the relationship between local unemployment rates and males' risk and time preferences since the crisis.

Table 7: Exploring the link between unhappiness and time preferences (higher values indicate more impatience).

Dependent variable: Time preferences (mean = 4.13)	Men		Women	
	(1)	(2)	(3)	(4)
Unhappiness	0.058***	0.058***	0.045***	0.045***
	(0.010)	(0.010)	(0.009)	(0.009)
Post-crisis		0.171***		0.151***
		(0.056)		(0.055)
Regional unemployment rate		-0.001		0.005
		(0.008)		(0.007)
Post-crisis × regional unemployment rate		0.019*		0.009
		(0.010)		(0.009)
Individual fixed effects	×	×	×	×
Control variables[a]	×	×	×	×
# of individuals	10,945	10,945	11,853	11,853
# of waves	8	8	8	8
N	42,122	42,122	47,662	47,662

Notes: Standard errors clustered at the region level are displayed in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.
[a]Includes measures for age, age squared, income, and number of children, as well as indicators for marital status (8 categories) and educational achievement (8 categories).

While the above results indicate no mediating effect for emotional well-being, it is still possible that emotions are important and we want to briefly discuss this here. First, while laboratory experiments provide evidence that short-term elicited emotions can alter risk aversion (e.g., see Cohn et al., 2015), the causal sequence of the process with naturally occurring annual data remains less understood. For instance, local economic conditions may only momentarily lower one's mood but have a longer-lasting influence on risk aversion or impatience through emotional well-being more generally. Prior research indeed finds that major life events produce distinct effects on both affective and cognitive well-being (Luhmann et al., 2012). Unfortunately, with only information on the frequency of temporary emotions felt during the past 4 weeks, it is challenging to investigate this possibility directly.

Second, worsening economic conditions may correlate more strongly with heightened negative affect, such as sadness, than lower positive affect (e.g., see Kushlev et al., 2015). Related research finds positive and negative emotions to be related but distinct constructs (Watson et al., 1988), and sadness in particular to have an independent effect on preferences (Lerner et al., 2013). Thus, using our measure of (un)happiness may not accurately capture the avenue of operation via which local economic conditions could influence preferences.

Alternatively, it is quite possible that other feelings or moods, such as anger, fear, or stress, are avenues of operation. Another emotion commonly related to financial busts, and specifically to the recent crisis, is fear (Cohn et al., 2015; Guiso et al., 2018). Unfortunately, HILDA does not include explicit questions on sadness and fear (or anger and stress for that matter), and thus, we cannot examine them in this study.

Third, recent insights from experimental work by Heilman et al. (2010), Martin and Delgado (2011), and others, suggests emotion regulation in response to negative stimuli to be what matters, and it is the inability to use self-regulation strategies (such as cognitive reappraisal or expressive suppression), rather than emotions per se, that may influence risky behavior. Using HILDA data, Kettlewell (2019) finds that emotional stability moderates the effect of life events on risk preferences. To investigate whether emotion regulation may be a moderator in our setting, we split our sample into individuals who report high emotional stability (at or above the median of the within-individual mean) and those with low emotional stability, following an approach based on Kettlewell (2019). Indeed, we find that the magnitude on the relationship between regional unemployment post-crisis and risk preferences is smaller for men who are more emotionally stable compared to those who are less, although this difference is not statistically significant (see Table A13).

Fourth and final, movements in both subjective emotional well-being and preferences could be merely linked because of an omitted variable. In particular, the perception of labor-market risk (both job security for the employed and job prospects for those unemployed) has been shown to be an important determinant of emotional well-being (Knabe and Rätzel, 2011) and may mediate the latter's relationship with regional unemployment (Clark et al., 2010). Recently, Hetschko and Preuss (2019) find evidence suggesting that anticipating job loss makes individuals more risk averse via lower future income expectations and more uncertainty about the future.[18]

To explore whether job insecurity in general (i.e., even for individuals who do not eventually lose their job) may play a mediating role in our setting, we exploit our unemployment data to reestimate our main regions using gender-specific regional unemployment rates. Recent studies show men to be more exposed to increased unemployment during recessions than women (e.g. see Hoynes et al., 2012 and Albanesi and Sahin, 2018). Indeed, we find the economic threat of gender-specific labor market conditions to be stronger for men since the crisis (see Tables A14 and A15).[19]

Of course, alternative interpretations of this result remain. Specifically, prior research indicates the potential existence of systematic differences in responses to economic fluctuations across gender (e.g. see Bryan and Venkatu, 2001, and Ehrmann and Tzamourani, 2012).[20] In fact, we also find the response to other economic variables, including national measures of uncertainty and state GDP growth, to be stronger for men, at least in our sample.

6 Conclusion

This paper posits that a major macroeconomic shock can affect people's sensitivity to local macroeconomic conditions when it comes to risk and time preferences. We access survey data from 22,579

[18]Closely related, Malmendier and Nagel (2011) show that experiencing a stock market crash results in more pessimistic beliefs about the economic future.

[19]Interesting, we observe the opposite pattern for unhappiness.

[20]See also Eckel et al. (2009) and Hanaoka et al. (2018), for examples documenting differential risk attitude responses to natural disasters by men and women.

Australian-based respondents in up to 11 waves (four before the crisis and seven thereafter) to explore this hypothesis. Information on an individual's location in each survey year allows us to exploit variation in regional economic conditions.

Our main results show that men's (but not women's) risk and time preferences have become sensitive to the local unemployment rate since the crisis. As the unemployment rate increases, the average man now becomes more risk averse and more impatient; this was not the case before the crisis. These results emerge after controlling for a comprehensive set of potentially confounding factors, fixed effects on the individual, time, and regional level, as well as macroeconomic conditions on the national level. A range of alternative specifications produces consistent conclusions, such as accounting for the individual's own employment situation. Interestingly, we identify no effects for women in any of our estimations, indicating stark gender differences in how major economic shocks can influence the sensitivity of preferences to local economic conditions.

Taking a step toward understanding potential mechanisms, we explore emotional well-being, based on recent insights from psychology and behavioral economics that suggest emotional reactions to negative events can systematically affect risk preferences. Indeed, we find that, since the financial crisis, the average man (but again not the average woman) becomes more unhappy if local unemployment increases. In turn, happiness emerges as a meaningful predictor of risk and time preferences, yet happiness is unable to explain our identified relationship between local unemployment and risk preferences post-crisis.

Overall, our findings suggest that the Financial Crisis may have influenced people in indirect, subtle ways that are not easily observable in macroeconomic aggregates or conventional economic data. It is particularly interesting that men and women appear to be affected in such different manners, and we hope that our results inspire future research into gaining a better understanding of gender differences in the formation of risk and time preferences. Although our results are directly applicable to Australia, they may also encourage comparable analyses in other countries, most importantly those that suffered even more from the Financial Crisis or other, comparable events.

Finally, our results carry implications for financial and labor markets, as well as economic growth. For instance, increased risk aversion in difficult economic conditions may impact individuals' willingness to attempt new business ventures. Similarly, elevated risk aversion may lead to economic behavior and outcomes that are potentially disadvantageous at the individual level. For example, poverty has been closely linked to a perpetuation of negative affective states and risk averse decision-making (e.g., see Haushofer and Fehr, 2014). Thus, in terms of policy relevance, mitigating instances of large-scale economic crises could prevent a surge in potentially disadvantageous behavior that is not immediately observable.

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A Validity of Risk Preference Measure

Table A1: Validity of risk preference measure, predicting risky behavior and general risk attitude.

	Equity market participation	Share of assets in equity	Risk attitude in general
	(1)	(2)	(3)
Risk preference measure	-0.153***	-0.021***	1.257***
	(0.004)	(0.001)	(0.030)
N	37,269	28,967	11,846
R^2	0.047	0.021	0.127

Notes: For our risk preference measure, higher values indicate greater risk aversion. Information on equities and total assets are available for waves 2, 6, 10, and 14 (2002, 2006, 2010, and 2014), while risk preferences in the general domain are elicited in wave 14 (2014) only. Standard errors are displayed in parentheses.. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

B Additional Summary Statistics

Table A2: Summary statistics for additional outcome variables and covariates.

Variables	N	Mean	(Std. Dev.)	Min	Max
Panel A: Additional outcome variables					
Time preferences (increasing from 1 to 6)	90,424	4.13	(1.54)	1	6
Happiness (decreasing from 1 to 6)	108,223	2.53	(1.03)	1	6
Panel B: Individual control variables					
Unemployed	108,866	0.03	(0.16)	0	1
Fired	108,653	0.03	(0.16)	0	1
Changed jobs	108,665	0.11	(0.32)	0	1
Home ownership	108,866	0.77	(0.42)	0	1
Property value (in A$)	106,565	423,583	(442,735)	0	8,000,000
Stimulus payments (in A$)	92,861	603	(1,035)	0	14,600
Panel D: Country-wide control variables					
Realized volatility	108,866	17.47	(4.39)	10.75	35.15
Implied volatility	108,866	17.17	(4.45)	10.75	35.56
Economic policy uncertainty index	108,866	113.91	(40.26)	44.18	215.28

Notes: The number of observations for fired, changed jobs, property value, and happiness differs slightly because of missing values. In addition, estimates on stimulus payments are only calculated for responding individuals in wave 9 (2009), while our measure of time preferences is only available in nine waves.

C Alternative Regression Results

Table A3: Alternative regression results, incorporating individuals who moved between survey interviews.

Dependent variable: Risk preferences (mean = 3.39)	Full sample	Men	Women
	(1)	(2)	(3)
Post-crisis	-0.008	-0.020	0.005
	(0.019)	(0.023)	(0.023)
Regional unemployment rate	0.000	-0.001	0.001
	(0.002)	(0.003)	(0.003)
Post-crisis × regional unemployment rate	0.003	0.008*	-0.001
	(0.003)	(0.004)	(0.004)
Individual fixed effects	×	×	×
Controls[a]	×	×	×
# of individuals	23,980	12,391	11,589
# of waves	11	11	11
N	118,090	61,361	56,729

Notes: Standard errors clustered at the region level are displayed in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.
[a]Includes measures for age, age squared, income, and number of children, as well as indicators for marital status (8 categories) and educational achievement (8 categories).

Table A4: Alternative regression results, employing a fixed effects ordered logit model.

Dependent variable: Risk preferences (mean = 3.39)	Full sample	Men	Women
	(1)	(2)	(3)
Post-crisis	0.917	0.849	0.992
	(0.064)	(0.089)	(0.093)
Regional unemployment rate	0.994	0.992	0.998
	(0.009)	(0.013)	(0.013)
Post-crisis $\times$ regional unemployment rate	1.026**	1.046***	1.002
	(0.012)	(0.016)	(0.017)
Individual fixed effects	$\times$	$\times$	$\times$
Controls^{a}	$\times$	$\times$	$\times$
# of individuals	22,579	10,898	11,681
# of waves	11	11	11
N	108,858	52,293	56,565

Notes: Exponentiated coefficients (odds ratios) from an estimation of the blow up and cluster (BUC) ordered fixed effects logit model are reported. Standard errors are displayed in parentheses.. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. ^{a}Includes measures for age, age squared, income, and number of children, as well as indicators for marital status (8 categories) and educational achievement (8 categories).

Table A5: Alternative regression results, using the mean adjusted rate of unemployment at the region level.

Dependent variable: Risk preferences (mean = 3.39)	Full sample	Men	Women
	(1)	(2)	(3)
Post-crisis	0.012	0.026*	-0.001
	(0.009)	(0.014)	(0.011)
Regional unemployment rate	-0.001	-0.003	0.001
	(0.004)	(0.006)	(0.005)
Post-crisis × regional unemployment rate	0.007	0.017**	-0.002
	(0.006)	(0.007)	(0.006)
Individual fixed effects	×	×	×
Controls[a]	×	×	×
# of individuals	22,579	10,898	11,681
# of waves	11	11	11
N	108,858	52,293	56,565

Notes: Exponentiated coefficients (odds ratios) from an estimation of the blow up and cluster (BUC) ordered fixed effects logit model are reported. Standard errors are displayed in parentheses.. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. [a]Includes measures for age, age squared, income, and number of children, as well as indicators for marital status (8 categories) and educational achievement (8 categories).

Table A6: Alternative regression results, interacting full with a gender dummy.

Dependent variable: Risk preferences (mean = 3.39)	Full sample		Men	Women
	(1)	(2)	(3)	(4)
Post-crisis	-0.012	-0.031	-0.030	0.005
	(0.019)	(0.024)	(0.024)	(0.021)
Regional unemployment rate	-0.001	-0.001	-0.002	0.000
	(0.002)	(0.004)	(0.004)	(0.003)
Post-crisis × Female		0.037		
		(0.024)		
Regional unemployment rate × Female		0.001		
		(0.005)		
Post-crisis × regional unemployment rate	0.004	0.008*	0.010**	-0.001
	(0.004)	(0.004)	(0.004)	(0.004)
Post-crisis × regional unemployment rate × Female		-0.007*		
		(0.004)		
Individual fixed effects	×	×	×	×
Controls^{a}	×	×	×	×
# of individuals	22,579	22,579	10,898	11,681
# of waves	11	11	11	11
N	108,858	108,858	52,293	56,565

Notes: Standard errors are displayed in parentheses.. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. ^{a}Includes measures for age, age squared, income, and number of children, as well as indicators for marital status (8 categories) and educational achievement (8 categories).

D Employment Status, Profession, and Industry

Table A7: Robustness checks, including covariates measuring employment status, profession, and industry.

Dependent variable: Risk preferences (mean = 3.39)	Men			Women		
	(1)	(2)	(3)	(4)	(5)	(6)
Post-crisis	-0.030	-0.029	-0.029	0.005	0.006	0.005
	(0.024)	(0.024)	(0.024)	(0.021)	(0.021)	(0.021)
Regional unemployment rate	-0.002	-0.002	-0.002	0.000	0.000	0.000
	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)
Post-crisis $\times$ regional unemployment rate	0.010**	0.010**	0.010**	-0.001	-0.001	-0.001
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Individual fixed effects	$\times$	$\times$	$\times$	$\times$	$\times$	$\times$
Control variables^{a}	$\times$	$\times$	$\times$	$\times$	$\times$	$\times$
Employment status	$\times$	$\times$	$\times$	$\times$	$\times$	$\times$
Profession		$\times$	$\times$		$\times$	$\times$
Industry			$\times$			$\times$
# of individuals	10,898	10,898	10,898	11,681	11,681	11,681
# of waves	11	11	11	11	11	11
N	52,293	52,293	52,293	56,565	56,565	56,565

Notes: Standard errors clustered at the region level are displayed in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.
^{a}Includes measures for age, age squared, income, and number of children, as well as indicators for marital status (8 categories), educational achievement (8 categories), employment status (3 categories), profession (11 categories), and industry (23 categories).

E Country-Wide Economic Conditions

Table A8: Robustness checks, including country-level measures of economic conditions.

Dependent variable: Risk preferences (mean = 3.39)	Men			Women		
	(1)	(2)	(3)	(4)	(5)	(6)
Post-crisis	-0.001	-0.027	-0.047	-0.066	-0.129**	-0.016
	(0.050)	(0.054)	(0.030)	(0.045)	(0.050)	(0.025)
Regional unemployment rate	-0.000	0.001	-0.003	0.002	0.003	0.001
	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)
Post-crisis × regional unemployment rate	0.010**	0.010**	0.011**	-0.001	-0.002	-0.001
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Realized volatility	0.005**			-0.001		
	(0.002)			(0.002)		
Post-crisis × realized volatility	-0.003			0.003		
	(0.003)			(0.002)		
Implied volatility		0.005**			-0.001	
		(0.002)			(0.002)	
Post-crisis × implied volatility		-0.002			0.005**	
		(0.003)			(0.003)	
EPU			0.004**			-0.000
			(0.002)			(0.002)
Post-crisis × EPU			-0.002			0.001
			(0.002)			(0.002)
Individual fixed effects	×	×	×	×	×	×
Control variables[a]	×	×	×	×	×	×
# of individuals	10,898	10,898	10,898	11,681	11,681	11,681
# of waves	11	11	11	11	11	11
N	52,293	52,293	52,293	56,565	56,565	56,565

Notes: Standard errors clustered at the region level are displayed in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.
[a] Includes measures for age, age squared, income, and number of children, as well as indicators for marital status (8 categories) and educational achievement (8 categories).

F Alternative Definitions of Interview Dates, Time-Fixed Effects, and a Post-Crisis Trend

Table A9: Robustness checks for exploring alternative assignment dates for survey dates. PQ stands for personal questionnaire, whereas HQ is short for household questionnaire.

Dependent variable: Risk preferences (mean = 3.39)	Men			Women		
Regional unemployment rate assigned to	PQ (1)	HQ (2)	June (3)	PQ (4)	HQ (5)	June (6)
Post-crisis	-0.030	-0.029	-0.036	0.005	0.005	0.001
	(0.024)	(0.024)	(0.025)	(0.021)	(0.021)	(0.021)
Regional unemployment rate	-0.002	-0.002	-0.003	0.000	0.000	0.001
	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
Post-crisis × regional unemployment rate	0.010**	0.010**	0.010**	-0.001	-0.001	0.000
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Individual fixed effects	×	×	×	×	×	×
Control variables[a]	×	×	×	×	×	×
# of individuals	10,898	10,898	10,898	11,681	11,681	11,681
# of waves	11	11	11	11	11	11
N	52,293	52,293	52,293	56,565	56,565	56,565

Notes: Standard errors clustered at the region level are displayed in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.
[a]Includes measures for age, age squared, income, and number of children, as well as indicators for marital status (8 categories) and educational achievement (8 categories).

Table A10: Robustness checks for including wave-fixed effects and a post-crisis trend.

Dependent variable: Risk preferences (mean = 3.39)

	Men		Women	
	(1)	(2)	(3)	(4)
Regional unemployment rate	-0.004	-0.004	0.002	0.002
	(0.004)	(0.004)	(0.003)	(0.003)
Post-crisis $\times$ regional unemployment rate	0.011^{**}	0.014^{**}	-0.002	-0.003
	(0.004)	(0.006)	(0.004)	(0.005)
Post-crisis (trend) $\times$ regional unemployment rate		-0.010		0.001
		(0.015)		(0.008)
Individual fixed effects	$\times$	$\times$	$\times$	$\times$
Control variables[a]	$\times$	$\times$	$\times$	$\times$
Wave fixed effects	$\times$	$\times$	$\times$	$\times$
# of individuals	10,898	10,898	11,681	11,681
# of waves	11	11	11	11
N	52,293	52,293	56,565	56,565

Notes: Standard errors clustered at the region level are displayed in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.
[a] Includes measures for age squared, income, and number of children, as well as indicators for marital status (8 categories) and educational achievement (8 categories).

G Alternative Measures of Economic Conditions and Risk Preferences

Table A11: Robustness checks, examining regional unemployment rate versus state GDP growth.

Dependent variable: Risk preferences (mean = 3.39)	Men		Women	
	(1)	(2)	(3)	(4)
Post-crisis	-0.030	-0.016	0.005	-0.006
	(0.024)	(0.020)	(0.021)	(0.015)
Regional unemployment rate	-0.002		0.000	
	(0.004)		(0.003)	
State GDP growth		-0.010***		-0.000
		(0.004)		(0.003)
Post-crisis × regional unemployment rate	0.010**		-0.001	
	(0.004)		(0.004)	
Post-crisis × State GDP growth		0.008*		0.002
		(0.004)		(0.004)
Individual fixed effects	×	×	×	×
Control variables[a]	×	×	×	×
# of individuals	10,898	10,898	11,681	11,681
# of waves	11	11	11	11
N	52,293	52,293	56,565	56,565

Notes: Standard errors clustered at the region level are displayed in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.
[a] Includes measures for age squared, income, and number of children, as well as indicators for marital status (8 categories) and educational achievement (8 categories).

Table A12: Robustness checks for alternative measures of risk preferences (see footnote).

Dependent variable: Risk preferences (alternative measures)

	Men			Women		
	(1)[b]	(2)[c]	(3)[d]	(4)[b]	(5)[c]	(6)[d]
Post-crisis	-0.033	-0.023	-0.021	0.003	0.009	0.006
	(0.022)	(0.016)	(0.022)	(0.017)	(0.015)	(0.020)
Regional unemployment rate	-0.002	-0.004	0.000	0.000	0.001	0.003
	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)
Post-crisis × regional unemployment rate	0.009**	0.006**	0.008**	0.001	-0.001	-0.001
	(0.004)	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)
Individual fixed effects	×	×	×	×	×	×
Control variables[a]	×	×	×	×	×	×
# of individuals	10,784	10,898	11,459	11,619	11,681	12,382
# of waves	11	11	11	11	11	11
N	50,859	52,293	59,099	55,916	56,565	66,164

Notes: Standard errors clustered at the region level are displayed in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. [a]Includes measures for age, age squared, income, and number of children, as well as indicators for marital status (8 categories) and educational achievement (8 categories). [b]Excludes the highest risk-return combination. [c]Collapses the four risk-return combinations into a binary indicator for whether one is willing to take any risks at all, or not. [d]Includes risk-return choices from the follow-up question.

H Emotional Stability

Table A13: Investigating emotion regulation.

Dependent variable: Risk preferences (mean = 3.39)	Men			Women		
	All	High emotional stability	Low emotional stability	All	High emotional stability	Low emotional stability
	(1)	(2)	(3)	(4)	(5)	(6)
Post-crisis	-0.056*	-0.010	-0.053*	0.049	-0.028	0.050
	(0.032)	(0.031)	(0.032)	(0.033)	(0.024)	(0.033)
Regional unemployment rate	-0.005	0.001	-0.005	0.004	-0.002	0.004
	(0.005)	(0.005)	(0.005)	(0.006)	(0.004)	(0.006)
Post-crisis × regional unemployment rate	0.016***	0.005	0.017***	-0.009	0.006	-0.009
	(0.006)	(0.006)	(0.006)	(0.006)	(0.004)	(0.007)
Post-crisis × high emotional stability	0.047			-0.076**		
	(0.043)			(0.039)		
Regional unemployment rate × high emotional stability	0.006			-0.007		
	(0.007)			(0.007)		
Post-crisis × regional unemployment rate × high emotional stability	-0.011			0.014**		
	(0.008)			(0.007)		
Individual fixed effects	×	×	×	×	×	×
Control variables[a]	×	×	×	×	×	×
# of individuals	8,676	4,263	4,413	9,579	4,944	4,635
# of waves	11	11	11	11	11	11
N	48,828	25,353	23,475	53,296	29,753	23,543

Notes: Standard errors clustered at the region level are displayed in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.
[a]Includes measures for age, age squared, income, and number of children, as well as indicators for marital status (8 categories) and educational achievement (8 categories).

I Gender-specific Unemployment

Table A14: Exploring the link between gender-specific unemployment rates and risk preferences before and after the crisis.

Dependent variable: Risk preferences (mean = 3.39)	Men		Women	
	(1)	(2)	(3)	(4)
Post-crisis	-0.025	-0.018	-0.004	0.015
	(0.022)	(0.023)	(0.019)	(0.020)
Male regional unemployment rate	-0.002		-0.001	
	(0.003)		(0.003)	
Female regional unemployment rate		-0.001		0.003
		(0.003)		(0.003)
Post-crisis × male regional unemployment rate	0.009**		0.001	
	(0.004)		(0.004)	
Post-crisis × female regional unemployment rate		0.006		-0.003
		(0.004)		(0.003)
Individual fixed effects	×	×	×	×
Control variables[a]	×	×	×	×
# of individuals	10,898	10,898	11,681	11,681
# of waves	11	11	11	11
N	52,293	52,293	56,565	56,565

Notes: Standard errors clustered at the region level are displayed in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.
[a] Includes measures for age squared, income, and number of children, as well as indicators for marital status (8 categories) and educational achievement (8 categories).

Table A15: Exploring the link between gender-specific unemployment rates and time preferences before and after the crisis.

Dependent variable: Time preferences (mean = 4.13)	Men		Women	
	(1)	(2)	(3)	(4)
Post-crisis	0.172***	0.202***	0.166***	0.158***
	(0.053)	(0.054)	(0.055)	(0.049)
Male regional unemployment rate	-0.006		0.001	
	(0.007)		(0.006)	
Female regional unemployment rate		0.003		0.007
		(0.008)		(0.007)
Post-crisis × male regional unemployment rate	0.019*		0.005	
	(0.010)		(0.010)	
Post-crisis × female regional unemployment rate		0.012		0.008
		(0.009)		(0.008)
Individual fixed effects	×	×	×	×
Control variables[a]	×	×	×	×
# of individuals	10,973	10,973	11,881	11,881
# of waves	8	8	8	8
N	42,426	42,426	47,987	47,987

Notes: Standard errors clustered at the region level are displayed in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.
[a]Includes measures for age, age squared, income, and number of children, as well as indicators for marital status (8 categories) and educational achievement (8 categories).

Table A16: Exploring the link between gender-specific unemployment rates and unhappiness before and after the crisis.

Dependent variable: Unhappiness (mean = 2.53)	Men		Women	
	(1)	(2)	(3)	(4)
Post-crisis	-0.005	-0.051	-0.017	-0.038
	(0.031)	(0.033)	(0.029)	(0.036)
Male regional unemployment rate	0.004		-0.002	
	(0.005)		(0.004)	
Female regional unemployment rate		-0.001		-0.002
		(0.006)		(0.005)
Post-crisis × male regional unemployment rate	0.005		0.000	
	(0.006)		(0.006)	
Post-crisis × female regional unemployment rate		0.013**		0.005
		(0.006)		(0.006)
Individual fixed effects	×	×	×	×
Control variables[a]	×	×	×	×
# of individuals	10,878	10,878	11,662	11,662
# of waves	11	11	11	11
N	51,978	51,978	56,237	56,237

Notes: Standard errors clustered at the region level are displayed in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.
[a] Includes measures for age, age squared, income, and number of children, as well as indicators for marital status (8 categories) and educational achievement (8 categories).