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Happy Voters

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Happy Voters ☆

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Abstract

Empirical models of retrospective voting primarily employ standard monetary and financial indicators to proxy for voters' utility and to explain voters' behavior. We show that subjective well-being explains variation in voting intention that goes beyond what is captured by these monetary and financial indicators. For example, individuals who are satisfied with their life are 1.6% more likely to support the incumbent; by contrast, a 10% increase in family income leads to a 0.18% increase in an individual's support of the incumbent. We use difference-in-differences analysis to identify how voter intention is affected by a negative shock to well-being: the death of a spouse. Individuals who experience the death of a spouse are around 10% less likely than those in the control group to support the incumbent. The results hold even if elected officials' policies (health care, social welfare) cannot reasonably be blamed for the death.

Keywords: Subjective Well-being, Happiness, Retrospective Voting.

JEL CLASSIFICATION: H1, D6, D0, D1.

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1. Introduction

There is a wide consensus in economics and political science that past outcomes affect current voting decisions. In particular, according to the retrospective voting literature (e.g., Kramer, 1971; Fiorina, 1978, 1981; Kinder and Kiewiet, 1981; Markus, 1988; Lewis-Beck, 1990), voters compare past levels of utility and evaluate diagnostic information, such as macroeconomic trends and personal financial circumstances, to re-elect good incumbents and punish those who are believed to be corrupt, incompetent, or ineffective. At the same time the political business cycle literature (e.g. Frey and Lau, 1968; Nordhaus, 1975) has shown that policymakers, aware of this mechanism, regularly attempt to boost their chances of staying in power by maximizing voters' utility just before each election. The common denominator of most of the empirical studies in these literatures is the use of financial and economic indicators as proxies for voters' utility.

More recently, the idea that policymakers should consider not only monetary and financial indicators, but also rely on more comprehensive measures of well-being to inform policies has become a subject of considerable debate among western policymakers and scholars. Steps in this direction have been taken by the British and French governments as well as by international organizations such as the World Bank, the European Commission, the United Nations, and the OECD.[2]

This paper investigates whether subjective well-being (SWB) measures can be used to proxy for utility, and explain the variation in voting intentions that goes beyond what is captured by standard financial and economic indicators. In this respect, there is growing consensus that indices of SWB constitute reasonably good proxies for utility. In particular they can be understood as an application of experienced utility that – as discussed in Kahneman and Thaler (1991) – is the pleasure derived from consumption. There is a relatively old debate, mostly among psychologists, on whether individuals correctly recollect their pleasure from past experiences (see Rabin, 1998, for review of this debate) and whether individuals really make choices aimed to maximize their pleasure (e.g. Tversky and Griffin,

[2]For example, in 2008, the French government set up a Commission led by Joseph Stiglitz for the measurement of economic performance and social progress. The aim of the commission was to make proposals about incorporating the new indicators of economic outputs in national accounts. In the UK, following the initiative taken by the Prime Minister, David Cameron, the Office for National Statistics initiated the National Wellbeing Project, culminating with the construction of a "happiness index."

1991; Hsee, 1999). In general, psychologists emphasize the existence of biases in the relation between choice and predicted affective reactions. Recently Benjamin et al. (2012) test explicitly in a lab setting if individuals tend to maximize SWB when choosing between different scenarios; they show that this occurs in 80% of the cases. Furthermore, there are several studies in economics using SWB indicators to infer the marginal rate of substitutions between goods or state of the words under the implicit assumption of SWB being a proxy for utility, see for example Di Tella, MacCulloch, and Oswald (2001), Benjamin et al. (2014) and also Clark, Frijters, and Shields (2008) for a review of papers along these lines.

To address our question we introduce indicators of well-being as additional explanatory variables in standard models of retrospective voting to serve as proxies for utility and to explain individuals' voting decisions. We use the well-being measures along with the traditionally used measures of financial economic conditions. We construct measures of voting intentions and SWB using the British Household Panel Survey (BHPS), a rich database started in 1991 containing information on over 10,000 British individuals on a yearly basis.

Consistent with the retrospective voting hypothesis, we find that SWB affects the probability of supporting the party of the Prime Minister together with and independently from variables reporting improvement or worsening in family finances. Our estimates indicate that individuals who are satisfied with their lives are 1.6% more likely to support the incumbent. It is instructive to compare this figure with the one obtained from financial indicators: for individuals who feel that their financial situation has improved (worsened) over time the probability of supporting the incumbent is around 1.2% higher (lower); and an individual whose family has experienced a 10% increase in family income is around 0.18% more likely to support the incumbent party. Our findings suggest that both SWB and financial position indicators contribute to explaining voters' behavior and both should be included as regressors in the final econometric model.

Obvious concerns when exploring the relationship between voting and well-being are reverse causality and omitted variable bias: the happiness of citizens with strong ideological identities can be affected by an electoral success *per se*, rather than by the positive outcomes of valid implemented policies, as Di Tella and MacCulloch (2005) have shown. We address this concern in two different ways: (i) we analyze the responses of a sub-sample of ideologically neutral individuals (i.e. those who do not have *a priori* party bias) whose well-being should not be affected by the identity of the ruling party *per se*; and (ii) we identify the effect of SWB on voting intentions by analyzing individuals' responses to an exogenous shock of (un)happiness. We consider these issues in turn.

Reverse causality between SWB and voting intentions can occur because some voters may have *ideological* preferences for one party. Our idea is to replicate our estimations for the subsample of respondents who are ideologically neutral (following the literature, we refer to them as *swing* voters henceforth). Selected questions asked in the BHPS allow us to identify these individuals: our swing voters subsample covers about 30% of the full sample. SWB measures remain very significant for this second set of estimations, but their magnitude is much larger: swing voters who are satisfied with their life are 2.4% more likely to support the incumbent. Furthermore, for the full sample, an increase of 1 unit in the reported life satisfaction raises the probability of supporting the incumbent by 0.013 standard deviations, while for the swing voter subsample this increment is nearly double. This result acquires particular relevance in the context of the open debate on micro-targeting of floating voters during election campaigns.

The second way we address the concern of identification is by analyzing variation in respondents' voting intentions due to a shock of SWB. We exploit the fact that some respondents have experienced the death of their spouse during the period covered by the BHPS .[3] We treat this event as an exogenous variation of SWB. We use difference-in-differences (DiD) analysis and propensity score matching to identify the effect on voting intention due to this shock. We compare before- and after-the-shock changes in political support responses of affected individuals to changes in political support responses of unaffected individuals. This set-up not only provides a way to address concerns related to the identification of the effect running from SWB to voting, but also allows us to analyze another important issue still open in the literature: *do voters punish or reward policymakers for events that are largely independent from government's actions?* It is reasonable to think that the death of a spouse is an event largely beyond government's control, however confounding factors can complicate the identification of the extent to which changes in wellbeing affect voting intentions. For example, in some cases one could argue that the death of an individual results from poor health care, for which the current government is ultimately accountable. If this is the case, punishing the government is not an irrational behavior. We address this

[3]This event has been widely documented as having a deep, negative impact on the SWB of the surviving spouse (Clark and Oswald, 2002; Clark et al., 2008).

point by exploiting the fact that in 1996 the Labour Party took over from the Conservative Party in ruling the country. As a result, those individuals who became widows during the Conservatives years should be unlikely to blame the government for the death of the partner when a Labour government was in power.

We find that, in the two years following the death of a spouse, subjects in the treated group are about 8% less likely to be pro-incumbent than individuals in the control group. Interestingly, women seem to experience a sharper decline in SWB than men, and, consistently with our hypothesis, women also show a stronger decline in incumbent support. The different effect between men and women seems to be also in line with the evidence of a gender gap in happiness, as highlighted by Stevenson and Wolfers (2009). Moreover, we find evidence in support of the hypothesis that voters tend to blame the government for events for which it is not generally responsible, by showing that the change of the party ruling the country does not affect individuals' attitudes towards the government.[4]

There is a related literature consistent with our conclusions. Achen and Bartels (2004) show that voters are more likely to oust incumbents for the economic consequences of natural disasters. Healy, Malhotra, and Hyunjung Mo (2010) explore the electoral impact of local college football games just before an election and find that a win in the ten days before Election Day causes the incumbent to receive an additional 1.6 percentage points. In the same vein, Wolfers (2002) measures the extent to which voters in state gubernatorial elections irrationally hold the state governor accountable for economic fluctuations that are unrelated to his or her actions in office. More recently, Bagues and Esteve-Volart (2016), considering the Spanish Christmas Lottery, find that incumbents receive significantly more votes in lottery-winning provinces. Crucially, this literature does not analyze the role of SWB in mediating voting intention. In addition, the literature uses aggregated data on electoral results, which does not guarantee a connection between the exogenous event under analysis and the individuals personally affected by it. A criticism usually directed to some contributions in this literature is that exogenous shocks make voters more aware about the quality of incumbent politicians (e.g. Ashworth and Bueno de Mesquita, 2016). Using SWB indicators in our analysis suggests that more information cannot be the only explanation.

[4]Gurdal, Miller, and Rustichini (2013) suggest a rational explanation for this mechanism; they argue that holding others responsible for events is efficient - even when this blame is unjustified - because it nonetheless provides appropriate incentive for an agent (in our case, the politician) to produce benefits.

We find that government's popularity mirrors the patterns of SWB, i.e. within three years of a shock, an individual's support for the government returns to the level indicated prior to the occurrence of the shock. There is no particular reason to justify the fact that a better informed voter "forgives" the incumbent once the negative shock is reabsorbed.

To the best of our knowledge, we are the first to directly analyze the effect of SWB indicators on incumbent support. Several contributions have analyzed the effect of SWB on political participation rather than voting decision (e.g., Dolan, Metcalfe, and Powdthavee, 2008; Killian, Schoen, and Dusso, 2008; Weitz-Shapiro and Winters, 2011; Flavin and Keane, 2012; Pacheco and Lange, 2010). These contributions indicate a positive link especially going from SWB to participation.

A related literature looks at the relationship between partisanship and well-being; notably, Di Tella and MacCulloch (2005) show that left-wing voters' well-being is positively affected by left-wing party victories and *left-wing* policy outcomes (like unemployment), and the right-wing voters' well-being, by right-wing electoral victories and *right-wing* policy outcomes (inflation targeting). Powdthavee and Oswald (2010, 2014) and Giuliano and Spilimbergo (2014) show that exogenous shocks affect individuals' political stances. Following these contributions, we test the hypothesis that the effect on voting as the result of a spouse's death is different when the incumbent is left- or right-win. We do not find any significant difference.

Finally, we would like to emphasize that one of the novelty of our analysis is the use of individual data and the identification of a personal link between the exogenous shock and the affected respondents. This comes at the cost of restricting the analysis to only a small sample. Other (bigger) shocks – such as sporting events, changes in weather conditions or natural disasters – would have not allowed such precise identification of the way in which the shock affects individual voters. Our DiD analysis looking at respondents affected by the personal shock of widowhood only allows us to make predictions on how changes in the voting behavior of these individuals differ by observing the voting behavior of individuals who are not affected by such personal shock. This obviously may not have an observable effect on election outcomes. We want to stress that the aim of our paper is not to make predictions on electoral results but to establish the magnitude and direction of the effect of changes of subjective well-being on voting intention.

Even though our paper does not aim to directly address the factors that are relevant in predicting elections outcomes and policy choices, it does shed light on this issue in an indirect way, by enhancing understanding of whether or not voters exhibit a rational behavior. The understanding of how individuals form their political preferences and the rationality of these decisions is important to predict policymakers' behavior and policy outcomes, as a recent important paper by Asworth and Bueno de Mesquita (2014b) has shown. Their paper makes a very clear point that in order to understand policymakers' behavior and policy outcomes it is important to understand how voters form their voting choices. Elections are strategic interactions between relevant actors (voters and policymakers), and, as a result, voters' behavior affects policymakers' behavior and, ultimately, the equilibrium policy.

The remainder of the paper is organized as follows. Section 2 presents and discusses the data; Section 3 is devoted to the estimation the political support model; Section 4 presents the analysis of the effect of widowhood on voting intention. Section 5 concludes the paper.

2. The Data

The empirical work is based on data from the 18 existing waves of the BHPS, spanning the period 1991–2008. The BHPS is a rich database that collects information on over 10,000 British residents on a yearly basis. In addition to well-being questions, the BHPS contains information on political orientation and participation, voting behavior and intentions, as well as personal information on finances, jobs, family status, and region of residence.

Our main variable of interest is a measure of *voting intentions* (*SupportInc*); to construct this measure we use the question: *"If there were to be a General Election tomorrow, which political party do you think you would be most likely to support?"* The variable takes a value equal to 1 if the named party is the same as the national government party (i.e., Conservative Party in the period 1991–1997, and the Labour Party from 1997 onwards) and zero otherwise, we exclude those respondents who answered *"none"* or *"can't vote"*. Note that the same individuals are interviewed every year, which allows us to exploit the properties of a panel.

As an alternative, we could have used *actual (declared)* votes instead of voting intentions. This would have involved using answers related to past general elections, instead of answers related to *hypothetical* elections ("*if there were to be a general elections tomorrow...*"). However, an impediment prevents us from pursuing this route: most of the questionnaires are compiled between October and December, while British elections always take place in May.

So, in order to use actual (declared) votes instead of "voting intention" at a hypothetical election, we would have to make the "strong" assumption that the level of life satisfaction is constant in the period between the election day and the interview date (representing an average lag of about six months). We believe that we cannot make this assumption, because we would not be able to capture the "mood" of the respondent at the time when she forms her political decisions.

Moreover we use two further questions to identify the strength of political ideology: first, respondents are asked if they consider themselves *"supporters of any political parties"* and, in case of a negative answer, whether *"they consider themselves a little closer to one political party than to the others"*. We define as *swing* those respondents who are not close to any particular party, i.e. those who reply *"no"* to both questions, and therefore are likely to swing their vote from one party to the other, and we define as *partisan* those respondents who answer *"yes"* to one of the above two questions. The identification of these two groups will be discussed in detail in Section 3.2 and will be important for the analysis developed later in the paper.

Our key explanatory variable in the analysis of voting intentions is SWB. We derive the main measures of well-being from the responses to the question *"How dissatisfied or satisfied are you with your life overall?"* This question is asked to all respondents every year in the BHPS starting from 1996 (with the exclusion of 1997). Respondents have seven possible categories among which to choose; these range from 1 to 7, where #1 is "not satisfied at all", #4 "not satisfied/dissatisfied", #7 "completely satisfied".

Figure 1 shows the distribution of life satisfaction across British individuals interviewed between 1996 and 2008. The unconditional mean for life satisfaction reported over these years is 5.2, with a median of 5. Table 1 shows the mean of life satisfaction during the different legislatures covered by the period 1996–2008, conditional on the respondents' political ideology (they have been classified according to their answers to the above-mentioned questions on political partisanship).

These statistics lead to some preliminary observations: nonpartisan voters report, on average, a lower life satisfaction than partisan voters (independent of their political orientation), and Labour partisan voters report, on average, a lower life satisfaction than Conservative partisan voters. Both observations suggest there could be reverse causality between political ideology and life satisfaction, which provides valid support to our strategy of conducting the baseline analysis on the subsample of swing voters only.

As mentioned earlier, the literature on retrospective voting has recognized the importance of monetary and financial indicators in determining voting choices. Following Fiorina (1978) and many others, we use a subjective indicator to account for these monetary and financial factors, which we derive from the responses to the question *"How is your financial situation compared to last year?"* Respondents can choose from three possible answers: the financial situation is *better*, the *same as*, or *worse* compared to last year. Taking these answers, we construct the dichotomous variables $BetterFin$ and $WorseFin$, taking values of one when respondents believe that their financial situation is, respectively, better or worse than last year, and zero otherwise.

We also compute the respondents' family-equivalized income in logarithmic term,[5] and we include this measure in all our estimations. Controlling for an *objective* monetary measure of the household income is fundamental because it allows us to interpret the *subjective* assessment of the household financial condition (measured by $BetterFin$ and $WorseFin$) as a broader evaluation of the individual economic situation. Finally, we include a set of controls that are usually employed in the literature of well-being and voting behavior: age of respondents (linear and squared), sex and marital status. Summary statistics for these controls are displayed in table 2.

3. The Models

The empirical strategy is based on testing the main assumptions of retrospective voting models augmented by well-being measures to show that SWB explains voting intentions *in addition* to the usually employed financial indicators. Therefore, our hypothesis is that through well-being indicators it is possible to capture the share of utility related to factors that are not measurable in monetary terms.

We proceed as follows: We first start by replicating the main estimations employed in previous research, to investigate whether voting decisions depend on financial situation indicators. In particular, we include in the following estimation family income to account

[5] We follow the standard procedure of computing the equivalized income by dividing the total income of a household by the squared number of household members. This statistical method allows to account for the difference in the households' size and composition. As a robustness check, we repeated the analysis using simple household income in logarithmic term. Results are qualitatively similar to those reported in the paper, and are available upon request.

for an objective measure of family finances and, following Fiorina (1978), we use subjective questionnaire responses of voters' financial situation.

Accordingly, we first estimate our *traditional* model (Model 1):

$$SupportInc_{it} = \beta_1 BetterFin_{it} + \beta_2 WorseFin_{it} + \beta_3 y_{it} + \gamma X_{it} + \eta_t + a_i + \varepsilon_{it}, \qquad (1)$$

where $SupportInc_{it}$ report the voting intention described in the previous section; $BetterFin_{it}$ and $WorseFin_{it}$ are two dummy variables taking values of 1 if the respondent has replied that her financial situation is respectively better or worse than in the past, aiming to capture variations in utility due to monetary/financial components; y_{it} is the natural logarithm of the yearly family income, and X_{it} is a vector of individuals' personal characteristics (age, sex, marital status, region of residence), note ; η_t denotes year effects; a_i is an individual effect (either random or fixed); and ε_{it} is the error term. The coefficients of interests are β_1 and β_2. Trivially, β_1 and β_3 are expected to be positive, and β_2, negative.

Next, we replace $BetterFin_{it}$ and $WorseFin_{it}$ with our well-being measures to account for the subjective non-financial component of individuals' utility. So we estimate the *well-being* model (Model 2):

$$SupportInc_{it} = \delta Wellbeing_{it} + \beta_3' y_{it} + \gamma' X_{it} + \eta_t + a_i + \varepsilon_{it}, \qquad (2)$$

where $WellBeing$ is constructed from respondents' answers on life satisfaction. The coefficient of interest is now δ, which is expected to be positive. Finally, we combine equations (1) and (2) to estimate a *full* model (Model 3) where both well-being and financial indicators are included as regressors:

$$SupportInc_{it} = \delta' Wellbeing_{it} + \beta_1' BetterFin_{it} + \beta_2' WorseFin_{it} + \beta_3'' y_{it} + \gamma'' X_{it} + \eta_t + a_i + \varepsilon_{it}. \quad (3)$$

We start off by estimating equations (1), (2), and (3) as a linear probability model (LPM) with fixed effects (FE), to control for the within-variation effect of life satisfaction on voting behavior. However, since $SupportInc_{it}$ is a dichotomous variable, we also propose an alternative specification where we estimate the conditional probability of supporting the incumbent party. For completeness of exposure, we do this by employing both a random effect (RE) Probit and a fixed effect Logit, despite preferring the former to the latter.[6] To allow for correlation in the RE Probit between the model's covariates and the unobserved heterogeneity, a_i, we apply Chamberlain's method (1980) and assume the latter follows a normal distribution with linear expectation and constant variance. So we augment our model with a series of individual specific observable characteristics. By adding these variables, Chamberlain's RE probit essentially estimates the effect of varying the model's covariates while holding these individual's specific characteristics fixed. [7]

3.1. Baseline results

Results for the FE-LPM are displayed in table 3. Results for the RE Probit and for the FE Logit are instead reported in the Online Appendix, in tables A.1 and A.2 respectively.[8] There are 4,882 individuals who were interviewed for the entire period and for which we have information on well-being and voting intentions. The dataset comprises nearly 50,000 observations.[9] In columns [1] and [2] of table 3, we report the coefficients for Model (1), the traditional retrospective voting model. Column [1] only controls for income, whereas column [2] augments the model by also allowing for a subjective measure of wealth obtained through the survey's question on perceived changes in the household financial situation. In columns [3] and [4], we display the results for Model (2), the well-being model. The different columns use two variations of $Wellbeing_{it}$. First, we construct a dummy variable taking the value 1 if the respondent has chosen the answer #5, #6, or #7 to the question on life satisfaction and zero otherwise; this indicates that the respondent is satisfied with life. Second, we treat the answers (from #1 to #7) to the question on life satisfaction as a cardinal variable. Finally, in the last two columns, we propose the results of the *full model*, where both well-being measures and financial indicators are included, as in equation (3). All

[6]Given the short length of our dataset (we have a small time dimension of T=12), the incidental parameter problem causes the FE Logit estimates of the parameters to be biased. In addition, we are interested in estimating the partial effect of our variables of interest.

[7]The vector of individual characteristics includes information such as whether the respondent regularly reads newspapers, whether she ever smoked over the years, whether her partner has ever been out of employment, and what is the average income of her household.

[8]For the RE Probit, we display the average partial effect (APE) of the SWB variables at the bottom of each regression.

[9]All results presented in the paper are based on this balanced sample. The baseline specifications discussed in Section 3 were also estimated using the full unbalanced panel: results are qualitatively identical, and available upon request. The balanced sample is also consistent with the DID analysis presented further in Section 4, where we make use of a propensity score equation based on respondents characteristics, as observed in the 1991 cross-section.

the regressions include the same controls, that is, marital status, sex, age, and age squared, along with a set of region of residence dummies, and a set of wave-dummies. Standard errors are clustered at the individual level.

Starting from the results on the *traditional model*, estimates from both the LPM (table 3) and the non-linear model (tables A.1 and A.2) are in line with the basic hypothesis on the retrospective voting model, according to which one's financial situation matters for voting decisions. All the relevant coefficients are highly significant, at least at the 5% level. In particular, respondents who believe that their financial situation has improved compared to the previous year are more likely to support the incumbent compared to those whose financial situation has not changed; the coefficients suggest that, approximately, the effect is a 1.3% increase in the likelihood of supporting the incumbent. Respondents who are instead worse off compared to the previous year appear to punish the incumbent by reducing the likelihood of granting their support by approximately 1.3%. Finally, we note that the income effect is quite small: an increase of 10% of the family income corresponds to a small increase, approximately 0.14%, of the likelihood of supporting the incumbent.

Moving on to the *well-being model*, where measures of subjective financial performances are substituted with life satisfaction indicators, we can see that all the coefficients of interest are again highly significant in all specifications, using both versions of well-being measures. The magnitude of the response is similar to those recorded for the previous model: if a respondent is satisfied with life, she will be about 1.8% more likely to support the incumbent than if not. Similarly, using life satisfaction as a cardinal variable, an increase of 1 unit in the life satisfaction scale is associated with an increase of about three quarters of a percentage point in the likelihood of being pro-incumbent.[10]

In the final model, we include both indicators of well-being and of financial position. We find that all indicators retain the same sign and magnitude as in the previous set of regressions and they do not lose significance, which indicates that the two sets of measures do capture different channels of support for the incumbent.

It is also interesting to compare the relative importance of subjective financial situation measures with SWB ones. For the LPM displayed in Table 3 we compute y-standardised

[10]Remarkably, the coefficients related to the well-being variables for table 3, using an OLS estimator, are very similar to the average partial effect (APE) reported at the bottom of table A.5, which uses a random effect probit estimator. The coefficient of the family income is slightly higher than in column [1].

coefficients as proposed by Winship and Mare (1984) and Long and Freese (2006) and we can see that the probability of supporting the incumbent is 0.025 standard deviations higher for those whose financial situation has improved, and 0.24 lower for those whose financial situation has worsen off compared to those whose financial situation has not changed. For SWB instead we see that an increase of 1 unit in the reported SWB (measured on a 1-7 scale) raises the probability of supporting the incumbent by 0.13 standard deviations.

In summary, our results support the idea that citizens' well-being matters for voting decisions, and in particular, our findings suggest that measuring utility in terms of only monetary and financial indicators leaves out a component, which has a significant impact on voting decisions.

3.2. Reverse causality? Tests on swing voters sample

In the voting literature, ideological preferences towards one party are generally assumed to be exogenously distributed within the population. Some citizens are assumed to have strong partisan preferences (either towards the incumbent or the challenger) while others are assumed to be ideologically neutral. In this setting, voting decisions become the outcome stemming from two different sources: the "ideological" component, originating from party bias, and the "policy" component, resulting from actual governmental choices. The vote of partisan citizens will be based on both the ideological and the policy related grounds, with the weight of each component depending on the intensity of the individual-specific party bias. The vote of ideologically neutral voters, instead, will swing exclusively in response to government policies.

As we said above, partisan voters may experience higher levels of life satisfaction as a consequence of their party electoral success or power endurance. This reverse causality represents a bias for the estimation of our model; our strategy to reduce this bias is to classify voters according to their political alignment and restrict the analysis to the voting behavior of the ideologically more neutral group of swing voters. Since this type of respondents have no (or very low) *ex ante* party preference, they should choose whom to vote mainly on the basis of observed government's policies.

Two questions asked in the BHPS allow us to split the sample between partisan voters and ideologically neutral voters. The survey questions used to this purpose are (i) *"Do you support any political party"*? and (ii) *"Are you close to any political party?"* If respondents answer *"No"* to both, we classify their position for that year to be one of a nonpartisan voter. Almost 80% of individuals declared to be a nonpartisan at least once in the entire period. Among this group, we define as *swing* voters those individuals who gave such answers more than the half of median time during the whole survey, which is eight times or higher.[11] This subsample is constituted by 1,520 respondents, about 30% of the full sample. Using the raw data, figure 2 shows that the share of respondents supporting the incumbent is higher among individuals who declare themselves satisfied, and this difference is wider when one considers only the swing voters sub-sample, which is consistent with the idea that ideologically neutral voters are more responsive to policies than partisan voters.

We employ this sub-sample to reestimate equations (1), (2), and (3). The results are reported in Table 4, which has the same format as Table 3. The same set of controls are used and standard errors are clustered at the individuals' level.

The results confirm our hypothesis. First, the coefficients on well-being measures reported in table 4 (and in tables A.3 and A.4 for the RE Probit and the FE Logit, respectively) are still very significant and, generally, larger in magnitude than those presented in tables 3. For example, looking at our preferred estimation, column [5] of table 4, the effect for $Wellbeing$ is now 0.0238 compared with 0.0161 in the corresponding column of table 3.[12] Second, the positive effect of *improved financial situation* and the negative effect of *worse financial situation* become non significant in all specifications. Third, the effect of family income is still significant and similar in magnitude to the one in the full sample presented in tables 3. Finally, note that in table A.6 of the online Appendix, as a robustness check, we report the results for the estimation of Models (1), (2), and (3) for each level of life satisfaction, for both the full sample and the restricted sample of swing voters. We observe a pattern consistent with a positive relationship between the probability of supporting the incumbent and the level of reported life satisfaction.

From the comparison of the coefficients on *financial situation (better and worse)* in column [2] with the correspondent coefficients in columns [5] and [6] for the LPM in tables 3 and 4, we observe that the inclusion of SWB does not affect the estimation of the coefficients

[11] We have experimented with several other possible definitions of swing voters, depending on the number of times the individuals answered the survey question regarding political ideology as described. These estimations bring similar results and are available upon request.

[12] Equivalently, looking at the y-standardised coefficients for the LPM in 3 and 5, in the full sample an increase of 1 unit in the level of reported life satisfaction raises the probability to support the incumbent by 0.013 standard deviations, for the swing voters sample this goes up to 0.022 standard deviations.

on financial indicators very much. This suggests that the correlation between well-being measures and financial situation dummies is not high; so, in principle, both measures should be included as covariates because they explain different components of voting behavior.

To expand on the results from the analysis of swing voters' support to the incumbent party, we need to address an additional concern regarding the possible endogeneity of self-reported life satisfaction. As stated earlier, the wellbeing of partisan voters can be improved by the mere fact that their preferred party holds power in the government or wins an election campaign. Swing voters are not subject to this ideological bias, yet - when rational - they are likely to experience an increase (decrease) in wellbeing, following the implementation of beneficial (harmful) governmental policies. For this reason, the political science literature argues that swing voters are often the target of *persuasive* campaigns, designed to resolve their political independence and undefined party preference (see Mayer, 2008).

In the context of this paper, swing voters are defined on the basis of their dissociation to any candidate political party. Two types of individuals fall into this definition: those who have high interest in political matters, but are cynic and disillusioned by current politicians, to the point of having no preference among available parties; and those who have low interest in political matters, are not well informed about campaign programs and policies, and therefore have no opinion about current politicians. Our conjecture is that the former type of swing voters would highly reward (harshly punish) politicians who implemented beneficial (harmful) policies, whereas the latter type of swing voter would experience low wellbeing fluctuations in response to implemented policies.

We are not able to identify the source of variation in the wellbeing of swing voters, but we can use personal characteristics and indicators of political involvement, in an attempt to isolate those individuals who are likely to experience stronger reactions to the government doing. In figure 3 we show that, as the number of waves an individual classifies as "swing voter" augments, characteristics like average political interest, general election participation rate, exposure to mainstream media and unions membership rate all decline. We exploit these characteristics in table 5, where we replicate the estimation of Model (3) on two separate samples of swing voters: those who define themselves as "fairly interested" or "very interested" in politics (columns [1] and [2]), and those who define themselves as "not very interested" or "not at all interested" in politics (columns [3] and [4]). The results suggest that the correlation between subjective wellbeing and incumbent support in the case of swing voters with high political interest is double in size, with respect to the case of swing voters with low political interest. This indicates that informed or politically-involved voters who define themselves as non-partisan are the group that is most likely to increase its support for the incumbent in response to changes in their level of life satisfaction. The question remains on whether this difference is due to the fact that these swing voters are those who are more sensitive to the consequences of implemented policies, and rationally reward the incumbent party for the results achieved during their time in power.

As a final robustness check, we propose an alternative definition of swing voters, and test the validity of our results. Always in figure 3, we show that there is a positive correlation between the absence of strong party preferences, or political ideology, and the likelihood of casting a vote in discordance with the pre-announced voting intention. To guarantee that the definition of swing voters is based on elections that occur before the period during which we observe our variable of interest, happiness, we focus on the two general elections of 1992 and 1997[13]. This allows us to exclude the hypothesis that individuals fall into the "swing voter" category because of low levels of wellbeing, due to contemporaneously implemented policy. We select the sample of 1,305 respondents who declared to have participated in these two early general elections, but qualify as "party switchers": these are the respondents whose actual vote went in favor of a party different from that mentioned as the one they would have "most likely voted for in the coming elections". Our definition of party switcher differs from the one found in earlier literature, according to which the "floating voters" are those switching supported party from one election to the others (see Zaller, 2004). Instead of comparing actual votes across elections, we compare actual votes with vote intentions reported in the time between elections. We believe this allows us to identify individuals with high propensity of being persuaded by government actions, so we then replicate on this sample the estimation of Model (3). As shown in columns [5] and [6] of table 5, the results we obtain are strikingly similar to those from column [5] and [6] of table 4, both in terms of coefficients significance and magnitude.

Overall we can say that, when taking out the ideological component from voting intentions, using well-being measures generates even more consistent and significant results. We investigate their relationship further in the next section.

[13]In this way we use characteristics that are predetermined with respect to the level of life satisfaction, which is reported starting from the survey wave of 1996.

4. Exogenous Shocks of (Un)Happiness

In the previous section we have shown that using well-being indicators together with financial indicators to proxy for utility is better than using only financial/economic measures. We have established that when a voter reports a higher (lower) level of well-being, she is also more (less) likely to support the incumbent.

In this section we present the results of an alternative exercise, which allows us to address two points. First, it provides a further test to identify the effect of SWB on voting intentions. Second, it allows us to test the hypothesis whether voters correctly attribute to the government the responsibility of their well-being when they form their voting intentions.

Our identification strategy is: (i) to find an exogenous shock of happiness affecting only some respondents, our *treated group*; (ii) to select a matched sample of individuals who did not experience this shock (matched control group), but who have similar *ex ante* probability of experiencing the shock (propensity score matching); and (iii), to compare *before*-and *after*-shock changes in political support responses of affected individuals to changes in political support responses of unaffected individuals (DiD estimation).

Our priority is to exploit an exogenous shock that allows us to identify a connection between a relevant event and the individuals personally affected by it. We exclude climate changes and sports events, previously used in the literature, because we do not have data on personal preferences about weather conditions or sport disciplines.[14] We use, instead, the death of the husband or wife as a shock of life satisfaction. This event, which is also arguably beyond government's control, is well known to have a deep *temporary* impact on well-being (see for example Clark and Oswald, 2002; Clark et al, 2008), and, its effect is recognized to be stronger for women than men (Clark et al, 2002). Widowhood fits well our purpose because it is possible to identify its exogenous component by using propensity score matching.

[14] The UK Meteorological Office provides time series of climatic conditions, aggregated at the station-level on a monthly average basis. To use these data we could have, at best, match an individual at the time of the survey with the monthly averaged meteorological conditions reported by the nearest station to his count of residence. Concerning sport events, instead, we could have, at best, match an individual respondent with performances from local sport teams, despite lack of information on actual intensity of support to the sport disciplines in question.

4.1. Propensity Score Matching

In order to be able to analyze the response to negative shocks of life satisfaction, such as those caused by an event like widowhood, we need to deal with two problems. First, a direct comparison between treated and untreated individuals is biased by the fact that differences across these two groups depend on selection. Second, the time of the treatment is respondent specific and cannot be imputed for the members of the non-treated group. Propensity score matching provides a solution to both problems. It involves relying on a set of observable characteristics that affect the "probability of being treated" (propensity score) in an attempt to reproduce the treatment group among the non-treated. Imputation of the time of treatment to the members of the control group is therefore made by pairing each of its individuals with a member of the treated group. Becker and Hvide (2013) use a similar approach to match firms with a deceased entrepreneur with firms where the organization never experienced a similar shock, despite having similar characteristics to those who did. In our setting, we use year of spouse death of treated respondents to impute the counterfactual year of spouse death of the matched control. So, in this way, we are able to define before and after spouse death for both treated respondents and matched controls.

We use nearest neighbor matching to select the group of individuals whose probability of experiencing widowhood between 1992 and 2008 (the whole length of the BHPS), conditional on characteristics observed in 1991, is the closest to that of the 363 individuals who did experience widowhood over the same period.[15] We begin computing the propensity score by estimating a probit for the likelihood of becoming a widow. Table 6 provides evidence of the good explanatory power of the chosen covariates, given the significance of their coefficients and the high $pseudo-R^2$ of 0.30. We also estimated this model with a larger set of variables controlling for a full set of personal, health-related, and financial characteristics. Other explanatory variables not included in this preferred specification resulted as consistently insignificant in all other robustness checks. The predicted probabilities estimated from this model constitute our propensity scores. Before matching, the average propensity score is 0.352 for the treated group, and only 0.073 for the non-treated group. After imposing a radius of 0.01 for the identification of the nearest neighbor to any individual belonging to the control group, we discard 134 individuals and remain with a sample of 230 respondents

[15]This procedure involved omitting from the sample the individuals who had never been married, those who were always reported as widows, and those who remarried after widowhood.

(153 of these are women and 77 men) who did experience widowhood and 230 matched respondents who didn't. In the matched sample, the average propensity score is reduced to 0.1963 for the treated group and 0.1952 for the control group. Histograms for the estimated propensity score before and after matching and other more technical results are presented in sections A.2 and A.3 of the Appendix.

4.1.1. DiD Setup

Our main focus is now to show that the spouse death negatively affects the probability of supporting the incumbent, and that this negative effect fades away after three years from the event; hence, it follows a pattern similar to the shock in SWB. We are mainly interested in the differences after the event, but we also look into the behavior before the death to check for the presence of any pre-treatment effect that could potentially invalidate our results.

Figures 4 and 5 provide graphical representations of how the drop in life satisfaction translates into a reduction of support for the incumbent party. The figures display the differences between the *treated* and the *untreated* individuals during the year of the treatment versus all other years. The *treatment* is defined as the respondent's loss of a spouse, while the *years of widowhood* refer to the year of the spouse's death and to the following two years. From the top left panel of figure 4, we can observe that treated individuals declare themselves significantly less satisfied (with $p - vlaue < 0.01$) during the years of widowhood than during all other years, and from the top right panel we observe that, during the years of widowhood, treated individuals are significantly less satisfied than the matched individuals who did not experience the same shock (with $p - vlaue < 0.01$). The bottom left and right panels replicate the analysis on the expected incumbent support. Figure 5 presents the same evidence in the form of an event study graph. In the top panel we observe clear similarities between the probability of incumbent support and the probability of reporting high levels of wellbeing for the treated group (solid lines), during the years preceding and following the loss of a respondent's spouse (normalized at period 0 for all respondents). As respondents start experiencing lower levels of life satisfaction, between three and two years before the loss of their spouse, we start seeing a decline in the support for the incumbent party. The control group is not affected by the shock of the spouse loss, and both variables seem to converge back to the same level around three years after the time of the shock. By looking at the lower panels of figure 5, we notice that the group of treated females follows, for both the incumbent support and the life satisfaction, a similar trend to the control group. There is an increase in incumbent support two years before the spouse loss among female treated respondents: this might cause concern regarding the presence of a pre-treatment effect, which will be tested in the difference-in-difference analysis. Once again, this result holds particularly for female respondents.

In order to analyze the dynamic of the probability of supporting the incumbent during the years, controlling for potential confounding, assessing the magnitude and the statistical significance of the effect represented in figures 4 and 5, we run a standard DiD regression, where we compare treated and matched controls to assess how voting intentions are affected by a spouse's death (treatment). We estimate the following model:

$$SupportInc_{it} = \alpha + \lambda_1 \times treated_i + \lambda_2 \times after_{it} \times treated_i + \lambda_3 \times after_{it} + \gamma \times X_{it} + \delta_t + u_{it} \quad (4)$$

The coefficient of interest is λ_2, which measures the difference between treated respondents and control respondents after the treatment. The coefficient λ_1 also presents some interest because it constitutes a test for the lack of pretreatment effect. We include all the controls that have been previously included in the regressions; these are age (in linear and squared form), logarithm of family income, sex, as well as year and region dummies. Standard errors are clustered at the individual level. We estimate equation (4) using the Linear Probability Model.

Finding that the effect on the probability of supporting the incumbent in the treated group lasts as long as the shock on life satisfaction and finding that the effect on women is stronger than in men, would allow us to attribute the effect of the treatment on voting intention to the shock of unhappiness.

4.1.2. DiD Main Results

We analyze whether individuals experiencing widowhood change their voting intention differently than how do individuals whose spouses survive. Estimation results for equation (4) and its variations are displayed in tables 7, 8, 9 and 10. In most of our regressions, we consider windows over intervals of three and two years before and after the spouse death, but we also experiment with shorter and longer periods.

Columns [1], [2], and [3] of table 7 present the results for λ_2, when the data are restricted to respectively 4, 3, and 2 years after and before the treatment. We observe that there is a negative effect of widowhood on the probability of incumbent support; an effect which is increasing and particularly significant in the sample restricted to the two-year window (column [3]), suggesting that the widowhood-shock reduces by about 8% the probability that the treated respondent gives support to the incumbent party. In table A.8, we obtain more precise estimates of the effect *duration*, by estimating separate coefficients for the year of the spouse death, the two years after, and simply the first and the second year after. The effect of the shock on the incumbent support appears to be decreasing over time, consistently with the pattern found on the life satisfaction variable.[16] In these first three columns, we impose the restriction that men and women react in the same way to the loss of their spouse.

However an analysis of the data, provided in the on line Appendix (Section A3), shows that the effect of the spouse's death on SWB is significantly higher for women than men. This motivates us to analyze the responses by gender. We do it in two ways: (i) by interacting $after_{it} \times treated_i$ with a dummy identifying the gender of the respondent; (ii) by running separate regressions for male and female respondents. Columns [4] to [6] repeat the estimates of columns [1] to [3], after relaxing the restriction of homogeneous treatment effect across gender. We estimate different coefficients for men and women in the treated group. Consistently with the asymmetry in the effect of this shock on life satisfaction, the results show clearly that women are the ones whose voting behavior is affected by the spouse death; the λ_2 are negative and become significant when we restrict the sample to two or three years from the treatment. Again, we first start by estimating a common λ_2 for all years after the spouse death. The results suggest that women are about 7% to 9% less likely to vote for the incumbent following the death of their husband. When analyzing the duration of the effect, we obtain significant and negative coefficients for women in the year of the event (about -9%) and in the following year (about -12%) and a smaller nonsignificant effect two year after the event (about -5%). Coefficients for men are smaller and nonsignificant. All in all we can say that: *the effect of the shock on the probability of supporting the incumbent party follows the effect of the shock on the level of SWB.*

As a robustness check, we run separate regressions for men and women. The results are displayed in tables A.9 and A.10. From the inspection of the tables, we can clearly see that

[16] In the on line Appendix (Section A3) we provide a formal analysis on the impact of the spouse death on wellbeing. In particular we find that that shock of wellbeing lasts for only two years after the death.

all the previous results are confirmed in terms of both magnitude and significance.[17]

4.2. Heterogeneous Responses: Income and Party Effect

There is a possibility that some of the individuals who experienced widowhood attribute to the government partial responsibility for the loss of their spouse, maybe due to strong existing dependence on national health programs, to changes in the succession law or to unfavorable retirement policies. A possible objection is that, in all such cases, the loss of one's spouse corresponds to a sudden change in one's personal financial condition, which itself justifies increased support for a particular political party.

The results presented in section 4.1 do not support these arguments. We control for wealth in all our estimations, measured as both objective income and subjective perceived changes in own financial situation, and find it plays no significant role in explaining the way individuals who experienced the loss of a spouse respond to voting intentions. Also, we can argue that if the partner's loss was perceived mainly in economic terms (i.e. as the loss of a portion of the household's income), then we would observe a permanent negative effect. Instead, in the contest of this paper, we find only a temporary effect, suggesting that widowhood affects voting behavior only for one, maximum two years after the shock.

To elaborate further on our argument, we proceed by augmenting our difference-in-difference setup with additional income controls. In table 8 we differentiate between alternative income sources (columns [1] and [2]), then we identify the respondents who qualified as the household's breadwinner for the majority of the years preceding the death of the spouse (columns [3] and [4]), and finally we allow for the effect of widowhood to differ according to weather the respondent was the breadwinner (columns [5] and [6]). If widowhood was perceived as a sudden change in the household financial condition, then we should observe stronger effects on voting behavior of individuals whose spouse had consistently raised the largest portion of the family income. Instead, we find that breadwinners, on average, have the same expected voting intention of other respondents and that also their reaction to widowhood is no significantly different from the reaction of other respondents.

[17] We can also observe that our matching technique has not left any pre-treatment effect, in Section 4.2 we have shown that there are no differences between control and treated group at the beginning of the period. When we estimate (4) we also carry out tests that the two groups remain comparable in the periods before the treatment, to make sure that there are no pre-treatment differences between the two groups. The coefficients λ_1 presented in the first row of tables A.9 to A.10 show that this is indeed the case. To provide further evidence we interact the treatment with pre-treatment years before {1,2, 1-2} dummies. The results displayed in the tables are again consistent with the assumption that there is no pre-treatment effect.

There is an alternative way to approach this issue. One can argue that a well-being shock affects an individual social status and political bias (pro Labour Party, in this case), rather than simply her support for the incumbent.[18] A preliminary analysis suggests that this argument does not hold in the empirical data. We only find evidence of a temporary effect on incumbent support induced by the shock. We believe this hypothesis is instead consistent with a long term (negative) effect of widowhood. To explore the issue further we carry out additional robustness checks. The idea is that the effect of the shock on political bias should take a different sign depending on the identity of the party in power, i.e. a positive sign under left wing governments and a negative sign under right wing ones. We can test this hypothesis of a widowhood-induced change in political bias directly, since the Conservative Party took over the Labour Party in 1996.[19] We do this by re-estimating equation (4) augmented with the interaction of the after treatment dummy with a temporal dummy identifying whether or not the government in power is led by the Labour Party.

Table 9 presents our results. Columns [1] to [5] estimate the same models as the corresponding columns of table 7 with the addition of the interaction terms. As we can see, the results seem to confirm our hypothesis that there is no significant difference between the two legislatures. The interaction of the after treatment dummy with the Labour temporal dummy is always nonsignificant.[20] Column [5] suggests that the probability of supporting the incumbent in the first year following the spouse's death is 0.183 lower for the control than for the treatment group. This coefficient is comparable in magnitude and significance with the effect found in column [5] of 7, our preferred specification (see also column [10] of the same table). Column [6] tests the presence of pretreatment effect, and again finds that voting behavior changes only after the spouse's death.

4.3. Are voters rational?

We finally address whether individuals reward policymakers only for the increase in SWB they are directly responsible for, or whether they also respond to events independent from government actions. Assuming that experiencing widowhood in the U.K. during the period 1992-2008 is an event largely beyond government's control, we convey that our preliminary

[18]Oswald and Powdthavee (2010, 2014) show that a shock that makes the individual more (less) needy might increase (decrease) her support for a left wing party (i.e. the Labour Party in our case).

[19]Our dataset covers six years of Conservative Governments and eleven years of Labour Governments.

[20]The sign and magnitude of the coefficient would indicate that voting behaviour differs in legislatures from the two parties, however our results remain insignificant to different specifications.

results seem to go in the same direction of a recent literature (Achen and Bartels (2004), Healy, Malhotra, and Hyunjung Mo (2010) Wolfers (2002) Bagues and Esteve-Volart (2016)) showing how voters irrationally punish (or reward) policymakers for events that are government unrelated. We use the same strategy of section 4.2. to further expand on this last point.

Blaming and punishing the government for the loss of one's spouse would be classified as rational behavior only if the responsibility of certain events could be traced back directly to the government. This would be the case, for example, if the spouse had been victim of negligence or malpractice on behalf of the NHS, for which the government in place is ultimately accountable. However, if the government in place at the time of the survey interview was different from the one in place at the time the shock was experienced by the respondent, then a blaming attitude would still be classified as irrational.

We exploit the fact that in 1996 the Labour Party took power after two decades of Conservative governments. Rational individuals whose spouse died during the Conservatives years, should have stopped blaming their government once the Labour party came in power. We construct an indicator variable $Switch_{it}$, which equals one for the respondents whose incumbent at the time of the interview is different from the incumbent at the time of the spouse death.[21] We then re-estimate an augmented version of equation (4) which includes $Switch_{it}$ along with its interactions to $after_{it} \times treated_i$. Our conjecture is that if widows were *rationally* blaming the government in power at the time of their spouse death, they would have no reason to punish a government lead by a different party. A coefficient on $Switch_{it} \times after_{it} \times treated_i$ significant and of opposite sign to the coefficient on $after_{it} \times treated_i$ would give evidence of such rational behavior.

Table 10 displays the results for this exercise. From the inspection of the table we can clearly see that the newly introduced interaction is never significant. So we gather no evidence that a switch of the party in power affects individuals response to the widowhood shock, which would have indeed supported the conjecture of rational behavior.

[21] By construction, this indicator variable always equals zero before 1996.

5. Conclusion

Motivated by recent initiatives taken by governments and international organizations to build measures of well-being that can be integrated with standard monetary and financial measures to create informed policies, we test if well-being data can be used to predict voting behavior.

Our aim is to contribute to the empirical literature on retrospective voting by augmenting standard models of voting behavior with measures of well-being, to proxy for utility. Preliminary results suggest that survey respondents modify their voting intentions in response to changes in their level of life satisfaction.

The identification of the causal effect of SWB on voting intentions is the main source of concern because of the potential for political ideology to enter the equation. For example, a strong Conservative supporter may be satisfied by the simple fact that the Tories are in power, rather than by the welfare enhancement brought by the party's implemented policies. We address this issue in two ways:*(i)* we split the sample between swing and partisan voters, and we show that swing voters have a stronger reaction to a SWB shock - the opposite behavior than would have taken place if our result were due to reverse causality; and*(ii)* we use widowhood as an exogenous variation to identify the model - thus, allowing us to conclude that changes in life satisfaction due to non-policy-related events also affect respondents' political intentions.

Having established that SWB measures are good indicators for predicting voters' behavior, we proceeded in the direction of asking whether or not voters are able to correctly reward or punish the incumbent government only for the variation in life satisfaction that can be directly attributed to government actions. People's happiness depends on several factors, and many of them cannot be directly linked to government action. To address this, we test whether or not widowhood affects voters' preferences toward incumbents. We use DiD estimation and propensity score matching to identify the effect that widowhood has on the probability of supporting the incumbent party. We find that a 1-point decrease in life satisfaction measured on a 7-point scale corresponds to a 12% decline in the support of the incumbent party. Consistent with our hypothesis, we find that the decline in support for the incumbent party follows the same pattern as the decline in well-being that occurs in the wake of widowhood. That is, the results follow the same trajectories. We confirm the above results by estimating the effect of the shock on SWB and on incumbent support together in a bivariate probit analysis.

Our analysis does not allow us to make predictions on electoral outcomes, as it does not use actual voting data, and it exploits an exogenous shock that only affects a small group of individuals. The paper allows us, instead, to evaluate the magnitude of the effect of changes of SWB on voting behavior. The use of individual data and the identification of a personal link between the exogenous shock and the affected respondents, we believe, helps us understanding whether or not voters exhibit a rational behavior, which in turn is important to predict policymakers decision and policy outcomes, as a recent important paper by Asworth and Bueno de Mesquita (2014b) has shown. This paper makes a very clear point that in order to understand policy outcomes it is important to understand how voters form their voting choices, because elections are strategic interactions between relevant actors (voters and policymakers).

We believe that our results have important implications. First, they motivate the efforts taken by governments and international organizations in producing better and more comprehensive measures for well-being. Our results show that well-being plays a role in voters' decision-making processes - a finding that is consistent with retrospective voting models, and one that underscores the growing awareness of the importance of taking well-being into account in policy formation. Second, they highlight citizens' inability to correctly blame or reward policymakers only for the actions they are responsible for. The results show that voters fail to distinguish whether elected officials' policies are responsible for a decline in well-being they experience. Thus, a fall in a well-being - regardless of the cause - leads voters to hold politicians in office responsible.

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6. Tables

Table 1: **Average Life Satisfaction, Conditional on Political Ideology**

	Labour Partisan			"Swing"	Conservative Partisan		
	Strong	Medium	Weak		Weak	Medium	Strong
Conservative 1992	5.111	5.135	5.172	5.201	5.420	5.467	5.638
	(1.558)	(1.435)	(1.306)	(1.337)	(1.147)	(1.307)	(1.435)
Labour 1997	5.176	5.223	5.186	5.182	5.371	5.448	5.433
	(1.582)	(1.362)	(1.296)	(1.320)	(1.182)	(1.284)	(1.491)
Labour 2001	5.474	5.299	5.202	5.190	5.367	5.464	5.497
	(1.421)	(1.323)	(1.269)	(1.316)	(1.151)	(1.201)	(1.339)
Labour 2005	5.418	5.263	5.196	5.166	5.348	5.326	5.450
	(1.438)	(1.274)	(1.217)	(1.282)	(1.102)	(1.222)	(1.279)

Note: descriptive statistics based on the balanced sample of survey respondents observed consecutively for all years between 1996 and 2008. Respondents dropped from the sample include those who were below the age of 16 in 1991, as well as the individuals in the top percentile of the income distribution and of the age distribution. Labour (Conservative) partisan are the respondents who declare the Labour (Conservative) party is either their favorite, or the party they feel closer to. Swing voters are the respondents who declare they don't particularly prefer any party.

Table 2: **Descriptive Statistics for Main Covariates**

	Obs.	Resp.	Mean	Std. Dev.	Min.	Max.
Support Incumbent	48,432	4,882	0.3749	0.4841	0	1
Life Satisfaction	48,432	4,882	5.2465	1.2236	1	7
Times Respondent Classifies as Nonpartisan	48,432	4,882	5.2037	5.3953	0	18
Widowhood	48,432	4,882	0.0049	0.0701	0	1
Income (ln)	48,432	4,882	7.3755	0.7116	-2.4	11.2
Age	48,432	4,882	49.6083	15.7044	18	97
Dummy (1 = female)	48,432	4,882	0.5541	0.4971	0	1
Dummy (1 = married)	48,432	4,882	0.6554	0.4752	0	1
Financial Situation Compared to Last Year = Better	48,432	4,882	0.2522	0.4343	0	1
Financial Situation Compared to Last Year = Worse	48,432	4,882	0.2388	0.4263	0	1

Note: Data used for these descriptive statistics include the balanced sample of all individuals observed consecutively for all years between 1996 and 2008. Respondents dropped from the sample include those who were below the age of 16 in 1991, as well as the individuals in the top percentile of the income distribution and of the age distribution.

Table 3: **Baseline Equation, Linear Probability Models on Full Sample of Respondents**

Dependent Variable: 1 If Supporting Incumbent Party		Financial Situation Only		Life Satisfaction Only		Financial Situation & Life Satisfaction	
		[1]	[2]	[3]	[4]	[5]	[6]
Family Income		0.0162***	0.0141***	0.0160***	0.0159***	0.0140***	0.0140***
		(0.0039)	(0.0039)	(0.0039)	(0.0039)	(0.0039)	(0.0039)
Financial Situation:	Better		0.0132***			0.0126***	0.0125***
			(0.0046)			(0.0046)	(0.0046)
	Worse		-0.0131***			-0.0120***	-0.0117**
			(0.0046)			(0.0046)	(0.0046)
Satisfied with Life: [5,6,7]				0.0185***		0.0161***	
				(0.0051)		(0.0051)	
Satisfaction with Life: [1,2,...,7]					0.0075***		0.0065***
					(0.0020)		(0.0020)
Observations		48,432	48,432	48,432	48,432	48,432	48,432
R-squared		0.0324	0.0330	0.0327	0.0328	0.0332	0.0333
Number of pid		4,882	4,882	4,882	4,882	4,882	4,882

*Note: Baseline model estimates the determinants of the probability of supporting the incumbent party. Models are estimated using a FE LPM. Sample composition: 4,882 respondents observed since 1996. All specifications include auxiliary control variables (a dummy for "married" individuals, age, age squared, and a dummy for female respondents). Region and wave dummies are also included. The variable "lfsato" from BHPS was used to define the level of life satisfaction. It is equal to seven different levels of life satisfaction, varying from completely satisfied (=7) to not at all satisfied (=1). For Model [2] and Model [4], the variable is recoded as a dummy identifying whether the individual is satisfied (>4), whereas for Model [3] and [5], life satisfaction is used as a continuous variable. Standard errors are clustered by respondent and reported in parenthesis. *** p<0.01, ** p<0.05, * p<0.1*

Table 4: **Reducing endogeneity bias, Linear Probability Models on a Restricted Sample of Swing Voters**

Dependent Variable: 1 If Supporting Incumbent Party		Financial Situation Only		Life Satisfaction Only		Financial Situation & Life Satisfaction	
		[1]	[2]	[3]	[4]	[5]	[6]
Family Income		0.0148**	0.0136*	0.0145**	0.0143**	0.0135*	0.0134*
		(0.0073)	(0.0074)	(0.0039)	(0.0073)	(0.0073)	(0.0074)
Financial Situation:	Better		0.0121			0.0111	0.0109
			(0.0089)			(0.0090)	(0.0089)
	Worse		-0.0030			-0.0011	-0.0002
			(0.0088)			(0.0088)	(0.0088)
Satisfied with Life: [5,6,7]				0.0249***		0.0238***	
				(0.0087)		(0.0087)	
Satisfaction with Life: [1,2,. . . ,7]					0.0112***		0.0108***
					(0.0034)		(0.0034)
Observations		12,926	12,926	12,926	12,926	12,926	12,926
R-squared		0.0768	0.0770	0.0774	0.0776	0.0776	0.0778
Number of pid		1,520	1,520	1,520	1,520	1,520	1,520

*Note: Baseline model estimates the determinants of the probability of supporting the incumbent party. Models are estimated using a FE LPM. Sample: 1,520 respondents who qualify as "swing voters" for 8 or more waves. All specifications include auxiliary control variables (a dummy for "married" individuals, age, age squared, and a dummy for female respondents). Region and wave dummies are also included. The variable "lfsato" from BHPS was used to define the level of life satisfaction. It is equal to seven different levels of life satisfaction, varying from completely satisfied (=7) to not at all satisfied (=1). For Model [2] and Model [4], the variable is recoded as a dummy identifying whether the individual is satisfied (>4), whereas for Model [3] and [5], life satisfaction is used as a continuous variable. Standard errors are clustered by respondent and reported in parenthesis. *** p<0.01, ** p<0.05, * p<0.1*

Table 5: **Alternative Definition of Swing Voters: Political Interest and Vote-Switch**

Dependent Variable:1 If Supporting Incumbent Party		Swing Voters with High Political Interest		Swing Voters with Low Political Interest		Vote Switchers	
		[1]	[2]	[3]	[4]	[5]	[6]
Family Income		0.0074	0.0075	0.0134	0.0132	0.0144	0.0140
		(0.0134)	(0.0134)	(0.0089)	(0.0089)	(0.0089)	(0.0090)
Financial Situation:	Better	0.0028	0.0030	0.0150	0.0146	0.0015	0.0007
		(0.0167)	(0.0166)	(0.0105)	(0.0105)	(0.0094)	(0.0093)
	Worse	-0.0057	-0.0045	0.0004	0.0013	-0.0138	-0.0125
		(0.0158)	(0.0159)	(0.0105)	(0.0105)	(0.0091)	(0.0091)
Satisfied with Life: [5,6,7]		0.0369**		0.0180*		0.0244**	
		(0.0159)		(0.0103)		(0.0099)	
Satisfaction with Life: [1,2,. . . ,7]			0.0186***		0.0081**		0.0152***
			(0.0069)		(0.0038)		(0.0040)
Observations		4,321	4,321	8,605	8,605	12,465	12,465
R-squared		0.0996	0.1002	0.0784	0.0785	0.0656	0.0665
Number of pid		530	530	990	990	1,305	1,305

*Note: models replicates the specifications from columns [5] and [6] of Table 3 and 4, which control for household income, changes in perceived financial situation and the two alternative measures of satisfaction with overall life. Auxiliary control variables are the same as in Tables 3 and 4 (a dummy for "married" individuals, age, age squared, and a dummy for female respondents). All models are estimated using an FE LPM. In columns [1] and [2], the Swing Voters sample is restricted to the respondents who reported to be - on average over the observational period - "fairly interested" or "very interested" in politics. In columns [3] and [4], the Swing Voters sample is restricted to the respondents who reported to be - on average over the observational period - "not very interest" or "not at all interested" in politics. In columns [5] and [6], instead, the Swing Voters sample is defined using the respondents whose pre-electoral voting intentions did not match with the self-reported actual vote for the general elections of the years 1992 and 1997. Standard errors are clustered by respondent and reported in parenthesis. *** p<0.01, ** p<0.05, * p< 0.1*

Table 6: **Propensity Score Regression - Probit Model on Individual Characteristics**

Dependent Variable: Probability of Becoming Widowed between 1992 and 2008	
Age in 1991	0.0446***
	(0.00416)
Female	0.580***
	(0.0895)
In Working Age in 1991	-0.332**
	(0.138)
Dummy: 1 If Ever Smoked in Life	0.103
	(0.0788)
Dummy: 1 If Had Permanent Job in 1991	-0.113
	(0.0997)
Dummy: 1 If Employed Full Time in 1991	0.187*
	(0.101)
Dummy: 1 If Spouse/Husband Was Employed in 1991	-0.335***
	(0.0897)
ln (Household Income) in 1991	-0.116*
	(0.0649)
Dummy: 1 If in Good Health in 1991	0.0146
	(0.0866)
Dummy: 1 If Visited GP More Than Twice in 1991	-0.157*
	(0.0872)
Dummy: 1 If Ever Hospitalized in 1991	0.00542
	(0.121)
Dummy: 1 If Ever Used Alternative Medicine	0.211
	(0.155)
Dummy: 1 If Regularly Checks Blood Pressure	-0.0260
	(0.0798)
Dummy: 1 If Regularly Does Chest X-ray	0.108
	(0.104)
Dummy: 1 If Regularly Checks Cholesterol	-0.2013*
	(0.115)
Dummy: 1 If Regularly Checks Cancer	0.0134
	(0.0876)
Constant	-2.321***
	(0.674)
Observations	3,644
Log-likelihood	-825.06916
Pseudo R-squared	0.3030

*Note: Probit model for the likelihood of experiencing widowhood between 1992 and 2008, conditional on characteristics observed in 1991. Sample of 3,644 respondents (obtained by excluding from the original sample of 4,882 individuals those who were not observed continuously between 1991 and 2008, those who were never married, and those who were always recorded as widow(er)s). There are 363 respondents who experienced widowhood. Region and household-type dummies are included. Standard errors are reported in parenthesis. *** p<0.01, ** p<0.05, * p<0.1*

Table 7: **DiD on Full Matched Sample (Linear Probability Model)**

Dependent Variable: Support Incumbent	Homogeneous Treatment Effect			Gender Specific Treatment Effect		
	±4 Years [1]	±3 Years [2]	±2 Years [3]	±4 Years [4]	±3 Years [5]	±2 Years [6]
Treated	0.0404	0.0458	0.0583	0.0405	0.0459	0.0584
	(0.0405)	(0.0422)	(0.0451)	(0.0405)	(0.0423)	(0.0452)
After	0.0252	0.0333	0.0445*	0.0253	0.0336	0.0446*
	(0.0297)	(0.0271)	(0.0251)	(0.0297)	(0.0271)	(0.0251)
After*Treated	-0.0388	-0.0536	-0.0751**			
	(0.0398)	(0.0374)	(0.0358)			
After*Treated*Female				-0.0512	-0.0675	-0.0894**
				(0.0460)	(0.0442)	(0.0438)
After*Treated*Male				-0.0160	-0.0284	-0.0495
				(0.0597)	(0.0585)	(0.0580)
Family Income	0.0025	0.0008	-0.0095	0.0026	0.0009	-0.0092
	(0.0233)	(0.0243)	(0.0267)	(0.0234)	(0.0244)	(0.0268)
Perceived Better Financial Situation	0.0022	-0.0049	-0.0075	0.0020	-0.0053	-0.0085
	(0.0275)	(0.0313)	(0.0353)	(0.0275)	(0.0313)	(0.0353)
Perceived Worse Financial Situation	-0.0680***	-0.0395	-0.0181	-0.0681***	-0.0395	-0.0178
	(0.0257)	(0.0280)	(0.0316)	(0.0257)	(0.0280)	(0.0316)
Observations	3,146	2,530	1,851	3,146	2,530	1,851
R-squared	0.036	0.037	0.041	0.036	0.037	0.041

Note: Sample composition is 230 treated and 230 matched control individuals; Models [1]-[6] and [2]-[7] further restrict, respectively, to four and three years before and after spouse death; Models [3] to [5] and [8] to [10] restrict to only two years before and after spouse death. OLS estimates are based on the regression showed in equation 4 ($SupportInc_{it} = \alpha + \lambda_1 xTreated_i + \lambda_2 xafter_{it} xtreated_i + \lambda_3 xafter_{it} + X'_{it}\gamma + \delta_t + u_{it}$)*, where* $after_{it}$ *is set to 1 in the years after spouse death. All specifications also include auxiliary control variables. Region and wave dummies are also always used. Standard errors are clustered by respondent and reported in parenthesis. *** p<0.01, ** p<0.05, * p<0.1*

Table 8: **DiD on Full Matched Sample, the role of Income**

Dependent Variable: Support Incumbent	Alternative Income Sources		Breadwinner		Interaction Breadwinner	
	Full	Female	Full	Female	Full	Female
	[1]	[2]	[3]	[4]	[5]	[6]
Treated	0.0583	0.0473	0.0595	0.0475	0.0605	0.0489
	(0.0452)	(0.0555)	(0.0451)	(0.0554)	(0.0451)	(0.0554)
After	0.0444*	0.0755**	0.0445*	0.0761**	0.0447*	0.0768**
	(0.0252)	(0.0313)	(0.0251)	(0.0311)	(0.0251)	(0.0312)
After*Treated	-0.0752**	-0.0930**	-0.0744**	-0.0920**	-0.120**	-0.193**
	(0.0359)	(0.0449)	(0.0358)	(0.0449)	(0.0501)	(0.0763)
After*Treated*No Breadwinner					-0.0379	-0.0547
					(0.0480)	(0.0532)
Respondent is Breadwinner			0.0250	0.0132	0.0493	0.0508
			(0.0462)	(0.0550)	(0.0507)	(0.0626)
Individual Income, by type:						
Labour & Non-Labour	-0.0094	-0.0162				
	(0.0268)	(0.0329)				
Only Labour	-0.0099	-0.0199				
	(0.0272)	(0.0328)				
Family Income			-0.00887	-0.0163	-0.00683	-0.0126
			(0.0265)	(0.0319)	(0.0265)	(0.0318)
Perceived Better Financial Situation	-0.0075	-0.0584	-0.00709	-0.0590	-0.00681	-0.0592
	(0.0353)	(0.0446)	(0.0353)	(0.0446)	(0.0352)	(0.0447)
Perceived Worse Financial Situation	-0.0181	-0.0467	-0.0187	-0.0470	-0.0190	-0.0484
	(0.0316)	(0.0373)	(0.0316)	(0.0373)	(0.0317)	(0.0374)
Observations	1,851	1,083	1,851	1,083	1,851	1,083
R-squared	0.041	0.049	0.041	0.049	0.043	0.052

*Note: Sample composition is 230 treated and 230 matched control individuals, then restricted to only female respondents in columns [2], [4] and [6]. OLS estimates are based on the regression showed in equation 4 ($SupportInc_{it} = \alpha + \lambda_1 xTreated_i + \lambda_2 xafter_{it} xtreated_i + \lambda_3 xafter_{it} + X'_{it}\gamma + \delta_t + u_{it}$), where $after_{it}$ is set to 1 in the years after spouse death, and include the same control variables, and the same fixed effects used in previous DID models. Column [1] and [2] additionally differentiate between labour and non-labour income sources, column [3] and [4] identify weather the respondent was the breadwinner for the majority of years preceding widowhood, and columns [5] and [6] allow for an heterogeneous treatment effect among the respondents who were and were not breadwinners. Standard errors are clustered by respondent and reported in parenthesis. *** p<0.01, ** p<0.05, * p<0.1*

Table 9: **DiD on Full Matched Sample, Effect of Labour Legislatures**

Dependent Variable: Support Incumbent	[1]	[2]	[3]	[4]	[5]	[6]
Treated	0.0410	0.0448	0.0581	0.0581	0.0581	0.0682
	(0.0406)	(0.0427)	(0.0458)	(0.0459)	(0.0459)	(0.0484)
After	0.0008	0.0047	0.0138	0.0138	0.0138	0.0136
	(0.0258)	(0.0240)	(0.0230)	(0.0231)	(0.0231)	(0.0231)
After*Treated	-0.0694	-0.0734	-0.114			
	(0.0760)	(0.0750)	(0.0709)			
After*Treated*Labour	0.0347	0.0247	0.0483			
	(0.0820)	(0.0816)	(0.0782)			
Treated*1 Year Before Spouse Death						-0.00712
						(0.0755)
Treated*1 Year Before Spouse Death* Labour						-0.0167
						(0.0927)
Treated*Year of Spouse Death				-0.0749	-0.0749	-0.0828
				(0.0744)	(0.0744)	(0.0857)
Treated*Year of Spouse Death* Labour				0.0143	0.0143	0.0116
				(0.0840)	(0.0841)	(0.0953)
Treated*(1,2)				-0.139*		
				(0.0779)		
Treated*(1,2) Years After Spouse Death*Labour				0.0705		
				(0.0839)		
Treated*1 Year After Spouse Death					-0.183**	-0.191**
					(0.0794)	(0.0891)
Treated*1 Year After Spouse Death*Labour					0.117	0.114
					(0.0860)	(0.0958)
Treated*2 Years After Spouse Death					-0.0811	-0.0891
					(0.0975)	(0.105)
Treated*2 Years After Spouse Death*Labour					0.0102	0.00744
					(0.104)	(0.112)
Labour Legislature	0.0622	0.0476	0.0394	0.0392	0.0393	0.0419
	(0.0471)	(0.0503)	(0.0553)	(0.0553)	(0.0554)	(0.0609)
Family Income	0.0001	-0.00188	-0.00957	-0.00941	-0.00968	-0.00969
	(0.0234)	(0.0243)	(0.0268)	(0.0268)	(0.0268)	(0.0269)
Perceived Better Financial Situation	0.00550	0.00327	-0.00463	-0.00526	-0.00549	-0.00612
	(0.0275)	(0.0312)	(0.0352)	(0.0354)	(0.0355)	(0.0355)
Perceived Worse Financial Situation	-0.0739***	-0.0455	-0.0260	-0.0272	-0.0271	-0.0273
	(0.0259)	(0.0283)	(0.0319)	(0.0321)	(0.0322)	(0.0323)
Observations	3,146	2,530	1,851	1,851	1,851	1,851
R-squared	0.022	0.019	0.019	0.019	0.020	0.020

Note: Sample composition is 230 treated and 230 matched control individuals; Models [1] and [2] further restrict, respectively, to four and three years before and after spouse death; Models [3] to [6] restrict to only two years before and after spouse death. OLS estimates are based on the regression showed in equation 4 ($SupportInc_{it} = \alpha + \lambda_1 xTreated_i + \lambda_2 xafter_{it} xtreated_i + \lambda_3 xafter_{it} + X'_{it}\gamma + \delta_t + u_{it}$)*, where* $after_{it}$ *is set to 1 in the years after spouse death. All specifications include the same control variables used in previous DID models, but in addition they introduce an interaction with the dummy Labour, which is 1 for all years when the Labour party held power. Standard errors are clustered by respondent and reported in parenthesis. *** p<0.01, ** p<0.05, * p<0.1*

Table 10: **DiD on Full Matched Sample, Voters Rationality**

Dependent Variable: Support Incumbent	[1]	[2]	[3]	[4]	[5]	[6]
Treated	0.0402	0.0457	0.0583	0.0583	0.0583	0.0634
	(0.0406)	(0.0423)	(0.0452)	(0.0452)	(0.0453)	(0.0475)
After	0.0243	0.0330	0.0441*	0.0441*	0.0440*	0.0440*
	(0.0301)	(0.0274)	(0.0253)	(0.0253)	(0.0254)	(0.0254)
After*Treated	-0.0450	-0.0562	-0.0768**			
	(0.0392)	(0.0368)	(0.0354)			
After*Treated*Switch	0.0556	0.0323	0.0360			
	(0.0985)	(0.109)	(0.131)			
Treated*1 Year Before Spouse Death						-0.00991
						(0.0284)
Treated*Year of Spouse Death					-0.0694*	-0.0744*
					(0.0381)	(0.0400)
Treated*Year of Spouse Death*Gov. Transition						
Treated*(0,1,2)				-0.0768**		
				(0.0354)		
Treated*(0,1,2) Years After Spouse Death*Gov. Transition				0.0360		
				(0.131)		
Treated*1 Years After Spouse Death					-0.0827**	-0.0879**
					(0.0399)	(0.0438)
Treated*1 Years After Spouse Death*Gov. Transition					-0.109	-0.108
					(0.169)	(0.170)
Treated*2 Years After Spouse Death					-0.0788*	-0.0839*
					(0.0430)	(0.0468)
Treated*2 Years After Spouse Death*Gov. Transition					0.131	0.131
					(0.138)	(0.138)
Family Income	0.00215	0.000601	-0.00952	-0.00952	-0.00921	-0.00922
	(0.0233)	(0.0243)	(0.0267)	(0.0267)	(0.0268)	(0.0268)
Perceived Better Financial Situation	0.00229	-0.00462	-0.00720	-0.00720	-0.00725	-0.00753
	(0.0274)	(0.0313)	(0.0354)	(0.0354)	(0.0356)	(0.0357)
Perceived Worse Financial Situation	-0.0681***	-0.0396	-0.0186	-0.0186	-0.0184	-0.0185
	(0.0257)	(0.0280)	(0.0317)	(0.0317)	(0.0320)	(0.0321)
Observations	3,146	2,530	1,851	1,851	1,851	1,851
R-squared	0.036	0.037	0.041	0.041	0.042	0.042

*Note: Sample composition is 230 treated and 230 matched control individuals; Models [1] and [2] further restrict, respectively, to four and three years before and after spouse death; Models [3] to [6] restrict to only two years before and after spouse death. OLS estimates are based on the regression showed in equation 4 ($SupportInc_{it} = \alpha + \lambda_1 x Treated_i + \lambda_2 x after_{it} x treated_i + \lambda_3 x after_{it} + X'_{it}\gamma + \delta_t + u_{it}$), where $after_{it}$ is set to 1 in the years after spouse death. All specifications include the same control variables used in previous DID models, but in addition they introduce an interaction with the dummy $Gov.Transition$, which is 1 for all cases where the party in power at the time of the interview differs from the party in power at the time of the spouse death. Standard errors are clustered by respondent and reported in parenthesis. *** p<0.01, ** p<0.05, * p<0.1*

7. Figures

Figure 1: **Distribution of Life Satisfaction Levels among British People.** Sample Composition: the 4,882 respondents observed over the interviews made between 1996 and 2008, in the context of the BHPS suvery.

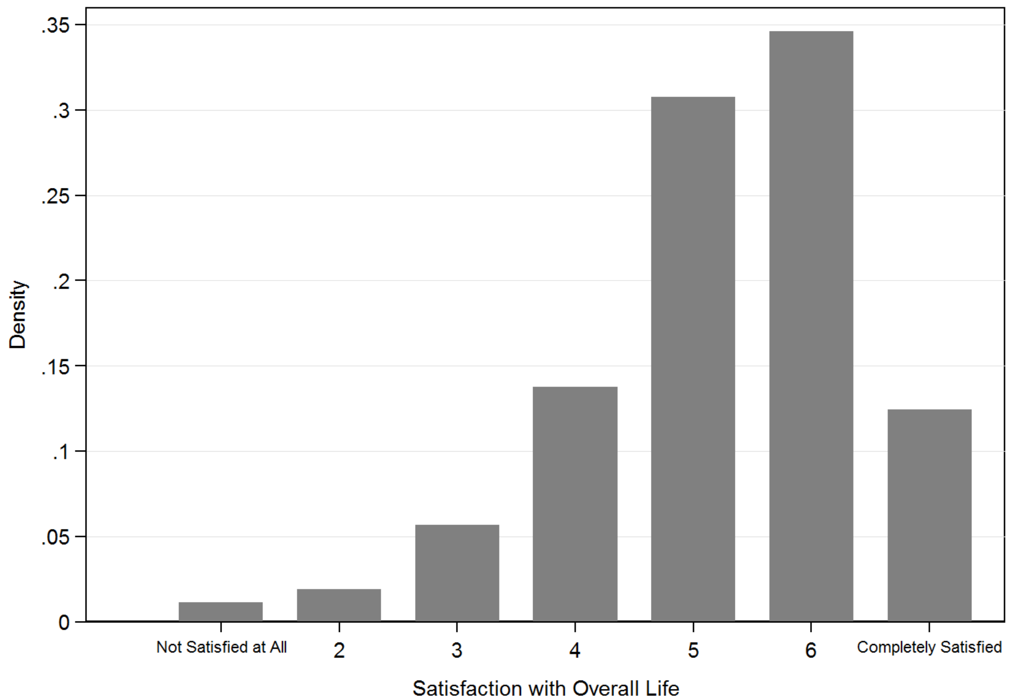


Figure 2: **Probability of Supporting the Incumbent Party.** Sample Composition: "all voters" refer to the 4,882 respondents observed over the interviews made between 1996 and 2008, while "swing voters" refer to the 1,520 respondents who classify as "swing" for at least 8 different years.

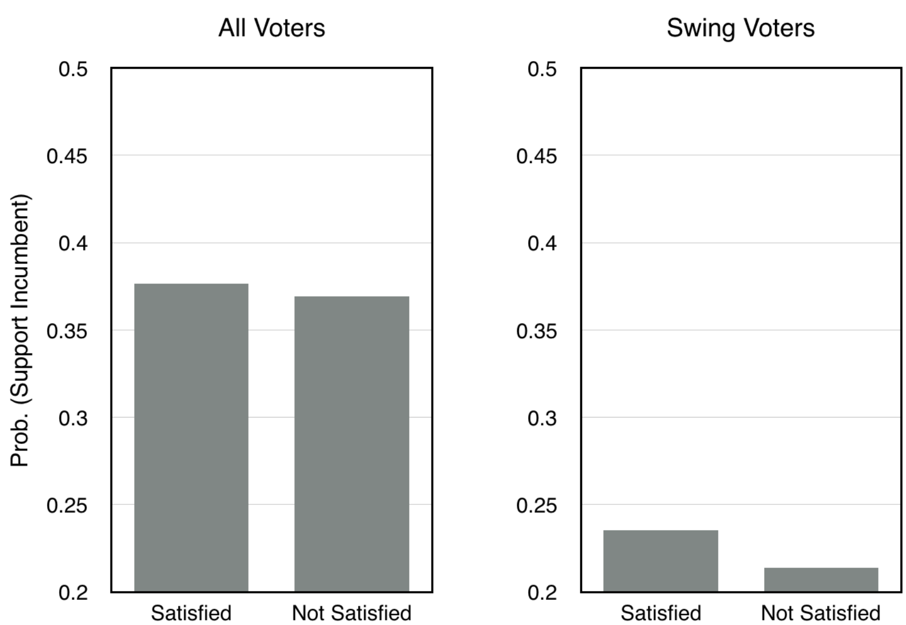


Figure 3: **Political Involvement of Swing Voters.** Sample Composition: the 4,882 respondents from the baseline sample are grouped according to the number of times they qualify as "swing" voters. The five variables of interest are normalized on the [0,1] interval, and averaged within respondent and over survey years.

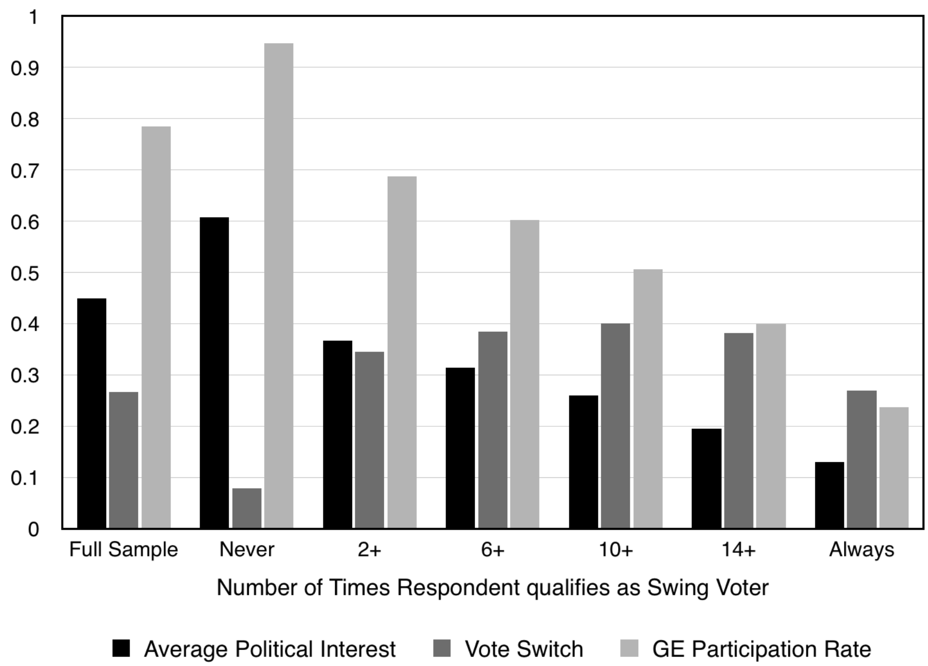


Figure 4: **Incumbent Support and Overall Life Satisfaction among Treated Respondents.** Sample Composition: the "Treated Group" figures compare the year of treatment for the 230 treated respondents with all the other years in the observational period; the "Years of Widowhood" figures compare the treated and the control group, for the year of the spouse's death and the two subsequent years.

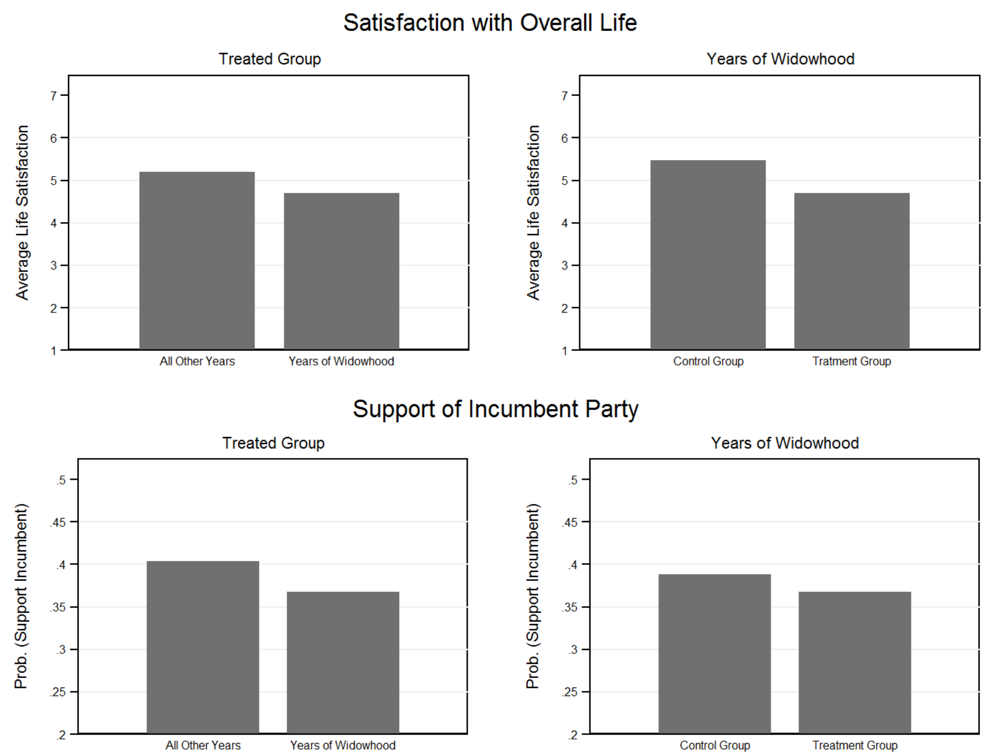
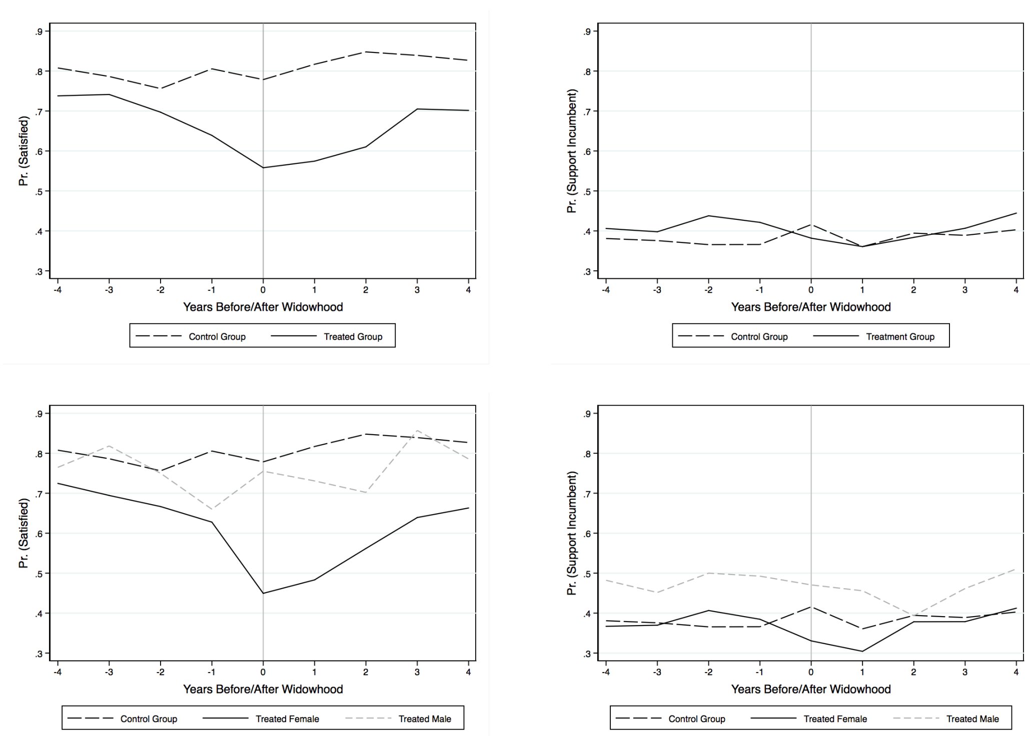


Figure 5: **Satisfaction with Overall Life and Support of Incumbent Party in the four Years Interval before and after Widowhood** Sample Composition: the top panel compares the treated and control group in the time preceding and following the year of death of the spouse; the bottom panels compare the control group with the separate subsamples of female and male respondents belonging to the treated group.



Online Appendix

A.1. Non-linear Estimation of Baseline Model

Tables A.1 and A.2 display the results from estimating the baseline model using a RE Probit and a FE Logit, respectively. Tables A.3 and A.4 repeat the same exercise, after restricting the sample to *swing* voters only.

For the RE-Probit models displayed in Tables A.1 and A.3 a direct comparison of the coefficients is not possible, because the change in the coefficient on the financial situation dummies from column [2] to columns [5] and [6] cannot be directly attributed to the inclusion of the SWB indicators (the confounding variable), due to rescaling.[22] Wooldrige (2002) and Cramer (2007) show that average partial effects (APE) derived from probit models are unaffected by rescaling only if financial situation and SWB indicators are uncorrelated. But, if this is not the case the APEs are biased. Karlos, Holm and Breen (2011) propose a method to decompose the change in probit coefficients into confounding and rescaling[23], which allows to make a direct comparison of the coefficients in nested models, i.e. equation (1) vs (3). Since our aim is to test how including measures of SWB affects previous standard models of retrospective voting, we follow their approach which consists on substituting the additional variable (*satisfaction with life* in this case) in (3) with the residuals from a regression of *satisfaction with life* on all the other controls included in (1).

The output from this exercise is displayed in the table A.5. The table is divided into two vertical panels, the first one reports regression outputs for the full sample of respondents, and the second one for the swing voters sample. In each panel there are three columns, the first and the third ones, denoted [2] and [6b], correspond respectively to columns [2] and [6] in tables A.1 and A.3. The second column, denoted [6a], reports regression outputs when the method proposed by Karlos, Holm and Breen (2011) is applied. The bottom part of the table reports the average partial effects.

[22] This is due to the fact that the variance of the underlying latent variable is not identified and will be different between models.

[23] Karlos, Holm and Breen (2011) offer a method that gives unbiased comparisons of logit or probit coefficients of the same variable (x) across same-sample nested models successively including control variables (z). This solution decomposes the difference in the logit or probit coefficient of x between a model excluding z and a model including z, into a part attributable to confounding (i.e., the part mediated or explained by z) and a part attributable to rescaling of the coefficient of x.

The interpretation of the results is as follow. Looking at the full sample, an improvement in the financial situation compared to the previous year increases the probability of supporting the incumbent by 1.41 percentage points. An increase of 10 % of the family income increases the probability of voting the incumbent of about 0.18 %. Note that the coefficients of better financial situation in columns [2] and [6b] are the same, suggesting that rescaling does not affect confounding. Controlling for satisfaction with life, this effect goes down to 1.36 percentage points, which is about a 4% decrease in the effect, due to confounding and net of rescaling. If we look instead at the effect of *satisfaction with life* on the worse financial situation dummy, we can see that there is a 14% reduction of the effect due to confounding net of rescaling. The coefficient on income is almost unaffected.

For the sample of swing voters, the confounding effect of life satisfaction on financial situation is stronger, for example there is a reduction of the effect of better financial situation dummy of about 12% due to the inclusion of life satisfaction measures, but for worse financial situation dummy this reduction is over 62%.

So in summary, this exercise have confirmed that SWB measures and financial situation indicators affect voting decisions mainly through different channels, and therefore should be both included as regressors. Note also the SWB measures appear to be to some extent more robust than financial indicators.

A.2. Validation of Propensity Score Regression

Table A.7 reports statistics for the reduction in bias attained through the matching procedure: it reports the test of equality in the means of all used covariates across the treated and control groups, both before and after matching. The results from the last column suggest that, for all covariates, we fail to reject the null of mean equality after the matching procedure is concluded. Figure A.1 and A.2 provide a graphical representation of the same bias reduction.

A.3. The Effect of Widowhood on SWB

To support the validity of our empirical strategy, we show in this section that widowhood actually constitutes a negative shock to life satisfaction, measured by self-reported subjective well-being. Using our matched sample, we run a difference-in-difference model to compare the effect widowhood had on the life satisfaction of the individuals who did experience such a shock to the effect such an event would have had on the counterfactual group. The respondents included in the analysis are the same used for the analysis in Section 4, but the sample is restricted to the years following 1996, as that is when we start observing SWB.

The study by Clark et al. (2008) shows that reported life satisfaction starts decreasing in the two years preceding the death of a spouse, reaches its lowest peak during the year of the spouse death, and then quickly readjusts toward the average level during the two years following the loss of the spouse. To test that our dataset also follows the same pattern, we estimate the following model:

$$Wellbeing_{it} = \alpha + \sigma_1 \times treated_i + \sigma_2 \times after_{it} \times treated_i + \sigma_3 \times after_{it} + \gamma \times X_{it} + \delta_t + u_{it}$$

The coefficient of interest is σ_2, which is the effect of widowhood on well-being for those individuals whose spouse died. We estimate several variations of this model, which include interacting $treated_i$ both with the sex of the respondents as well as with dummies indicating the number of years after the event, {*year of the death*}, {1, 2, 3, or 4 years after}.

The results for this exercise are reported in table A.12. Overall, in line with previous research, the shock of unhappiness is only significant for women, and it is reabsorbed after two years from the event. There is no evidence of a significant difference in the level of well-being between the treated and control groups three years from the event.

A.4. Widowhood as an Instrument of SWB

Our analysis relies on the underlying assumptions that experiencing widowhood directly affects subjective wellbeing. To further support the assumptions that motivated our identification strategy, we estimate a model where widowhood is explicitly used as an instrument for life satisfaction. Accounting for the fact that both the outcome variable, *SupportInc*, and the endogenous variable, $Wellbeing$, are discrete, we choose to estimate the following recursive bivariate probit model on the full sample of just above 4,800 individuals:

$$\begin{cases} SupportInc_i &= \delta_0 + \delta Wellbeing_i + \gamma_1 X_i + \epsilon_{1i} \\ Wellbeing_i &= \beta_0 + \beta Widowhood_i + \gamma_2 X_i + \epsilon_{2i} \end{cases} \tag{D.1}$$

where ϵ_{1i} and ϵ_{2i} are jointly distributed as bivariate normal with zero means, unit variances, and correlation ρ.[24] In this specification, the equation for well-being can be interpreted as the first step of an instrumental variable two-stage procedure, where widowhood plays the role of an exogenous instrument. The linear alternative to this specification (a standard IV-OLS model) provides consistent estimates of the average treatment effect, but is biased and has low small sample performance.[25]

The results from the estimation of this model are presented in table A.13, where we only show the estimated relevant parameters. Model (5) is estimated on the full sample. The negative ρ reported at the bottom of the table indicates that the estimated correlation between the errors of the two equations (which is the conditional tetrachoric correlation) is negative and highly significant. The table additionally confirms that experiencing widowhood has a negative and significant effect on well-being, which, in turn, has a significant effect on the probability of supporting the incumbent. These results confirm our previous findings and validate our DiD approach.

[24]The parameters of interest can be estimated by full information maximum likelihood (FIML).

[25]Chiburis, Das, and Lokshin (2011) run simulations similar to ours, and find that when there are no covariates, biprobit outperforms IV for sample sizes below 5000, and with a continuous covariate, biprobit outperforms IV in all of their simulations. They note that biprobit performs especially well when the treatment probability is close to 0 or 1, where linear methods are more likely to produce infeasible estimates.

A.5. Tables

Table A.1: **Baseline Equation, RE Probit Models on Full Sample of Respondents**

Dependent Variable: 1 If Supporting Incumbent Party		Financial Situation Only		Life Satisfaction Only		Financial Situation & Life Satisfaction	
		[1]	[2]	[3]	[4]	[5]	[6]
Family Income		0.0893***	0.0787***	0.0880***	0.0879***	0.0783***	0.0783***
		(0.0180)	(0.0181)	(0.0180)	(0.0180)	(0.0181)	(0.0181)
Financial Situation:	Better		0.0627***			0.0602***	0.0602***
			(0.0213)			(0.0213)	(0.0213)
	Worse		-0.0736***			-0.0682***	-0.0670***
			(0.0215)			(0.0216)	(0.0217)
Satisfied with Life: [5,6,7]				0.0829***		0.0699***	
				(0.0231)		(0.0233)	
Satisfaction with Life: [1,2,. . . ,7]					0.0317***		0.0263***
					(0.0086)		(0.0087)
Log-likelihood		-22134	-22119	-22128	-22127	-22114	-22114
Observations		48,432	48,432	48,432	48,432	48,432	48,432
Number of pid		4,882	4,882	4,882	4,882	4,882	4,882
A.P.E w.r.t. Satisfaction with Life				0.0185	0.0071	0.0156	0.0059
				(0.0049)	(0.0018)	(0.0050)	(0.0018)

*Note: Baseline model looking at determinants of the probability of supporting the incumbent party. Models are estimated using an RE probit. Sample: 4,882 respondents observed since 1996. All specifications include auxiliary control variables (a dummy for "married" individuals, age, age squared, and a dummy for female respondents). Region and wave dummies are always included. The variable "lfsato" from BHPS was used to define the level of life satisfaction. It is equal to seven different levels of life satisfaction, varying from completely satisfied (=7) to not at all satisfied (=1). For Model [2] and Model [4], the variable is recoded as a dummy identifying whether the individual is satisfied (>4), whereas for Model [3] and [5], life satisfaction is used as a continuous variable. The Chamberlain RE probit estimates are obtained after controlling for observable respondent-specific time invariant characteristics. Standard errors are reported in parenthesis. *** p<0.01, ** p<0.05, * p<0.1*

Table A.2: **Baseline Equation, FE Logit Models on Full Sample of Respondents**

Dependent Variable: 1 If Supporting Incumbent Party		Financial Situation Only		Life Satisfaction Only		Financial Situation & Life Satisfaction	
		[1]	[2]	[3]	[4]	[5]	[6]
Family Income		0.1463***	0.1270***	0.1433***	0.1430***	0.1258***	0.1257***
		(0.0328)	(0.0330)	(0.0328)	(0.0328)	(0.0330)	(0.0330)
Financial Situation:	Better		0.1132***			0.1085***	0.1082***
			(0.0394)			(0.0394)	(0.0394)
	Worse		-0.1147***			-0.1048***	-0.1033***
			(0.0397)			(0.0399)	(0.0399)
Satisfied with Life: [5,6,7]				0.1527***		0.1303***	
				(0.0438)		(0.0441)	
Satisfaction with Life: [1,2,...,7]					0.0592***		0.0499***
					(0.0167)		(0.0168)
Log-Likelihood		-11321	-11309	-11315	-11315	-11304	-11304
Observations		37,902	37,902	37,902	37,902	37,902	37,902
Number of pid		3,705	3,705	3,705	3,705	3,705	3,705

*Note: Baseline model looking at determinants of the probability of supporting the incumbent party. Models are estimated using an Conditional FE Logit. Sample: 3,705 respondents observed since 1996 and changing political intention at least once during the course of the survey. All specifications include auxiliary control variables (a dummy for "married" individuals, age, age squared, and a dummy for female respondents). Region and wave dummies are always included. The variable "lfsato" from BHPS was used to define the level of life satisfaction. It is equal to seven different levels of life satisfaction, varying from completely satisfied (=7) to not at all satisfied (=1). For Model [2] and Model [4], the variable is recoded as a dummy identifying whether the individual is satisfied (>4), whereas for Model [3] and [5], life satisfaction is used as a continuous variable. *** $p<0.01$, ** $p<0.05$, * $p<0.1$*

Table A.3: **Reducing endogeneity bias, RE Probit Models on a Restricted Sample of Swing Voters**

Dependent Variable: 1 If Supporting Incumbent Party		Financial Situation Only		Life Satisfaction Only		Financial Situation & Life Satisfaction	
		[1]	[2]	[3]	[4]	[5]	[6]
Family Income		0.0917**	0.0849**	0.0894**	0.0890**	0.0840**	0.0840**
		(0.0369)	(0.0371)	(0.0369)	(0.0073)	(0.0369)	(0.0371)
Financial Situation:	Better		0.0528			0.0494	0.0479
			(0.0405)			(0.0417)	(0.0406)
	Worse		-0.0291			-0.0176	-0.0139
			(0.0436)			(0.0441)	(0.0438)
Satisfied with Life: [5,6,7]				0.1277***		0.1218***	
				(0.0445)		(0.0448)	
Satisfaction with Life: [1,2,. . . ,7]					0.0540***		0.0518***
					(0.0163)		(0.0169)
Log-likelihood		-5,419	-5,417	-5,415	-5,413	-5,414	-5,412
Observations		12,926	12,926	12,926	12,926	12,926	12,926
Number of pid		1,520	1,520	1,520	1,520	1,520	1,520
A.P.E. w.r.t. Satisfaction with Life				0.0242	0.0104	0.0231	0.0100
				(0.0085)	(0.0032)	(0.0086)	(0.0033)

*Note: Baseline model looking at determinants of the probability of supporting the incumbent party. Models are estimated using an RE probit. Sample: 1,520 respondents who are classified as "Swing voters'. All specifications include auxiliary control variables (a dummy for "married" individuals, age, age squared, and a dummy for female respondents). Region and wave dummies are always included. The variable "lfsato" from BHPS was used to define the level of life satisfaction. It is equal to seven different levels of life satisfaction, varying from completely satisfied (=7) to not at all satisfied (=1). For Model [2] and Model [4], the variable is recoded as a dummy identifying whether the individual is satisfied (>4), whereas for Model [3] and [5], life satisfaction is used as a continuous variable. The Chamberlain RE probit estimates are obtained after controlling for observable respondent-specific time invariant characteristics. Standard errors are reported in parenthesis. *** p<0.01, ** p<0.05, * p<0.1*

Table A.4: **Reducing endogeneity bias, FE Logit Models on a Restricted Sample of Swing Voters**

Dependent Variable: 1 If Supporting Incumbent Party		Financial Situation Only		Life Satisfaction Only		Financial Situation & Life Satisfaction	
		[1]	[2]	[3]	[4]	[5]	[6]
Family Income		0.1388**	0.1284*	0.1344**	0.1331**	0.1263*	0.1259*
		(0.0664)	(0.0665)	(0.0664)	(0.0664)	(0.0665)	(0.0665)
Financial Situation:	Better		0.1032			0.0979	0.0934
			(0.0771)			(0.0771)	(0.0772)
	Worse		-0.0237			-0.0032	0.0023
			(0.0806)			(0.0811)	(0.0811)
Satisfied with Life: [5,6,7]				0.2287***		0.2205**	
				(0.0863)		(0.0870)	
Satisfaction with Life: [1,2,. . . ,7]					0.1022***		0.0987***
					(0.0326)		(0.0330)
Log-Likelihood		-2,686	-2,684	-2,682	-2,681	-2,681	-2,680
Observations		8,057	8,057	8,057	8,057	8,057	8,057
Number of pid		920	920	920	920	920	920

*Note: Baseline model looking at determinants of the probability of supporting the incumbent party. Models are estimated using an Conditional FE Logit. Sample: 8,057 respondents observed since 1996 who are classified as "Swing voters' and who change political intention at least once during the course of the survey. All specifications include auxiliary control variables (a dummy for "married" individuals, age, age squared, and a dummy for female respondents). Region and wave dummies are always included. The variable "lfsato" from BHPS was used to define the level of life satisfaction. It is equal to seven different levels of life satisfaction, varying from completely satisfied (=7) to not at all satisfied (=1). For Model [2] and Model [4], the variable is recoded as a dummy identifying whether the individual is satisfied (>4), whereas for Model [3] and [5], life satisfaction is used as a continuous variable. *** p<0.01, ** p<0.05, * p<0.1*

Table A.5: **Baseline Equation, Average Partial Effect (APE) Comparison**

	Full Sample:			Swing Voters:		
Dependent Variable:	Financial Situation	Financial Situation and Life Satisfaction		Financial Situation	Financial Situation and Life Satisfaction	
1 If Supporting Incumbent Party	[2]	[6a]	[6b]	[2]	[6a]	[6b]
Financial Situation: Better	0.0627***	0.0602***	0.0631***	0.0528	0.0479	0.0531
	(0.0213)	(0.0213)	(0.0204)	(0.0405)	(0.0406)	(0.0405)
Worse	-0.0736***	-0.067***	-0.0731***	-0.0291	-0.0139	-0.0288
	(0.0215)	(0.0217)	(0.0210)	(0.0436)	(0.0438)	(0.0437)
Family Income	0.0787***	0.0783***	0.0785***	0.0849**	0.0840**	0.0847**
	(0.0181)	(0.0181)	(0.0161)	(0.0371)	(0.0371)	(0.0347)
Satisfaction with Life: [1,2,. . . ,7]		0.0263***	0.0263***		0.0518***	0.0518***
		(0.0087)	(0.0083)		(0.0169)	(0.0169)
Log-likelihood	-22,119	-22,114	-22,115	-5,417	-5,412	-5,412
Observations	48,432	48,432	48,432	12,926	12,926	12,926
Number of pid	4,882	4,882	4,882	1,520	1,520	1,520
A.P.E. w.r.t. :						
Better Financial Situation	0.0141	0.0136	0.0141	0.0103	0.0093	0.0103
	(0.0046)	(0.0046)	(0.0046)	(0.0079)	(0.0079)	(0.0079)
Worse Financial Situation	-0.0163	-0.0148	-0.0162	-0.0056	-0.0027	-0.0055
	(0.0046)	(0.0047)	(0.0046)	(0.0084)	(0.0084)	(0.0084)
Family Income	0.0176	0.0175	0.0175	0.0164	0.0162	0.0163
	(0.0036)	(0.0036)	(0.0036)	(0.0067)	(0.0067)	(0.0067)
Satisfaction with Life		0.0059	0.0059		0.0100	0.0100
		(0.0018)	(0.0018)		(0.0033)	(0.0033)

*Note: Baseline model looking at determinants of the probability of supporting the incumbent party. Models are estimated using an RE probit. All specifications include auxiliary control variables (a dummy for "married" individuals, age, age squared, and a dummy for female respondents). Region and wave dummies are always included. For Models [5b], the variable "Satisfaction with Life" is replaced by the residuals from a regression of "Satisfaction with Life" on all other control variables included in Model [1]. The Chamberlain RE probit estimates are obtained after controlling for observable respondent-specific time invariant characteristics. Standard errors are reported in parenthesis. *** p<0.01, ** p<0.05, * p<0.1*

Table A.6: **Robustness Checks to Baseline Model (RE Probit), Each Level of Life Satisfaction**

Dependent Variable: 1 If Supporting Incumbent Party		Full Sample [1]	Swing Voters [2]
Financial Situation:	Better	0.0589***	0.0457
		(0.0213)	(0.0418)
	Worse	-0.0680***	-0.0195
		(0.0217)	(0.0443)
Level of Life Satisfaction:	[=1]	-0.0279	-0.1620
		(0.0880)	(0.1629)
	[=2]	-0.0006	0.1015
		(0.0683)	(0.1297)
	[=3]	-0.1750***	-0.2944***
		(0.0481)	(0.0921)
	[=4]	-0.0889**	-0.1571**
		(0.0385)	(0.0734)
	[=5]	-0.0493	-0.1088*
		(0.0338)	(0.0656)
	[=6]	-0.0044	0.0334
		(0.0316)	(0.0619)
Constant		-0.687*	-0.2424
		(0.398)	(0.6612)
Log-Likelihood		-22107	-5403.50
Observations		48,432	12,926
Number of Respondents		4,882	1,520
APE w.r.t. Life Sat.= 3		-0.0382	-0.0533
		(0.0100)	(0.0156)
APE w.r.t. Life Sat.= 4		-0.0195	-0.0296
		(0.0081)	(0.0135)
APE w.r.t. Life Sat.= 5		-0.0107	-0.0210
		(0.0070)	(0.0124)

*Note: Robustness check for baseline model looking at determinants of the probability of supporting the incumbent party. Models are estimated using an RE probit model. Sample: full sample of 4,882 respondents, as in tables 3 and 4, and restricted sample of 1,520 less partisan voters, as in tables 5 and 6. All specifications include auxiliary control variables (a dummy for "married" individuals, the natural logarithm of yearly household income, age, and age squared, and a dummy for female respondents), and time invariant characteristics used for Chamberlain specification. Region and wave dummies are always included. Life satisfaction = 7 is the baseline level. Standard errors are reported in parenthesis. *** p<0.01, ** p<0.05, * p<0.1*

Table A.7: **Propensity Score - Test on Mean Equality Before and After Matching**

	Sample	Bias		Mean		Equality of Means	
		Treated	Control	%	% Red.	t-test	p>t
Age in 1991	*Unmatched*	56.436	39.116	135.2		24.890	0.000
	Matched	50.561	50.522	0.3	99.8	0.030	0.972
Female	*Unmatched*	0.732	0.545	39.6		6.880	0.000
	Matched	0.665	0.665	0	100	0.000	1.000
In Working Age in 1991	*Unmatched*	0.556	0.958	-106		-29.560	0.000
	Matched	0.822	0.809	3.4	96.8	0.360	0.719
Dummy: 1 If Ever Smoked in Life	*Unmatched*	0.260	0.275	-3.3		-0.590	0.558
	Matched	0.283	0.243	8.8	-171.3	0.950	0.342
Dummy: 1 If Had Permanent Job in 1991	*Unmatched*	0.381	0.695	-66.2		-12.270	0.000
	Matched	0.539	0.565	-5.5	91.7	-0.560	0.575
Dummy: 1 If Employed Full Time in 1991	*Unmatched*	0.288	0.580	-61.6		-10.800	0.000
	Matched	0.413	0.426	-2.8	95.5	-0.280	0.777
Dummy: 1 If Spouse/Husband Was Employed in 1991	*Unmatched*	0.318	0.629	-65.5		-11.710	0.000
	Matched	0.465	0.474	-1.8	97.2	-0.190	0.852
ln (Household Income) in 1991	*Unmatched*	9.461	9.899	-63.5		-11.970	0.000
	Matched	9.658	9.731	-10.5	83.4	-1.150	0.251
Dummy: 1 If in Good Health in 1991	*Unmatched*	0.764	0.792	-6.7		-1.230	0.219
	Matched	0.757	0.804	-11.5	-72.7	-1.240	0.216
Dummy: 1 If Visited GP More Than Twice in 1991	*Unmatched*	0.737	0.763	-6.1		-1.120	0.262
	Matched	0.704	0.709	-1	83.5	-0.100	0.919
Dummy: 1 If Ever Hospitalized in 1991	*Unmatched*	0.093	0.114	-6.8		-1.200	0.230
	Matched	0.104	0.078	8.6	-25	0.970	0.333
Dummy: 1 If Ever Used Alternative Medicine	*Unmatched*	0.055	0.040	6.8		1.320	0.187
	Matched	0.057	0.061	-2	70.1	-0.200	0.843
Dummy: 1 If Regularly Checks Blood Pressure	*Unmatched*	0.548	0.525	4.5		0.820	0.411
	Matched	0.522	0.522	0	100	0.000	1.000
Dummy: 1 If Regularly Does Chest X-ray	*Unmatched*	0.156	0.135	5.9		1.090	0.274
	Matched	0.148	0.143	1.2	79.1	0.130	0.895
Dummy: 1 If Regularly Checks Cholesterol	*Unmatched*	0.110	0.131	-6.7		-1.180	0.239
	Matched	0.139	0.117	6.7	0.3	0.700	0.487

Note: Sample composition is 363 treated observations, 230 of which are on support, and 3,3280 control observations, 230 of which are matched. The table reports the mean of the covariates relevant to the propensity score estimation, across the treated and control groups for both the matched and the unmatched samples. It also indicates the bias across the treated and control groups and a reduction in bias when adopting the matching procedure. Finally, it shows the results for a test of equality in the means of these covariates across the treated and control groups before and after the matching.

Table A.8: **DiD on Full Matched Sample (Linear Probability Model)**

Dependent Variable: Support Incumbent	Homogeneous Treatment Effect		Gender Specific Treatment Effect	
	[1]	[2]	[3]	[4]
Treated	0.0583	0.0584	0.0584	0.0584
	(0.0452)	(0.0452)	(0.0452)	(0.0452)
After	0.0444*	0.0445*	0.0445*	0.0446*
	(0.0251)	(0.0251)	(0.0251)	(0.0252)
Treated*Year of Spouse Death	-0.0694*	-0.0696*		
	(0.0380)	(0.0381)		
Treated*Year of Spouse Death*Female			-0.0909*	-0.0912*
			(0.0483)	(0.0484)
Treated*Year of Spouse Death*Male			-0.0317	-0.0317
			(0.0620)	(0.0620)
Treated*(1,2) Years After Spouse Death	-0.0780**			
	(0.0386)			
Treated*(1,2) Years After Spouse Death*Female			-0.0886*	
			(0.0467)	
Treated*(1,2) Years After Spouse Death*Male			-0.0589	
			(0.0615)	
Treated*1 Year After Spouse Death		-0.0895**		
		(0.0408)		
Treated*1 Year After Spouse Death*Female				-0.124**
				(0.0500)
Treated*1 Year After Spouse Death*Male				-0.0302
				(0.0658)
Treated*2 Years After Spouse Death		-0.0658		
		(0.0434)		
Treated*2 Years After Spouse Death*Female				-0.0516
				(0.0522)
Treated*2 Years After Spouse Death*Male				-0.0908
				(0.0696)
Family Income	-0.0094	-0.0095	-0.0093	-0.0100
	(0.0268)	(0.0268)	(0.0268)	(0.0268)
Perceived Better Financial Situation	-0.0080	-0.0074	-0.0089	-0.0099
	(0.0356)	(0.0356)	(0.0355)	(0.0356)
Perceived Worse Financial Situation	-0.0185	-0.0178	-0.0181	-0.0176
	(0.0318)	(0.0319)	(0.0318)	(0.0319)
Observations	1,851	1,851	1,851	1,851
R-squared	0.041	0.041	0.041	0.042

*Note: Sample composition is 230 treated and 230 matched control individuals; Models [1]-[6] and [2]-[7] further restrict, respectively, to four and three years before and after spouse death; Models [3] to [5] and [8] to [10] restrict to only two years before and after spouse death. OLS estimates are based on the regression showed in equation 4 ($SupportInc_{it} = \alpha + \lambda_1 xTreated_i + \lambda_2 xafter_{it} xtreated_i + \lambda_3 xafter_{it} + X'_{it}\gamma + \delta_t + u_{it}$), where $after_{it}$ is set to 1 in the years after spouse death. All specifications also include auxiliary control variables (a dummy for "married" individuals, age, and age squared). Region and wave dummies are also always used. Standard errors are clustered by respondent and reported in parenthesis. *** p<0.01, ** p<0.05, * p<0.1*

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Table A.9: **DiD on Matched Sample of Female Respondents, LPM**

Dependent Variable: Support Incumbent	[1]	[2]	[3]	[4]	[5]	[6]
Treated	0.0319	0.0372	0.0470	0.0470	0.0471	0.0508
	(0.0506)	(0.0527)	(0.0555)	(0.0555)	(0.0555)	(0.0583)
After	0.0576	0.0616*	0.0761**	0.0762**	0.0763**	0.0762**
	(0.0362)	(0.0332)	(0.0310)	(0.0311)	(0.0311)	(0.0311)
After*Treated	-0.0581	-0.0724	-0.0921**			
	(0.0490)	(0.0463)	(0.0449)			
Treated*1 Year Before Spouse Death						-0.007
						(0.0327)
Treated*Year of Spouse Death				-0.0938*	-0.0943*	-0.0980*
				(0.0490)	(0.0491)	(0.0512)
Treated*(1,2) Years After Spouse Death				-0.0912*		
				(0.0482)		
Treated*1 Year After Spouse Death					-0.126**	-0.130**
					(0.0513)	(0.0545)
Treated*2 Years After Spouse Death					-0.0552	-0.0589
					(0.0537)	(0.0574)
Family Income	0.00202	-0.00245	-0.0171	-0.0172	-0.0180	-0.0180
	(0.0269)	(0.0285)	(0.0325)	(0.0326)	(0.0327)	(0.0327)
Perceived Better Financial Situation	-0.0420	-0.0524	-0.0592	-0.0591	-0.0587	-0.0590
	(0.0345)	(0.0386)	(0.0447)	(0.0450)	(0.0450)	(0.0451)
Perceived Worse Financial Situation	-0.0874***	-0.0623*	-0.0469	-0.0468	-0.0450	-0.0451
	(0.0309)	(0.0332)	(0.0373)	(0.0376)	(0.0377)	(0.0377)
Observations	2,064	1,657	1,208	1,208	1,208	1,208
R-squared	0.031	0.037	0.048	0.049	0.049	0.049

*Note: Sample reduced to only female matched individuals; Models [1] and [2] further restrict, respectively, to four and three years before and after spouse death; Models [3] to [6] restrict to only two years before and after spouse death. OLS estimates are based on the regression showed in equation 4 ($SupportInc_{it} = \alpha + \lambda_1 xTreated_i + \lambda_2 xafter_{it} xtreated_i + \lambda_3 xafter_{it} + X'_{it}\gamma + \delta_t + u_{it}$), where $after_{it}$ is set to 1 in the years after spouse death. All specifications also include auxiliary control variables (a dummy for "married" individuals, age, and age squared). Region and wave dummies are also always used. Standard errors are clustered by respondent and reported in parenthesis. *** p<0.01, ** p<0.05, * p<0.1*

Table A.10: **DiD on Matched Sample of Male Respondents, LPM**

Dependent Variable: Support Incumbent	[1]	[2]	[3]	[4]	[5]	[6]
Treated	0.0548	0.0579	0.0649	0.0649	0.0649	0.0693
	(0.0687)	(0.0718)	(0.0781)	(0.0782)	(0.0783)	(0.0835)
After	-0.0378	-0.0226	-0.0153	-0.0155	-0.0157	-0.0157
	(0.0520)	(0.0482)	(0.0445)	(0.0446)	(0.0446)	(0.0447)
After*Treated	-0.00222	-0.0177	-0.0333			
	(0.0701)	(0.0660)	(0.0612)			
Treated*1 Year Before Spouse Death						-0.0085
						(0.0556)
Treated*Year of Spouse Death				-0.0169	-0.0164	-0.0208
				(0.0618)	(0.0619)	(0.0677)
Treated*(1,2) Years After Spouse Death				-0.0420		
				(0.0666)		
Treated*1 Year After Spouse Death					-0.0140	-0.0184
					(0.0702)	(0.0804)
Treated*2 Years After Spouse Death					-0.0731	-0.0774
					(0.0757)	(0.0854)
Family Income	0.0012	0.0031	-0.0056	-0.0056	-0.0059	-0.0060
	(0.0470)	(0.0482)	(0.0485)	(0.0485)	(0.0485)	(0.0485)
Perceived Better Financial Situation	0.0861*	0.0854	0.0873	0.0861	0.0828	0.0828
	(0.0446)	(0.0522)	(0.0553)	(0.0557)	(0.0562)	(0.0562)
Perceived Worse Financial Situation	-0.0505	-0.0155	0.0214	0.0204	0.0184	0.0183
	(0.0467)	(0.0527)	(0.0612)	(0.0615)	(0.0620)	(0.0621)
Observations	1,083	874	644	644	644	644
R-squared	0.057	0.057	0.060	0.060	0.061	0.061

*Note: Sample reduced to only male matched individuals; Models [1] and [2] further restrict, respectively, to four and three years before and after spouse death; Models [3] to [6] restrict to only two years before and after spouse death. OLS estimates are based on the regression showed in equation 4 ($SupportInc_{it} = \alpha + \lambda_1 xTreated_i + \lambda_2 xafter_{it} xtreated_i + \lambda_3 xafter_{it} + X'_{it}\gamma + \delta_t + u_{it}$), where $after_{it}$ is set to 1 in the years after spouse death. All specifications also include auxiliary control variables (a dummy for "married" individuals, age, and age squared). Region and wave dummies are also always used. Standard errors are clustered by respondent and reported in parenthesis. *** p<0.01, ** p<0.05, * p<0.1*

Table A.11: **DID on Swing Voters**

Dependent Variable: Support Incumbent	Full Sample [1]	Females [2]	Males [3]
Treated	0.0274	0.0274	0.000371
	(0.0527)	(0.0643)	(0.0947)
After	0.0380	0.0775**	-0.0692
	(0.0306)	(0.0362)	(0.0613)
Treated * Year of Spouse Death		-0.120**	0.0416
		(0.0599)	(0.0850)
Treated * Year of Spouse Death * Female	-0.102*		
	(0.0585)		
Treated * Year of Spouse Death * Male	-0.0315		
	(0.0789)		
Treated * 1 Year after Spouse Death		-0.131**	0.0626
		(0.0647)	(0.0933)
Treated * 1 Year after Spouse Death * Female	-0.109*		
	(0.0626)		
Treated * 1 Year after Spouse Death * Male	-0.0117		
	(0.0839)		
Treated * 2 Year after Spouse Death		-0.0556	-0.0175
		(0.0669)	(0.106)
Treated * 2 Year after Spouse Death * Female	-0.0336		
	(0.0643)		
Treated * 2 Year after Spouse Death * Male	-0.103		
	(0.0906)		
Perceived Better Financial Situation	-0.000282	-0.0665	0.126*
	(0.0419)	(0.0523)	(0.0666)
Perceived Worse Financial Situation	-0.0295	-0.0682	0.0484
	(0.0381)	(0.0444)	(0.0759)
Family Income	-0.0349	-0.0457	-0.00959
	(0.0351)	(0.0433)	(0.0648)
Observations	1,310	901	409
R-squared	0.061	0.067	0.096

*Note: Sample reduced to only non-partisan voters, defined as in table 4; columns [2] and [3] further restrict, respectively, to only female and only males matched respondents. OLS estimates are based on the regression showed in equation 4 ($SupportInc_{it} = \alpha + \lambda_1 xTreated_i + \lambda_2 xafter_{it} xtreated_i + \lambda_3 xafter_{it} + X'_{it}\gamma + \delta_t + u_{it}$), where $after_{it}$ is set to 1 in the years after spouse death. All specifications also include auxiliary control variables (a dummy for "married" individuals, age, and age squared). Region and wave dummies are also always used. Standard errors are clustered by respondent and reported in parenthesis. *** p<0.01, ** p<0.05, * p<0.1*

Table A.12: **Results from Difference-in-Difference Estimates of Widowhood on Life Satisfaction**

Dependent Variable: Life Satisfaction	(1)	(2)	(3)	(4)	(5)	(6)
Treated	-0.210	-0.212	-0.212	-0.208	-0.210	-0.209
	(0.132)	(0.132)	(0.132)	(0.132)	(0.132)	(0.132)
After*Treated	-0.400***					
	(0.120)					
After*Treated*Female				-0.520***		
				(0.141)		
After*Treated*Male				-0.156		
				(0.157)		
Treated*Year of Spouse Death		-0.658***	-0.658***			
		(0.147)	(0.147)			
Treated*Year of Spouse Death*Female					-0.865***	-0.865***
					(0.180)	(0.181)
Treated*Year of Spouse Death*Male					-0.252	-0.252
					(0.193)	(0.193)
Treated*(1,2) Years After Spouse Death		-0.473***				
		(0.129)				
Treated*(1,2) Years After Spouse Death*Female					-0.615***	
					(0.156)	
Treated*(1,2) Years After Spouse Death*Male					-0.195	
					(0.173)	
Treated*(3,4) Years After Spouse Death		-0.192				
		(0.130)				
Treated*(3,4) Years After Spouse Death*Female					-0.258*	
					(0.149)	
Treated*(3,4) Years After Spouse Death*Male					-0.0565	
					(0.189)	
Treated*1 Year After Spouse Death			-0.514***			
			(0.139)			
Treated*1 Year After Spouse Death*Female						-0.624***
						(0.169)
Treated*1 Year After Spouse Death*Male						-0.304
						(0.192)
Treated*2 Years After Spouse Death			-0.428***			
			(0.146)			
Treated*2 Years After Spouse Death*Female						-0.606***
						(0.176)
Treated*2 Years After Spouse Death*Male						-0.0739
						(0.205)
Treated*3 Years After Spouse Death			-0.121			
			(0.143)			
Treated*3 Years After Spouse Death*Female						-0.181
						(0.167)
Treated*3 Years After Spouse Death*Male						0.0005
						(0.206)
Treated*4 Years After Spouse Death			-0.263*			
			(0.142)			
Treated*4 Years After Spouse Death*Female						-0.334**
						(0.161)
Treated*4 Years After Spouse Death*Male						-0.115
						(0.228)
Observations	2,617	2,617	2,617	2,617	2,617	2,617
R-squared	0.093	0.097	0.098	0.095	0.101	0.102

*Note: The sample used is restricted to 4 years before and after the event. All specifications also include auxiliary control variables (a dummy for "married" individuals, the natural logarithm of yearly household income, age, and age squared). Region and wave dummies are also always used. Robust standard errors, clustered at the individual level, are in parentheses. *significant at * 10, ** 5, *** 1%.*

Table A.13: **Bivariate Probit**

	Model (1): Full Sample		Model (2): Labour Legislations Only	
Dependent Variable:	Support Incumbent	Satisfied	Support Incumbent	Satisfied
Satisfied with Life [lfsato=5,6,7]	0.6349***		0.5759***	
	(0.0799)		(0.0863)	
Widowhood		-0.2244***		-0.1937**
		(0.0814)		(0.0844)
Constant	-0.7873***	0.3219***	0.1183	0.3616***
	(0.1038)	(0.0921)	(0.1142)	(0.0992)
Observations	48,432		44,149	
Log-Likelihood	-55533.84		-50547.93	
Rho	-0.3596***		-0.3324***	
	(0.0484)		(0.0519)	
Wald Test (rho = 0)	7.3776		4.8554	
	0.0066		0.0276	

*Note: Sample composition for Model (1) is all respondents observed since 1996; Model (2) restricts this sample to survey waves collected during Labour legislatures only. Respondents who never married and respondents always recorded as widow(er)s are excluded from the analysis. Models are estimated using a recursive bivariate probit, where the probability of supporting the incumbent depends on life satisfaction, which, in turn, is affected by widowhood. All specifications also include auxiliary control variables (a dummy for "married" individuals, the natural logarithm of yearly household income, age, and age squared), and region and wave dummies. Standard errors are in parenthesis. *** p<0.01, ** p<0.05, * p<0.1*

A.6. Figures

Figure A.1: **Covariates Imbalance Before and After Matching**

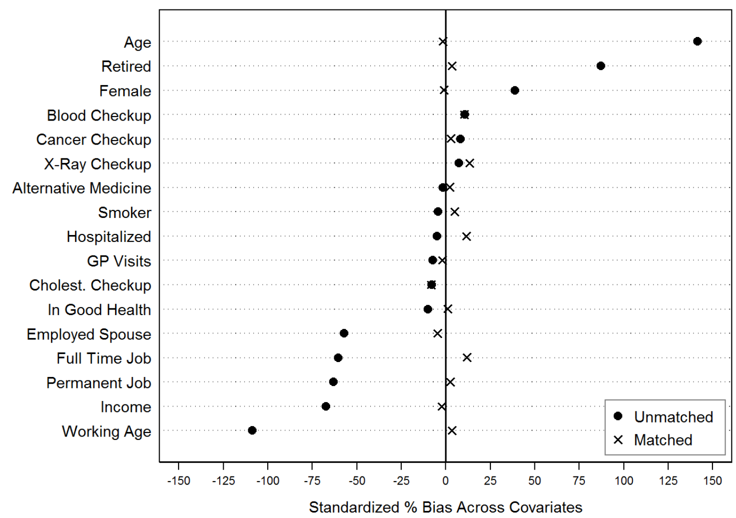

Figure A.2: **Histogram of Propensity Score, Conditional on Treatment Status**