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Labor Supply Response to Windfall Gains

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Abstract
Using a large survey of euro area consumers, we design an experiment in which respondents report how they would change the decision to participate in the labor market, the hours worked, and their search effort (if not employed) in response to randomly assigned windfall gain scenarios. Windfall gains reduce labor supply, but only if they are significant in size. At the extensive margin, we find no effect for gains below €25,000, and a decline in the probability of working of 3 percentage points for gains between €25,000 and €100,000. At the intensive margin, there is no effect for small gains, and a drop of roughly one weekly hour for gains above €50,000. Women and workers closer to retirement respond more strongly to windfall gains. Finally, the proportion of those who stop searching for a job or search less intensively falls by 1 percentage point for each €10,000 gain, and the effect is more pronounced for older individuals receiving the largest prize.

JEL Classification: E24, D10, J22, J68

Keywords: Survey Experiment; Labor Supply; Job Search; Wealth Shocks; Consumer Expectations Survey.

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1. Introduction

How much labor supply responds to wealth shocks is a long-standing issue in labor economics, as it allows researchers to draw a distinction between uncompensated and compensated labor supply responses to wage changes. From a policy perspective, understanding the labor supply effect of a transfer windfall is also key. The aggregate demand effects of fiscal stimulus programs might be considerably attenuated if government transfers induce individuals to consume more leisure and thus to earn less. An example of policies that are affected by these considerations is the fiscal interventions implemented during the pandemic and the recent energy crisis that have taken the form of (one-time) ad hoc bonuses/transfers. Another example is the evaluation of universal basic income (UBI) programs, implemented in various forms by governments on both sides of the Atlantic and selected countries in Asia. A recurrent criticism of such programs is that they discourage work or job search. Moreover, understanding the labor supply response to wealth changes is important for assessing the consequences of introducing a wealth tax, as often proposed in the US and other countries, or – for countries that already have one – the consequences of changing its progressivity or eliminating the tax altogether.

From an empirical point of view, the major challenge is that it is not easy to isolate changes in wealth that are truly exogenous. Moreover, labor supply responses may be attenuated by inattention, lack of salience, and other frictions such as adjustment cost in labor schedules or the illiquidity of the specific wealth change experienced. First-generation studies obtain estimates of the relevant elasticity using variation in unearned income (such as income from capital or income of the spouse), mostly from non-experimental data (Blundell and MaCurdy, 2000). However, these forms of unearned income may be correlated with preferences and other characteristics that affect labor supply decisions. More recent literature uses lottery prizes and unexpected bequests as more plausible sources of exogenous variation in wealth, see e.g., Joulfaian and Wilhelm (1994), Imbens et al. (2001) and Cesarini et al. (2017). The evidence, however, is limited to specific population groups that may not be representative of the general population, such as lottery winners and recipients of inheritances.

Against this background, we design a survey experiment that we implement in a large-scale, population-representative survey in which respondents report how they would change the decision to participate in the labor market, the hours worked, and the intensity of their search effort (if not employed) in response to various windfall gain scenarios. We randomly assign these windfall gains (ranging from €5,000 to €100,000), so they are by design orthogonal to respondents' observed and unobserved characteristics. Thus, our experiment allows us to estimate the causal impact of wealth shocks on labor supply and to uncover possible heterogeneous effects across different groups (e.g., by age, gender). More generally, we shed light on a widely debated policy issue, as many researchers have argued that programs that resemble our windfall gains end up reducing labor supply, increasing informal work, and discouraging job search activities by recipients.

Our approach has some additional novel features. While previous studies use specifications of labor supply or earnings that are linear in wealth shocks, our survey experiment allows us to examine whether responses are heterogeneous with respect to the *size* of the shock. This is important because in the absence of labor market frictions one should expect no such heterogeneity, i.e., that the labor supply effect of large wealth shocks is independent of the size of the shock. With market frictions or adjustment costs in labor supply, however, agents may find it optimal to respond only to shocks that are large enough to overcome the frictions.

Besides the non-linearities, the focus of most studies has been on earnings or hours worked, but these are only one dimension of labor supply. In models with labor market frictions, the unemployed trade off their leisure time with time spent searching for a job, which suggests that wealth shocks may not only reduce hours among workers but also discourage job search among the unemployed, a combination of intensive and extensive margin effects that we examine separately (see also Coibion et al., 2020).

We find that windfall gains reduce labor supply, but only if they are significant in size (effects are statistically undistinguishable from zero for gains below €25,000, while we estimate a 3 percentage points lower likelihood of working for gains between €25,000 and €100,000). At the intensive margin, there is no effect for relatively small gains, and a reduction of about one hour per week for prizes above €50,000. Women and workers closer to retirement respond more strongly to windfall gains. As regards the job search intensity of the non-employed, it falls by 1 percentage point for each €10,000 gain, and the effect is more pronounced for older individuals receiving larger prize.

These results suggest that only relatively large wealth shocks trigger labor supply responses that are economically sizeable, while within the range of transfers or bonuses that are typically observed the disincentive effect on labor supply is small or even absent. This non-linear response of labor supply to wealth shocks that we identify is consistent with the presence of labor market frictions and adjustment costs.

The paper is organized as follows. In Section 2 we review the relevant literature on the wealth effect on labor supply. In Section 3 we describe our data and in Section 4 the survey experiment. Sections 5, 6 and 7 present, respectively, evidence on the causal relation between wealth shocks and the probability of employment (the extensive margin), change in hours (the intensive margin), and search intensity, in each case distinguishing responses by shock size. Section 8 concludes.

2. The wealth effect on labor supply

One of the predictions of the classical labor supply model is that, under the assumption that leisure is a normal good, a change in unearned income (for instance, a transitory and unexpected windfall gain, a lottery winning, or an inheritance) leads individuals to work fewer hours (or even drop out of the labor market), and thus earnings fall in proportion to hours.

The prediction is not so simple in more realistic settings. When credit or insurance markets are missing, there might be additional effects, which may amplify, attenuate, or even revert the pure income effect. Banerjee et al. (2017) and Baird et al. (2018) discuss some of these effects, mentioning: (a) a self-employment effect, whereby individuals with valuable entrepreneurial projects and no access to credit might be able to use the windfall gain to start a new business or expand an existing one, which may be recorded as an *increase* in hours worked; (b) an insurance effect, inducing individuals to undertake riskier (and more rewarding) activities, since cash transfers provide a safety net in case of failure; (c) a labor search effect, since a cash transfer allows individuals to spend more time and resources (for instance, by traveling to other locations) in search of better job opportunities; and (d) a health productivity effect (particularly in developing countries), since a cash transfer may allow poor workers to invest in health, making them more productive at work, and thus increase their overall earnings.

In models with adjustment costs, labor supply responses to windfall gains might be small or absent because individuals change their hours worked only if the utility gain from the hour adjustment outweighs the cost of adjusting them. In general, the greater such costs, the lower the labor supply response, and hence one can expect hours to adjust only for relatively large income shocks.

All in all, the effect of unearned income on labor supply is an empirical question that can only be addressed with suitable data. Tackling this empirical question convincingly is difficult, since unearned income changes are often at least partly expected, are persistent over time, depend on economic and other conditions, and affect selected groups of individuals. In short, finding real-life windfall gains that apply to most members of the labor force is empirically challenging.

To address the issue, a first generation of studies estimates the effect of unearned income on labor supply using panel data and changes in capital income or the earnings of the spouse as a proxy for wealth shocks. Blundell and MaCurdy (2000) survey the evidence, and conclude that for men the elasticity of labor supply with respect to unearned income is rather small, and possibly zero, while women's labor supply is more sensitive to unearned income changes (typically arising from changes in the spouse's earnings, the so-called "added worker effect"). These studies have been criticized because unearned income is likely to be correlated with other variables (for instance, preference for hard work) that affect labor supply decisions.[1]

More recently, economists have used quasi-experiments to measure shocks to unearned income, providing more credible identification strategies to estimate the income effect on labor supply. For instance, Bibler et al. (2023) estimate the effects of transfers on labor market activity by exploiting the timing and variation of the Alaska Permanent Fund Dividend, while Powell (2020) studies the labor supply responses to unearned transitory income using the differential timing of the 2008 tax rebates in the US. Both studies find small labor supply effects of income shocks. In the context of developing countries, Banerjee et al. (2017) analyze data from seven randomized controlled trials of government-run cash transfer programs, and find no systematic evidence that the programs impact the propensity to work or the overall number of hours worked, for either men or women.

Another approach is to use inheritances as a source of unearned income shocks. Joulfanian and Wilhelm (1994) use data from the Michigan Panel Study of Income Dynamics (PSID) and from Federal Estate Tax returns, and find that inheritances have a small effect on labor supply, possibly because the PSID does not adequately capture large inheritances.[2] Bø et

[1] Moreover, if spouses have preferences for sharing leisure time together, using spousal earnings as a source of exogenous shocks to one's unearned income is invalid. The same applies if spouses are taxed on their joint earnings in progressive tax systems.
[2] Holtz-Eakin et al. (1993) examine tax-return data on the labor force behavior of people before and after they receive inheritances, and find a single person who receives an inheritance of about $150,000 is roughly four times

al. (2019) use information from administrative data covering the entire Norwegian population and find significant reductions in labor supply, but only for recipients of large inheritances. One concern with this approach is that inheritances are to some extent anticipated, so when the transfer takes place, it has been already absorbed in the life-cycle plan of recipients, at least according to standard life-cycle models. Another issue is that the propensity to leave bequests might correlate with unobserved preferences, such as workers' effort or propensity to undertake risky projects. Our survey experiment is robust to such concerns.[3]

Other studies use data on lottery winners to identify exogenous and unexpected unearned income shocks. Imbens et al. (2001) were the first to use this identification strategy, relying on a survey of lottery players in Massachusetts. They find that unearned income reduces labor earnings, with a marginal propensity to earn of approximately 11%, no difference between men and women, and larger effects for individuals between 55 and 65 years old.[4] Using Swedish lottery data, Cesarini et al. (2017) find instead a much smaller marginal propensity to earn out of unearned income, approximately 1.1%.[5] Picchio et al. (2018) using lottery data in the Netherlands find a marginal propensity to earn out of unearned income between 1 and 2%, and that the effect is stronger among young and single individuals without children. Golosov et al. (2021) study how earnings respond to changes in wealth combining administrative data on U.S. lottery winners with an event-study design that exploits variation in the timing of lottery wins. They find that for an extra \$100 in wealth, households reduce their annual earnings by approximately \$2.3, that the extensive margin explains roughly half of the response, and that the earnings responses are larger for households in the top quartile of the income distribution.

Other papers exploit shocks to financial asset prices (Bottazzi et al., 2021) or house prices as exogenous variation in unearned income (Disney and Gathergood, 2018; Li et al. 2020; Bernstein, 2021), generally finding relatively small effects of wealth shocks on labor supply for the average workers, but larger effects for individuals close to retirement. Coibion et al. (2020)

more likely to leave the labor force than a person with an inheritance below \$25,000. Their evidence suggests also that large inheritances depress labor supply.

[3] Some authors have also studied the labor supply effect of inheritances on retirement. For instance, Brown et al. (2010) use the Health and Retirement Study and find that inheritances (especially when unanticipated) increase the probability of retirement, and that the effect increases with the size of inheritances. Receiving an inheritance of \$100,000 increases the probability of early retirement by about 5%.

[4] One should keep in mind, however, that the population of lottery players is not necessarily representative of the population (in the U.S. or elsewhere).

[5] They find also that the winning spouse reacts more strongly than the non-winning one, thus rejecting the unitary model of labor supply which predicts identical responses because of income pooling (Chiappori and Mazzocco, 2017).

report direct survey evidence on the labor supply effect of the pandemic-induced stimulus payments in the US. They find that the payments affected the work effort of only 10% of the labor force, and that 20% of unemployed workers who received a payment claimed that this made them search harder for a job, while two-thirds report that it had no effect.

From the literature surveyed above we draw several lessons and insights about method, data and experimental design. In terms of *method*, to identify wealth effects on labor supply one key issue is to distinguish transitory from persistent components of unearned income changes, and expected from unexpected components of these changes, as only the latter should affect labor supply. It is also important to isolate the wealth shock from other incentive effects associated with wealth transfers. Ideally, the wealth shock should be orthogonal to all individual observed and unobserved characteristics, and with other shocks that they might experience at the same time.[6]

In terms of *data*, one should aim at distinguishing the separate effects of wealth shocks on the extensive and intensive margins of labor supply. However, separate information on hours and wages is seldom available, and most studies use total earnings as an outcome variable. But this implies that one needs to make additional assumptions to estimate the separate effect of wealth shocks on hours and wages (for instance that individual wages do not change when hours adjust to wealth shocks, an assumption obviously violated for overtime premia).

As for the experimental *design*, the wealth shock should also apply to a large segment of the labor force, to avoid selectivity issues and to explore possible heterogeneous effects. Many empirical studies show that the labor supply response of women is more sensitive to wage changes than that of men, and these differences might extend to the wealth effect as well. Older workers close to retirement should be more responsive than younger worker, as they have less time to adjust leisure after the shock. The labor supply of married couples might be more responsive to wealth shocks than that of single household heads, because when there are two earners one of the partners can more easily adjust labor supply. The evidence on the intensity of wealth effects on labor supply across the income distribution is mixed, but it is plausible that the effect is stronger for high-income earners, who have a larger buffer of accumulated wealth.

Finally, a concern with the approach used in the papers surveyed above is that the samples receiving large inheritances or lottery prizes are typically small. Regression models must

[6] For instance, consider someone who experiences a car accident or a health problem, and then receives a reimbursement from an insurance company. In most datasets, the econometrician only observes an increase in the unearned income component, but not the cause of the underlying shock.

impose parametric assumptions about the effect of wealth shocks on labor supply (linear or, occasionally, quadratic), as sample sizes do not allow to pin down heterogeneity in the size of the shock. However, in the presence of fixed costs of adjustment or jobs with inflexible hours, the wealth effect might well be non-linear, as one expects workers to respond only to sufficiently large shocks. To estimate this effect with any precision, one needs to observe many individuals receiving small and large shocks.

In addition to the points above, the literature so far has neglected the potential negative effect of wealth shocks on search intensity. Similarly, to the view that unemployment insurance creates moral hazard effects, receiving a transfer might discourage unemployed workers from searching (and even inducing them to stop searching altogether) and increase unemployment duration. They might also increase workers' reservation wages making workers "pickier". Le Barbachon et al. (2019) discuss these two effects in the context of the incentive effects of unemployment insurance. As we shall see, our survey experiment speaks only to the first effect, as we have no information on changes in reservation wages or the type of jobs that people search for. The wealth effect on job search needs not to be negative, however. If search is costly, receiving a wealth endowment allows some individuals to start searching, or to search more intensively. For instance, a young parent may spend money for childcare and devote more time to search for a job; other individuals might move to cities with brighter employment prospects; still others, might enroll in a training or education program. The wealth effect on search is therefore ambiguous a priori, likely to be heterogenous across the population, and is worth investigating also from a policy perspective.

To address all these issues, we rely on scenario questions using lottery prizes that are randomly assigned to labor force members. In terms of *method*, we fully control the nature of the resulting wealth shock, while the randomization implies that the size of the assigned shock is orthogonal to any other change in resource the individual may experience. Moreover, the randomly assigned shock is orthogonal to individual unobserved characteristics (such as work effort) that may confound the estimates. In terms of *data*, we isolate hours of work and job search responses from wage changes. Finally, in terms of *design*, we work with a large swath of the sample subject to shocks of different size, and can thus even non-parametrically identify the effect of shock size on labor supply. While many studies have used similar hypothetical questions to study the consumption response to unexpected and transitory cash transfers, as far as we know there is only one previous study applying them to the labor context, Kimball and

Shapiro (2008).[7] In particular, their study estimates the effect on employment and hours of a permanent income shock, using a special module designed in the Health and Retirement Study (HRS).[8]

3. The survey experiment

To study the labor supply effect of windfall gains, we use the ECB's Consumer Expectations Survey (CES), a high frequency panel survey of euro area consumer expectations and behavior. The CES was established in 2020 and originally covered the six largest euro area economies (Belgium, Germany, Italy, France, Spain, and the Netherlands) with a sample size of approximately 10,000 consumers.[9] In this paper, we use mostly data from a special-purpose survey that was fielded in June 2022. The sample is comprised of anonymized individual-level responses from approximately 3,000 survey participants from each of the four largest euro area countries (Germany, Italy, France, and Spain) and 1,000 in each of the two smaller countries (Belgium and the Netherlands).

In this paper, we make use of data collected via a special-purpose survey fielded in June 2022 and we combine it with background and other data collected via the regular CES modules After asking all respondents to report their labor market status, the survey experiment runs with a sequence of three questions, in which respondents are randomly assigned into five different hypothetical lottery wins of various euro amounts (5,000, 10,000, 25,000, 50,000, 100,000). Those who are working are asked the following question:

Imagine you win a lottery prize of <euro amount> today. What would be your plans for working over the next 12 months?

The possible answers are to reduce hours worked; continue to work the same number of hours; increase hours worked and stop working (by either resigning or taking unpaid leave).

[7] Many studies use survey data and qualitative or quantitative responses to transitory income and wealth shock scenarios where people are asked how much of the lottery they would spend, save, or use to repay debt, see for example Bunn et al. (2018), Christelis et al. (2019) and Jappelli and Pistaferri (2020), amongst others. Moreover, Stantcheva (2023) discusses the benefits of asking scenario questions in household surveys, and a wide range of applications in labor economics, health economics and macro-finance.

[8] The module asks respondents to imagine what they would do if they won a sweepstakes that would pay them an amount equal to last year's family income every year as long as they live. The survey then asks whether the workers would quit work entirely and, for those who would not quit, whether they would reduce hours and if so, by how much.

[9] Starting in 2022, the CES was also piloted in five additional countries (Austria, Finland, Greece, Ireland, and Portugal).

Subsequently, the employed report how many more/fewer weekly hours they would work over the subsequent 12 months. The coding of responses ranges from 0 to 11 hours or more.

Those who are not working are asked a different question:

Imagine you win a lottery prize of <euro amount> today. How actively would you look for a job over the next 12 months?

In this case, respondents choose from a menu of qualitative answers. Those who are currently looking for a job report whether they would look for a job more actively, less actively than before, or stop looking. Those who are not looking for a job report whether they would start looking or not. The Appendix reports the wording of the questions and the design of the experiment.

In experiments, it is typical to use a 'baseline' group for comparisons with the other groups. Our experiment features a group receiving a hypothetical "€5,000 prize" (the lowest amount possible). In estimation we hence pin down the effect of gains relative to this €5,000 prize baseline. When designing the survey, we considered using smaller prize amounts (€500 or €1,000), but decided that it would be implausible to expect important labor supply responses to one-time gains that – at least for most households - are negligible. For similar reasons, we also thought that a control group with no prize at all would make any comparison with other groups problematic (any aggregate effect should be captured by a common response across all lottery prize groupings). Notice that respondents who intend to change employment status, hours worked or search intensity in the months following the interview are equally likely to be assigned to lotteries of different sizes.

The size of higher prizes mimics some actual transfer programs. For instance, in Italy the basic income support program introduced in 2019 transfers up to €750 per month for 18 months to single people unemployed or out of the labor force.[10] A prize between €10,000 and €25,000 is roughly equivalent to this program, extended for one or two years. Higher amounts might be associated to inheritances or gifts received on special occasions, or to severance pay that could range, e.g., from 20 day pay per year of service in Spain to one-third of the monthly salary per

[10] Examples in other countries during the pandemic period include: Germany, where the short-time work allowance has been extended up to 28 months until 30 June 2022 (up to 12 months right after); France, where the government eased the eligibility criteria of the partial-activity allowance scheme during the pandemic; Spain, where the government provided furloughed workers with 70% of their base salary for the first six months, dropping to 50% for the following months; the Netherlands, where subsidies were introduced during COVID-19 outbreak; and Belgium, where the protection bonus during 2021 amounted to €780 for low-wage workers, with no limit to the duration of support.

year of service in France for longer-tenured (more than 10 years) employees. The range of prizes observed in the survey experiment also allow ready comparisons with previous studies based on actual lotteries.

Prizes are randomly assigned to five groups of respondents. Hence, by design the underlying windfall gains are orthogonal to individual observed and unobserved characteristics. In this set up, we can estimate the causal effects of exogenous and unanticipated windfall gains on labor supply and capture three dimensions of labor supply decisions. The first is an *extensive hours of work margin*, for those who work. The second is the *intensive hours of work margin*, measuring whether respondents reduce hours in response to the prize, as predicted by models in which leisure is a normal good.[11] The third explores the effect of wealth shocks on the time and intensity spent searching, for those who are currently not working.

Our approach has several advantages with respect to previous literature. Randomization of the lottery prize allows genuine identification of the causal effect of exogenous wealth shocks on labor supply, and to explore the heterogenous effect of wealth shocks among different households and shock sizes. In addition, our outcome variable for the intensive margin is weekly hours, while most previous literature uses earnings as outcome and assumes that earnings are proportional to hours, while in practice it may not be the case. This is relevant when looking at e.g., marginal adjustment, because often overtime is paid differently than regular hours. Another advantage is that the survey experiment allows us to study the wealth effect on search, while previous literature ignores that margin. Furthermore, we implement the experiment on a large and representative sample, and we can examine heterogeneous effects across different groups.

4. Empirical framework

To introduce our empirical framework, we posit a linear relation between hours worked, unearned income and other variables affecting labor supply:

[11] As discussed in Section 2, even if leisure is a normal good, some people might increase hours in response to unearned income, either because there are fixed costs of work (like traveling) that are overcome by the wealth shock, or because in the presence of liquidity constraints, some people need to invest (in cars, clothes, hiring a babysitter, etc.) to go to work.

$$h_{it} = \alpha + \beta Q_{it} + \gamma X_{it} + f_i + \nu_{it} \tag{1}$$

where h_{it} are hours worked by individual i in period t, Q_{it} is unearned income, X_{it} includes time-varying characteristics that are relevant for the labor supply decision (market wage rate, demographic variables), f_i is an individual (time invariant) fixed effect, and ν_{it} is an error term comprising individual time-varying unobserved characteristics and other shocks affecting labor supply.

Even if one observes unearned income, the challenge of estimating (1) in cross-sectional data is that Q_{it} is likely to be correlated with the fixed effect, so that $cov(Q_{it}, f_i) \neq 0$. For instance, suppose that one measures unearned income with capital income (dividends, rents, etc.) and suppose also that some people are hard-working, while others are not. Those who are hard-working tend to work more hours and (to the extent that this preference trait is constant over time) also worked longer hours in the past, implying they would have accumulated more wealth. There will be a positive correlation between current hours and Q_{it} not because a higher Q_{it} affects the demand for leisure (considering it an inferior good), but simply because people who have higher labor income tend to work longer hours, or because labor income correlates with their (unobserved) wealth accumulation.

The bias in the estimation of the parameter β may persist even when panel data are available, and equation (1) is estimated via fixed effects models. This is because $cov(Q_{it}, \nu_{it}) \neq 0$, where ν_{it} represents time-varying risk preferences, or unobserved shocks correlated with Q_{it} potentially affecting labor supply (e.g., a reimbursement from an insurance company following a health problem that reduces labor supply).

As discussed, our survey experiment is designed to overcome these identification and econometric issues using the randomization of the hypothetical unearned income shock. In practice, we consider a first-difference specification of equation (1):

$$\Delta h_{it} = \beta \Delta Q_{it} + \gamma \Delta X_{it} + \Delta \nu_{it} = \beta P_{it} + \Delta \nu_{it} \tag{2}$$

The second equality follows from the fact that $\Delta Q_{it} = P_{it}$, where P_{it} is the randomly assigned windfall gain. Notice that P_{it} is by design independent of any other unobserved variable that might affect the labor supply decision, and that within the narrow time interval covered by the experiment, we can safely assume that the X_{it} variables don't change. To explore the relation between the extensive margin of labor supply and the wealth shock, in Section 5 we estimate logit regressions for the probability of continuing to work after the experiment, which is $Prob(\Delta h_{it} \geq 0)$.

Table 1 reports sample statistics for the main variables used in the estimation. Means and standard deviations are computed using sample weights. We exclude the retired and 538 respondents (approximately 5% of the sample) who completed the survey in less than 2.5 minutes (while the envisaged time for the entire module is about 10 minutes), so that the resulting sample includes 9,438 working and 1,860 non-working respondents.[12] The latter group comprises those who are not retired and are currently looking for a job as well as those not looking but who are of working age.

For the employed, across all prizes, 81% mention that they would work the same as before. While 5% mention that they would stop working and 8.1% that they would work less, 6.1% mention that they would work more hours. On average, and across all prizes, the intended change in weekly hours is -0.19.

Among those not working, 31% mention that they would search the same as before, 36.2% that they are not working or searching, while 7.2% would search more, 9.6% would start searching, 10.9% would search less, and 5.1% would stop searching. As we shall see, these answers are more meaningful if examined across the prize distribution, rather than in the overall sample.

To check if the randomization is properly implemented, we provide statistics showing that the sample is balanced across the different sub-samples, and run regressions of the probability of being part of a particular randomized sub-sample. Table 2 reports sample means for key socio-economic variables across the randomly assigned lottery prizes. In terms of number of observations, the five sub-samples range from 1,853 to 1,925 for the employed, and between 362 and 405 for the non-employed. Most importantly, the sub-samples are well balanced in terms of gender, age, education, and disposable income. This can be also seen through a multinomial logit model that associates the five lottery windfalls with socio-economic characteristics and country fixed effects.[13] In the sample of employed individuals, the likelihood ratio test on the joint significance of the covariates from the multinomial logit suggests that the assignment of lottery windfalls is orthogonal to household characteristics (the χ^2 statistic is 37

[12] Results are almost identical if we do not make these exclusions.

[13] We condition on the following set of variables also used in our analysis below: age, gender, family size, education, occupation.

with a p-value of 58%). Results are similar for the sample of non-employed (χ^2 statistic of 22 with a p-value of 98%).

5. The extensive margin: probability of employment

Before estimating the intensive margin of equation (2), we present descriptive statistics and regressions for the probability of working following the experiment. Figure 1 plots the fraction of respondents who would stop working, work less (reduce hours) or work more (increase hours), depending on the hypothetical lottery prize. The omitted category is "work the same" and absorbs the largest fraction of respondents (around 80%). About 6% of respondents intend to work more, but this fraction is rather insensitive to the size of the prize. Instead, the fraction of those who intend to work less or stop working altogether increases with the prize size.

In the upper-left graph of Figure 2 we combine the fraction of those who intend to continue to work (less, the same, or more), and plot this fraction against the size of the prize. The figure shows that about 97% of respondents would continue to work for small prizes (up to €25,000), while the fraction falls to 94% for prizes between €25,000 and €100,000. Figure B1 in the Appendix shows that the negative employment effect at high prizes is about 3% in all countries except Belgium, where the line is essentially flat.

Table 3 reports the marginal effects of a logit regression for the extensive margin. We define a dummy equal to one for those who intend to continue to work after receiving the lottery prize, and 0 otherwise. In the baseline regression of column (1) we include only two controls: the lottery prize (in thousands of euros) and country dummies. The prize enters linearly and produces only a small effect on employment: €1,000 increase in unearned income reduces the probability of working by only 0.04%, implying that receiving the largest prize of €100,000 reduces employment rates by 4 percentage points (out of a 97% baseline). Results do not change when we expand the baseline specification to include dummies for gender, college education, age groups, family size, and a self-employment dummy (column 2).

The third specification allows for non-linear effects of lottery prizes, introducing different dummies for each of the hypothetical wealth shocks. Marginal effects are not statistically different from zero for prizes up to €25,000. Instead, the two largest prizes reduce employment rates by 1.5 and 3.5 percentage points, respectively. For robustness, in the last column we report the coefficients of a linear probability model, with almost identical results.

Given our large sample and the fact that our survey is representative of the population, we can explore heterogeneity of responses. We evaluate the marginal effects of the difference in the effect of wealth shocks on employment between different group pairs and present the results in graphical format in Figures 3 and 4. For comparison, the upper-left graph in Figure 3 plots the estimated probabilities and the associated 95% confidence intervals implied by the logit model of column (3) of Table 3, and shows graphically that the only significant effects emerge for those "exposed" to €100,000 wealth shocks (the effect of the €50,000 shock is significant at the 10%, as in Table 3).

In the upper-right graph of Figure 3 we use the same specification of the last column of Table 3, adding a dummy for gender interacted with each of the prize dummies. The results show that for prizes below €25,000 the employment response of women is not statistically different from that of men, while for a €25,000 prize female employment rates are 2.5 percentage points lower than males' (the effect of the €50,000 is significant at the 10% level). These results suggest that women respond slightly more to shocks, in line with previous evidence surveyed in Section 2 arguing that women are more likely to exit from the labor market in response to wealth shocks.

The other two graphs of Figure 3 explore other dimensions of heterogeneity, and are constructed in a similar way. The bottom-left graph considers possible age effects, interacting the prize dummies with dummies for older (over 45 years old) and younger (less than 45) workers. The graph shows that for the largest wealth shock the labor supply of older workers is more responsive than that of the young (4 percentage points higher decline in employment rate), even though the marginal effect is not statistically different from zero at the 5% level. This finding corroborates the fact that workers closer to retirement respond more to economic incentives, given that they have less time to adjust labor supply. Instead, the lower-left graph shows no significant differences when interacting the prize dummies with college education.

In Figure 4 we interact the wealth shock dummies with indicators of employment status (part-time or full-time workers), income (workers with income below or above the median), indebtedness (debt/income ratio below or above one), and geography (Southern or Northern Europe). We find that part-time workers (defined as those who work less than 20 hours per week) respond much more to the largest prize than full-time workers (a differential effect of 10 percentage points, and significant at the 5% level). The other group in which the marginal differences are significant is for workers with relatively low debt. For the largest wealth shock this group reports a 5 percentage points higher probability of exiting from the labor force relative to high indebted workers. We find no significant difference in the intention to continue to work by the level of income. Finally, Northern countries have a 5 percentage points lower probability of continuing employment, regardless of the prize.[14]

Regressions with interaction terms with the prize dummies allow testing for differential effects between groups but impose the restrictions that the effects of other variables are the same in the two groups. An alternative approach is to split the sample and run separate logit regressions. We report such regressions in Table B1 of the Appendix for the two most interesting variables of our analysis (gender and age). They show that for prizes of €50,000 and above, the estimated marginal effects are larger (in absolute value) for females and older workers, as in Figure 3.

So far, we have grouped in the "continue working" category those who report that they intend to work fewer hours, more hours, or make no change. One concern is that aggregating these indicators may mask heterogeneity across the different outcomes. In the Appendix we provide further results using a multinomial logit model for four different outcomes: increase hours worked, reduce hours worked, stop working, continue to work the same number of hours. We use the same list of covariates and report results in graphical form in Figure B2. The relation between the probability of increasing hours and lottery prizes is basically flat. On the other hand, the probability of reducing hours increases with the size of the wealth shock, and is statically different from zero for the largest shock. The probability of stopping to work altogether is statistically different for prizes above €50,000, confirming the logit results. These changes are reflected in the left-graph of Figure B2, showing that the proportion of those reporting no change in employment declines by about 14 percentage points (from 86% to 72%).

To summarize these results, we find that windfall gains reduce labor supply, but only if they are significant in size. Windfall gains of up to €25,000 do not produce economically meaningful or statistically significant responses, while the probability of continuing to work

[14] We also explore other dimensions of heterogeneity. For instance, we interact the lottery prizes with different levels of financial sophistication, measured as the number of financial literacy questions answered correctly. These might be associated with the ability to understand the hypothetical lottery questions correctly, and it is reassuring that we find no difference along this dimension. We also interact the prize dummies with a dummy for single individuals without children (or just singles) but find no differential effects between these groups.

falls by about 3 percentage points for larger wealth shocks. The point estimates suggest that the negative impact of wealth shocks on employment is stronger for women, workers close to retirement, part-time workers, and less leveraged households.

6. The intensive margin: change in hours

The upper-right graph in Figure 2 plots the average change in weekly hours of employed workers, considering that some intend to increase hours, while others intend to reduce hours or keep them unchanged. There is a negative gradient linking the change in hours and the prizes, but the effects are again not large. Even for the largest prizes (above €25,000) the drop is only 0.5 hours per week, compared to a sample mean of 35 reported weekly hours of work. The evidence is consistent with a low-income effect, or with adjustment costs in hours -- many workers cannot freely adjust hours worked without the employer's agreement, or if there are institutional, contractual or technological constraints within the firm.

The regressions of Table 4 confirm the descriptive evidence. In column (1) we report the baseline regression for the change in hours (estimated using OLS) including only the prize variable (in thousands of euros) and country dummies. The prize coefficient is precisely estimated, but small (-0.008). This estimate is virtually unchanged when we include a range of different controls. In fact, the estimate of Column 2 implies that for any increase of €10,000, weekly hours fall by only 0.08 (about 5 minutes per week). In the last column of Table 4 we introduce separate prize dummies to test for non-linear wealth shock effects on labor supply. We find no significant effect on hours for prizes up to €25,000. For higher wealth shocks the effect is -0.49 hours for a €50,000 prize and -0.72 hours for a €100,000 prize. If we consider an average workweek of 35 hours, this amounts to a reduction of 1.4% of hours for the €50,000 prize, and 2.1% for the €100,000 prize.

Next, we explore heterogeneity in the intensive margin, presenting results in graphical format, in line with those shown for the extensive margin. The upper-left graph of Figure 5 reproduces the results of the OLS regression of column (3) of Table 4, plotting the estimated change in hours for different prizes and the associated 95% confidence bands. The other graphs in Figure 5 show a stronger prize effect on hours by gender and age, but not by education. For instance, at the €50,000 prize, the prize effect for women is -0.78 hours, while the effect for men is -0.28. Also, older workers respond more to shocks relative to younger workers, particularly for large shocks (-0.80 against -0.42 for a €100,000 prize). In Table B2 of the Appendix we also report the prize effects on change in hours splitting the sample by age and gender. Results show that for prizes of €50,000 and above, the effects are larger (in absolute value) for females and older workers, as in Figure 5.

In Figure 6, the differences in the change in hours by income, actual hours worked (part-time vs. full-time), and indebtedness are not statistically different from zero across the entire prize distribution. For the self-employed, whose work schedule is more flexible, the marginal effect is sizable for large prizes (at the €100,000 prize, -1.1 for the self-employed against -0.6 for employees), but not statistically different at the 5%.

To summarize, for the intensive margin we find non-linear effects between hours and wealth shocks: a flat relation for shocks up to €25,000, and relatively small effects (less than one hour per week) for shocks above. Like for the extensive margin, heterogeneity analysis by different demographic groups shows that women and workers close to retirement respond more strongly to the windfall gains.

To compare our results with previous literature, we conclude this section by computing the effect of hypothetical €10,000 and €100,000 wealth shocks on earnings. To calculate these effects, we use the sub-sample receiving the above two prizes and merge data on actual earnings and hours available in the May 2022 CES with information from the June 2022 experiment on change in employment and change in hours after the hypothetical shock. The resulting sub-sample includes 1,348 observations with complete records on actual earnings, hours, and response to the hypothetical €100,000 wealth shock (1,358 for the €10,000 shock). We assume that earnings drop to zero for all those who report that they would stop working, that the wage is unchanged when people adjust working hours, and that on average employed people work 40 weeks per year. Table 5 shows that the average drop in earnings is €2,465 for a €100,000 prize, or 2.5% of the prize. Of this drop, about 2% is due to the drop in employment (the extensive margin) and 0.5% to the drop in hours (the intensive margin).

The 2.5% earnings effect is considerably smaller than that estimated by Imbens et al. (2001) using a sample of Massachusetts lottery winners (11%), but in line with the evidence from Sweden of Cesarini et al. (2017) and Netherlands by Picchio et al. (2018), who report marginal propensities to earn out of unearned income between 1 and 2%. The table also shows that the drop in earnings is higher for females (2.7%) than for males (2.3%), and for workers closer to retirement (3.1%) than for younger respondents (1.5%), in agreement with our estimates in Sections 5 and 6. In each case, the employment (extensive margin) effect is roughly four times larger than the hours (intensive margin) effect.

For comparison, Table 5 reports also the earnings effect of a relatively small shock (€10,000), which roughly mimics the size of typical UBI-style programs. Consistent with the non-linear effects of wealth shocks, the total drop in earnings is now less than 1% of the shock. Given that for relatively small shocks the change in hours is negligible, this negative average earnings effect is entirely attributable to the extensive margin response.

7. Search intensity

The experiment we describe in this section focuses on the sample of "not employed" individuals of the CES. We choose to focus on a broader sample than the conventional definition of unemployment. We exclude those who are already retired, but include people who are of working age (18-64 years) but classified as out of the labor force (potentially discouraged workers and individuals not actively looking for a job). This is because one possible effect of wealth shocks is to push people onto job search (for reasons detailed below). The sample we analyze comprises 1,860 individuals, including unemployed actively looking for a job, unemployed interested in having a job but not actively looking, those at school or in training, those looking after children or other persons, and those doing housework.

Table 1 shows that the sample of not employed is more skewed towards women, younger, poorer, and less well-educated respondents than the sample of employed individuals. Table 2 shows that the characteristics of the five randomized sub-samples are well balanced across the hypothetical lottery prizes of our experiment. In Figure 7 we plot histograms of the six possible outcomes of the search question. With respect to the baseline €5,000 prize, we observe an increase in the proportion of those who intend to reduce or stop searching after receiving the prize, and a corresponding drop in the proportion of those who intend to search the same or reduce search. Instead, the proportions of those not searching and of those who would start searching are rather flat across the prize distribution (but, interestingly, the latter are not zero).

In the lower-left panel of Figure 2 we plot "search intensity" against the wealth shocks, defining a dummy for "search intensity" which is equal to zero if respondents report that they would search less or stop the search altogether, and one otherwise. The figure shows that search intensity drops by about 10 percentage points across the prize distribution (from 88% to 78%).

In Table 6 we present the marginal effects of logit regressions for search intensity. In the linear specifications of columns (1) and (2) the effect of the lottery prize variable (measured in thousand euro) is negative and statistically different from zero. The marginal effect indicates that search intensity falls by 1.1 percentage points (out of a baseline of 84% in the total sample) for each €10,000 prize, even if we expand the specification with demographic variables (column 2). Distinguishing by the different prize levels in column (3) reveals that the disincentive effect of wealth shocks is negative for all prizes, and statistically different from zero for the two largest prizes (-8.6 and -10 percentage points, respectively). In the last column of Table 6 we report the OLS coefficients of a linear probability model for search intensity, with almost identical results.

Like for the intensive and extensive margins labor response to the lottery prizes, in Figures 8 and 9 we present marginal effects for different groups. We find some evidence that older individuals tend to reduce search intensity more than younger individuals for relatively large prizes (e.g., €50,000), but we detect no significant differences in the effects by gender, education, income, indebtedness, and geographical region.[15] For search intensity, we distinguish also the non-employed by their self-reported reservation wage (above or below median), available in May 2022 as a separate variable, to check whether individuals with higher reservation wages are more sensitive to wealth shocks. However, we find no statistically different effect for the two groups.

In the Appendix we check whether the search intensity indicator hides heterogeneity in responses using a multinomial logit model for six different outcomes (increase search for a job, reduce search, stop search, start search, search the same, not searching and not changing strategy). We use the same list of covariates and report results in graphical form in Figure B3. The relations between the prize and the probabilities of not searching, stop searching or increase searching are flat. Instead, the probability of searching the same or reduce search fall with the prize, confirming the logit regressions results.

[15] In Table B3 of the Appendix we report the prize effects on search intensity splitting the sample by age and gender. Results show that for prizes of €50,000 and above, the effects are larger (in absolute value) for females and older workers.

8. Summary

A classic question in labor economics is how labor supply responds to wealth shocks. The issue is empirically challenging, because to address it one needs to identify genuine variation in wealth or income that is not correlated with the labor market status of workers, their wage, and their preferences. Isolating the wealth or income effects from other, confounding effects, is important in many contexts, for instance to gauge the labor supply effect of cash transfers and the overall effectiveness of fiscal policy.

Labor economists have used a variety of approaches, including changes in capital income or the income of a spouse, as well as quasi-natural experiments based on the receipt of inheritances or lottery winnings. Most previous studies focus on earnings as the outcome variable, as separate information for hours and wages are seldom available. Furthermore, they estimate linear or log-linear relations between wealth shocks and labor supply indicators, and cannot test whether the response varies with the size of the prize. We implement a novel approach that can address both issues. In particular, we design and analyze a survey experiment in the CES, a large panel of individuals representative of the national populations of the six largest euro area countries. In our experiment people report how they would change the decision to participate in the labor market, their hours worked and their search effort (if not employed) in response to randomly assigned lottery prizes that vary in size and proxy for unexpected windfall gains.

At the extensive margin, we find that wealth shocks reduce employment, but only if they are significant in size. In particular, we find no effect of prizes below €25,000, and that the probability of employment falls by 3 percentage points for prizes that range from €25,000 to €100,000. At the intensive margin we find again no effect for small gains, and small effects (less than one hour per week) for prizes above €50,000. We also explore heterogeneity of responses, finding that women and workers closer to retirement respond more strongly to wealth shocks than men or younger individuals.

Using a similar experimental design, we also explore how the intensity of job search amongst the unemployed and working-age individuals not in the labor force reacts to the same randomly assigned lottery prizes. We find that search intensity drops by roughly one percentage point for each €10,000 prize, with the effect being particularly pronounced for older individuals receiving the largest hypothetical windfall gain.

Overall, the paper suggests that only relatively large shocks (due for instance to unanticipated inheritances) trigger economically meaningful labor supply responses, while within the range of realistic transfers or bonuses the disincentive effect on labor supply is small or even absent. This non-linear response of labor supply to wealth shocks is consistent with the presence of labor market frictions and adjustment costs. Given the size of the typical programs, the estimated responses also suggest that there are limited moral hazard effects related to UBI-style programs.

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Table 1. Descriptive statistics

Sample of working individuals	Mean	Standard deviation	Observations
Work more	.061	.240	9,438
Work the same	.807	.394	9,438
Work less	.081	.273	9,438
Stop working	.050	.218	9,438
Change in hours	-.196	2.741	8,967
Female	.476	.499	9,431
Age	43.372	11.045	9,438
Family size	2.807	1.255	9,438
College	.619	.486	9,438
Disposable income	37.191	22.871	9,438
Self-employed	.128	.334	8,356
€5,000 prize	.196	.397	9,438
€10,000 prize	.204	.403	9,438
€25,000 prize	.197	.398	9,438
€50,000 prize	.204	.403	9,438
€100,000 prize	.199	.399	9,438
Sample of non-working individuals			
Search more	.072	.259	1,860
Search the same	.310	.463	1,860
Search less	.109	.312	1,860
Stop searching	.051	.219	1,860
Not working or searching	.362	.481	1,860
Start searching	.096	.294	1,860
Female	.672	.470	1,859
Age	39.445	13.787	1,860
Family size	3.023	1.24	1,860
college	.383	.486	1,860
Disposable income	24.282	17.121	1,860
€5,000 prize	.217	.412	1,860
€10,000 prize	.190	.393	1,860
€25,000 prize	.195	.396	1,860
€50,000 prize	.198	.398	1,860
€100,000 prize	.199	.400	1,860

Note. Data are drawn from the June 2022 wave of the Consumer Expectations Survey (CES). We compute statistics using sample weights.

Table 2. Descriptive statistics, by lottery prize

	Female	Age	Family size	College	Disposable income	Self-employed	Observations
Working							
€5,000 prize	.48	43.43	2.82	.64	36,931	.13	1,853
€10,000 prize	.48	43.11	2.82	.63	37,499	.13	1,923
€25,000 prize	.48	43.30	2.82	.61	37,537	.12	1,859
€50,000 prize	.46	43.55	2.81	.61	37,221	.13	1,925
€100,000 prize	.47	43.47	2.78	.60	36,761	.13	1,878
Not working							
€5,000 prize	.65	38.90	3.07	.37	24,757	-.-	405
€10,000 prize	.69	40.03	3.01	.39	23,320	-.-	354
€25,000 prize	.71	39.77	3.02	.39	24,844	-.-	362
€50,000 prize	.64	39.48	2.98	.38	23,676	-.-	368
€100,000 prize	.68	39.14	3.02	.39	24,733	-.-	371

Note. Data are drawn from the June 2022 wave of the Consumer Expectations Survey (CES). The table reports, separately for working and non-working individuals, means of selected socioeconomic characteristics for each randomized sub-sample of the survey experiment. We compute statistics using sample weights.

Table 3. Effect of wealth shocks on the probability of working

	Baseline Logit	Logit with demographics	Logit with prize dummies	OLS with prize dummies
Prize	-0.0004	-0.0004		
	(0.0001)***	(0.0001)***		
High school		0.0129	0.0165	0.0181
		(0.0084)	(0.0085)*	(0.0092)*
College		0.0118	0.0134	0.0155
		(0.0078)	(0.0078)*	(0.0085)*
Age 18-34		-0.0168	-0.0229	-0.0190
		(0.0279)	(0.0275)	(0.0235)
Age 35-49		-0.0184	-0.0260	-0.0219
		(0.0277)	(0.0274)	(0.0233)
Age 50-64		-0.0255	-0.0289	-0.0250
		(0.0278)	(0.0274)	(0.0233)
Female		-0.0181	-0.0190	-0.0190
		(0.0048)***	(0.0047)***	(0.0047)***
Family size		0.0006	-0.0024	-0.0023
		(0.0019)	(0.0019)	(0.0019)
Self-employed		-0.0114	-0.0146	-0.0147
		(0.0066)*	(0.0066)**	(0.0071)**
€10,000 prize			-0.0033	-0.0022
			(0.0081)	(0.0074)
€25,000 prize			0.0010	0.0009
			(0.0084)	(0.0075)
€50,000 prize			-0.0146	-0.0134
			(0.0078)*	(0.0074)*
€100,000 prize			-0.0347	-0.0387
			(0.0074)***	(0.0074)***
N	9,438	8,351	8,351	8,351

Note. The table reports marginal effects from logit regressions (OLS in the last column). All regressions include country dummies. One star indicates significance at the 10%, two stars at the 5%, three stars at the 1%.

Table 4. Effect of wealth shocks on change in hours worked

	Baseline	Demographics	Prize dummies
Prize	-0.0080	-0.0083	
	(0.0008)***	(0.0009)***	
High school		0.0821	0.0894
		(0.1215)	(0.1215)
College		0.0209	0.0273
		(0.1122)	(0.1122)
Age 18-34		0.5908	0.5993
		(0.3046)*	(0.3046)**
Age 35-49		0.2520	0.2595
		(0.3024)	(0.3024)
Age 50-64		0.0848	0.0941
		(0.3030)	(0.3030)
Female		-0.2543	-0.2557
		(0.0614)***	(0.0614)***
Family size		0.0709	0.0709
		(0.0251)***	(0.0251)***
Self-employed		0.3762	0.3782
		(0.0930)***	(0.0930)***
€10,000 prize			0.0023
			(0.0961)
€25,000 prize			-0.0796
			(0.0969)
€50,000 prize			-0.4935
			(0.0962)***
€100,000 prize			-0.7233
			(0.0976)***
R^2	0.01	0.02	0.02
N	8,967	7,940	7,940

Note. All regressions are estimated by OLS and include country dummies. One star indicates significance at the 10%, two stars at the 5%, three stars at the 1%.

Table 5. Effect on earnings of €10,000 and €100,000 windfall gains (%)

€10,000 prize	Drop due to the extensive margin (%)	Drop due to the intensive margin (%)	Total drop in earnings (%)	Number of observations
Females	-1.147	0.080	-1.066	613
Males	-0.947	0.181	-0.766	745
Age<=40	-0.833	0.450	-0.382	526
Age>40	-1.166	-0.063	-1.230	832
College	-1.142	0.223	-0.919	853
No college	-0.861	-0.011	-0.872	505
Total sample	-1.037	0.136	-0.902	1358

€100,000 prize	Drop due to the extensive margin (%)	Drop due to the intensive margin (%)	Total drop in earnings (%)	Number of observations
Females	-2.157	-0.544	-2.701	625
Males	-1.890	-0.373	-2.264	722
Age<=40	-1.261	-0.218	-1.479	543
Age>40	-2.520	-0.611	-3.130	805
College	-2.068	-0.544	-2.612	827
No college	-1.924	-0.307	-2.231	521
Total sample	-2.013	-0.452	-2.465	1348

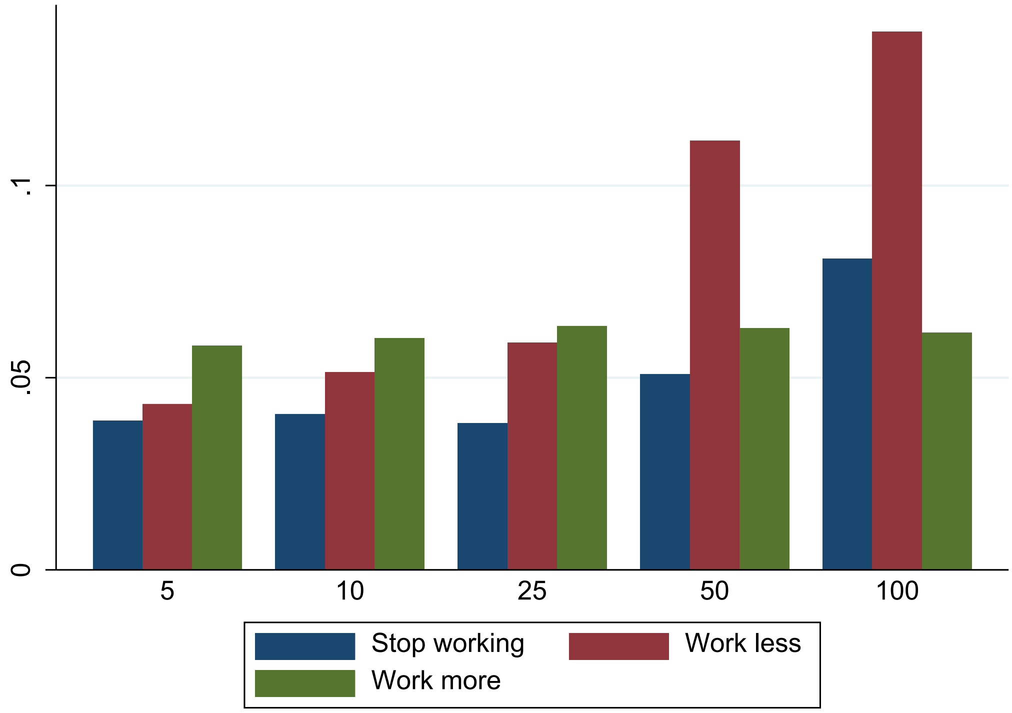
Note. The percentage drop in earnings is computed from the answers to the questions on employment and hours, combining the effect of a €100,000 hypothetical wealth shock on earnings of those who stop working and the change in earnings for those who report a change in hours (for those still working). Results are reported as a % of the windfall gain.

Table 6. Effect of wealth shocks on search intensity

	Baseline Logit	Logit with demographics	Logit with prize dummies	OLS with prize dummies
Prize	-0.0011	-0.0011		
	(0.0002)***	(0.0002)***		
High school		0.0155	0.0160	0.0171
		(0.0230)	(0.0230)	(0.0238)
College		0.0305	0.0305	0.0314
		(0.0227)	(0.0227)	(0.0236)
Age 18-34		0.0517	0.0540	0.0558
		(0.0623)	(0.0623)	(0.0662)
Age 35-49		0.0168	0.0201	0.0211
		(0.0623)	(0.0623)	(0.0665)
Age 50-64		0.0495	0.0522	0.0545
		(0.0626)	(0.0626)	(0.0664)
Female		0.0463	0.0450	0.0473
		(0.0181)**	(0.0181)**	(0.0187)**
Family size		0.0081	0.0078	0.0083
		(0.0071)	(0.0071)	(0.0071)
€10,000 prize			-0.0115	-0.0100
			(0.0294)	(0.0265)
€25,000 prize			-0.0280	-0.0247
			(0.0287)	(0.0263)
€50,000 prize			-0.0859	-0.0865
			(0.0265)***	(0.0262)***
€100,000 prize			-0.1004	-0.1033
			(0.0261)***	(0.0261)***
N	1,860	1,859	1,859	1,859

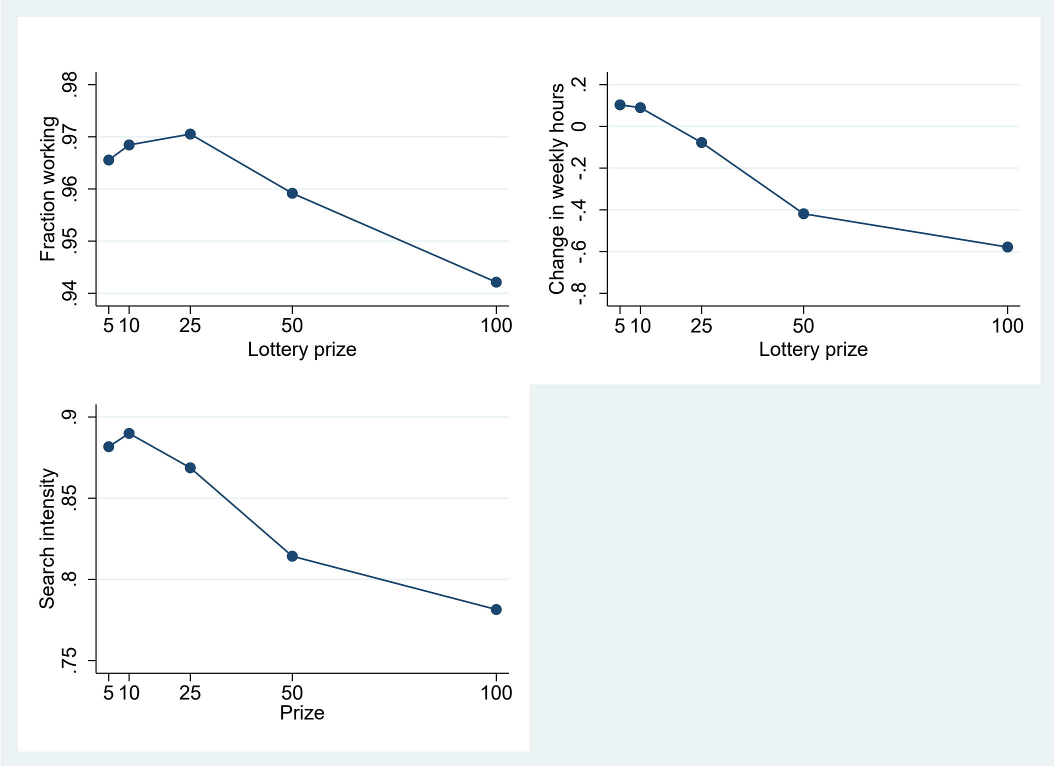
Note. The table reports marginal effects from logit regressions (OLS in the last column). All regressions include country dummies. One star indicates significance at the 10%, two stars at the 5%, three stars at the 1%.

Figure 1. Change in working status, by lottery prize



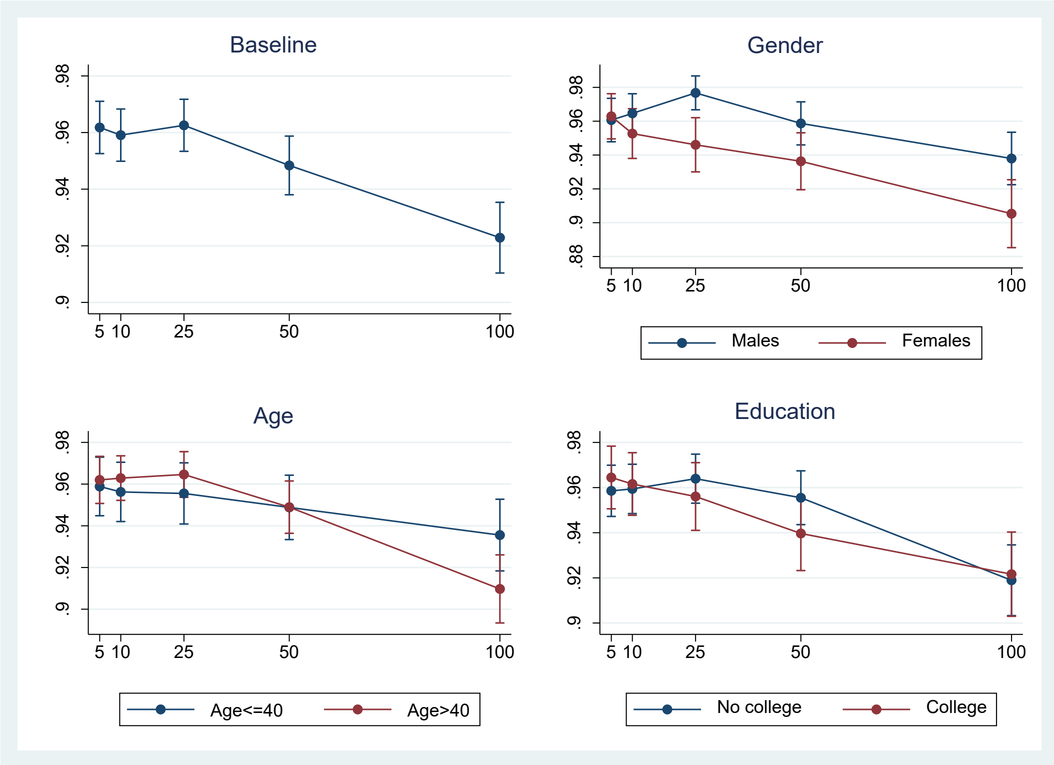
Note. The histogram plots the fraction of working respondents who after receiving the hypothetical lottery prize report that they would stop working, work less, or work more. We compute averages using sample weights.

Figure 2. Probability of working, change in hours, and search intensity by lottery prize



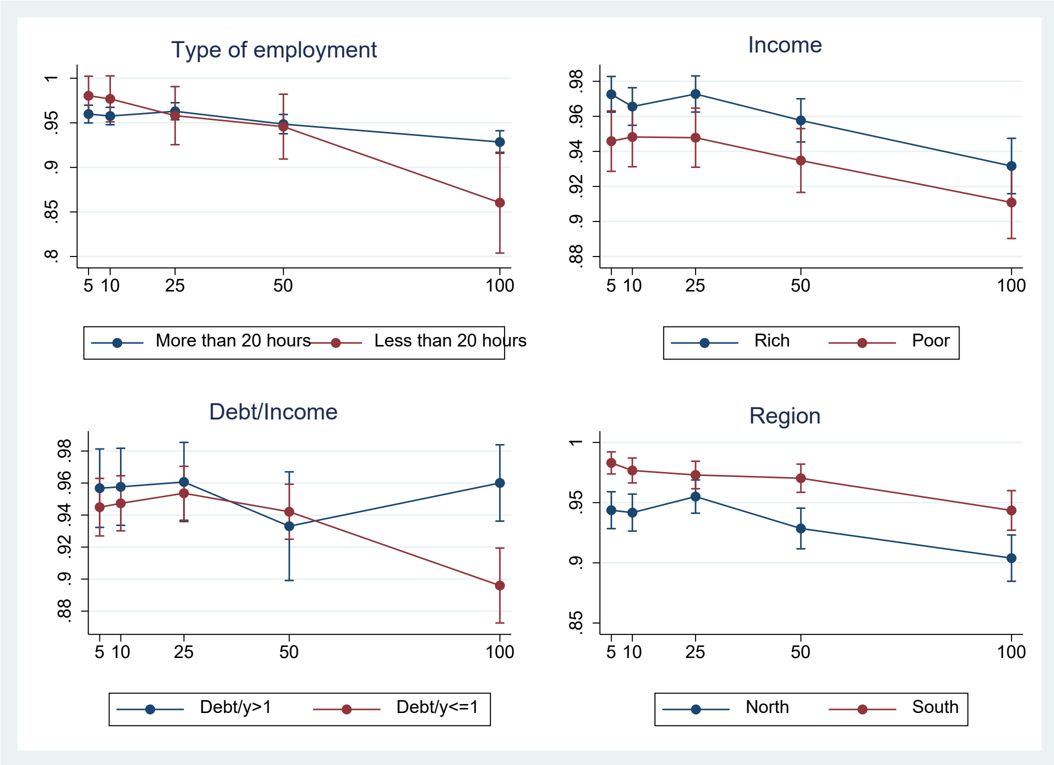
Note. Upper left graph plots the fraction of those working who intend to continue working after receiving the hypothetical prize (in thousands of euros). The upper right graph plots the change in weekly hours of those working after receiving the hypothetical prize. Search intensity in the bottom graph is a dummy defined in the sample of non-employed individuals, equal to zero if respondents intend to stop search or search less, and one otherwise, after receiving the hypothetical prize. We compute averages using sample weights.

Figure 3. The effect of lottery prize on the probability of working: baseline estimates, and effects of gender, age and education



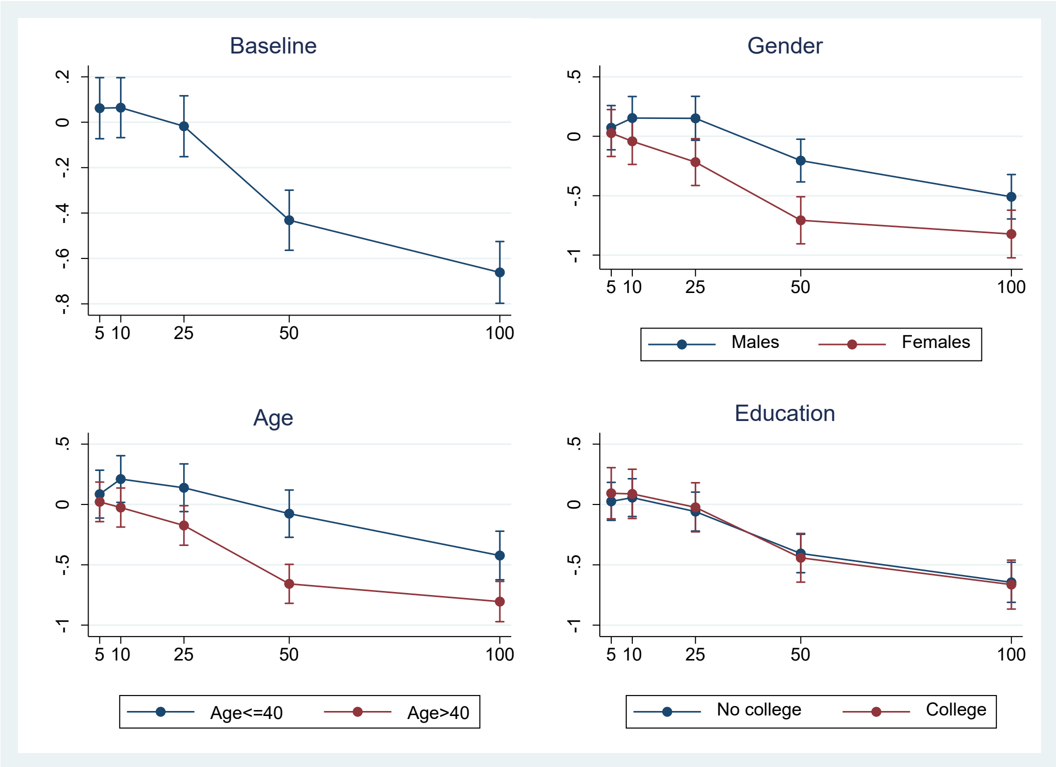
Note. Each figure plots the estimated probability of working and associated 95% confidence intervals from logit regressions of the probability of working on the wealth shock dummies, controlling for country dummies and socioeconomic variables (gender, age, education, family size, disposable income). The upper left graph is based on the regression of column 3 of Table 3. The other figures report the equivalent probabilities effects of two groups defined by gender, age (younger or older than 45 years) and education (college vs. non-college) across the wealth shocks. These are computed from logit regressions with full interaction of the lottery prize dummies and the group dummies.

Figure 4. The effect of lottery prize on the probability of working: effects of type of employment, income, debt and region



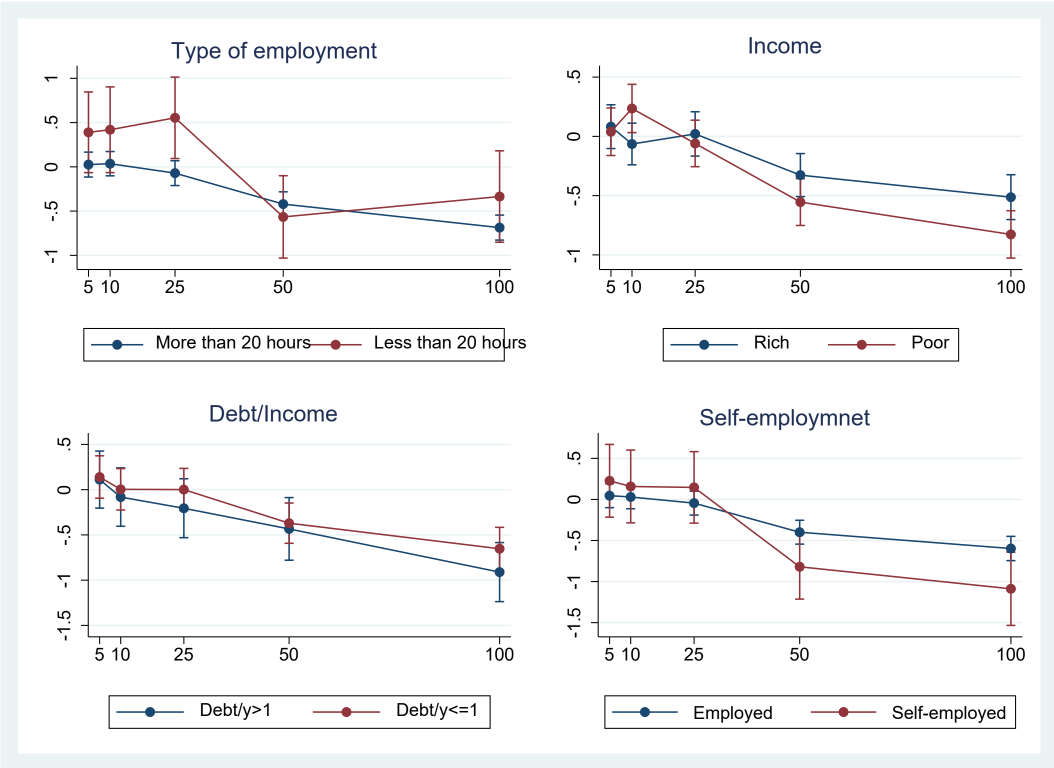
Note. Each figure plots the predicted probability of working and the associated 95% confidence intervals from logit regressions of the probability of working on the wealth shock dummies, controlling for country dummies and socioeconomic variables (gender, age, education, family size, disposable income). Results are reported for different groups distinguishing between part-time (working less than 20 hours) and fulltime (working more than 20 hours), income (below or above median disposable income), debt-income ratio (below or above one), region (Southern vs. Northern Europe) across the lottery prizes. These are computed from logit regressions with full interaction of the lottery prize dummies and the group dummies.

Figure 5. Change in hours: baseline estimates, and effects of by gender, age and education



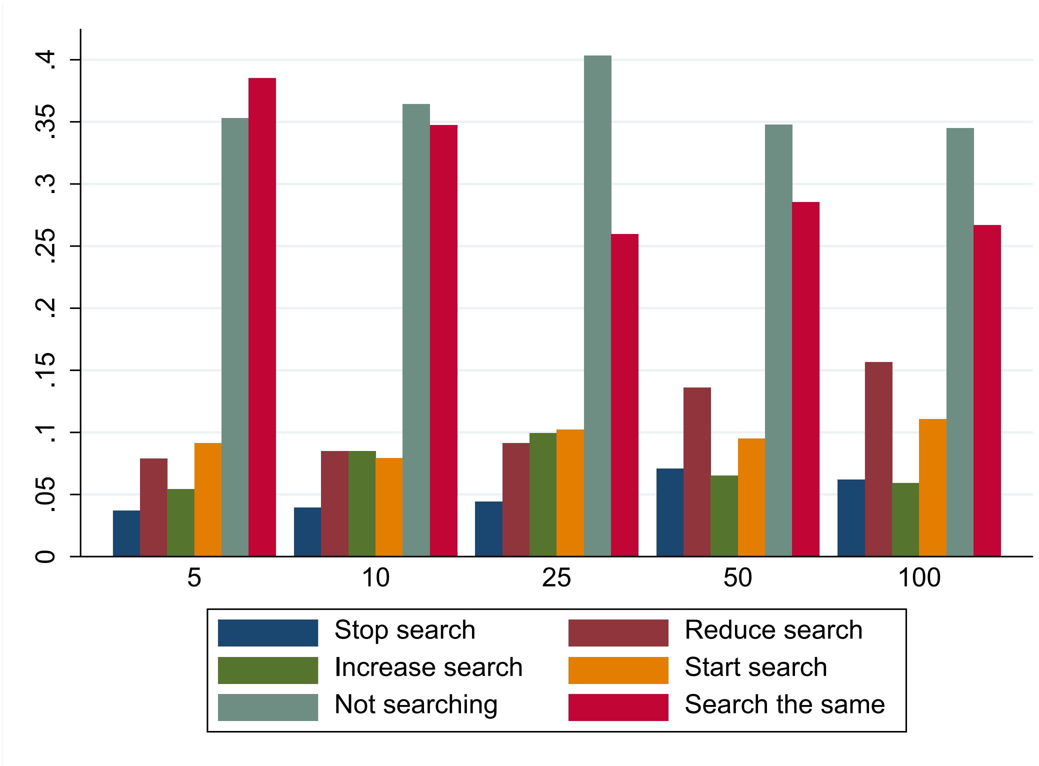
Note. Each figure plots the predicted change in hours and associated 95% confidence intervals from OLS regressions of the change in weekly hours on the wealth shock dummies, controlling for country dummies and socioeconomic variables (gender, age, education, family size, disposable income). The upper left graph reports the predicted change in hours and associated confidence intervals, based on the regression of column 3 of Table 4. The other figures report the predicted change in hours of different groups defined by gender, age (younger or older than 45 years) and education (college vs. non-college) across the lottery prizes. We compute the predicted change in hours from OLS regressions with full interaction of the lottery prize dummies and the group dummies.

Figure 6. Change in hours: effects of type of employment, income, debt exposure and region



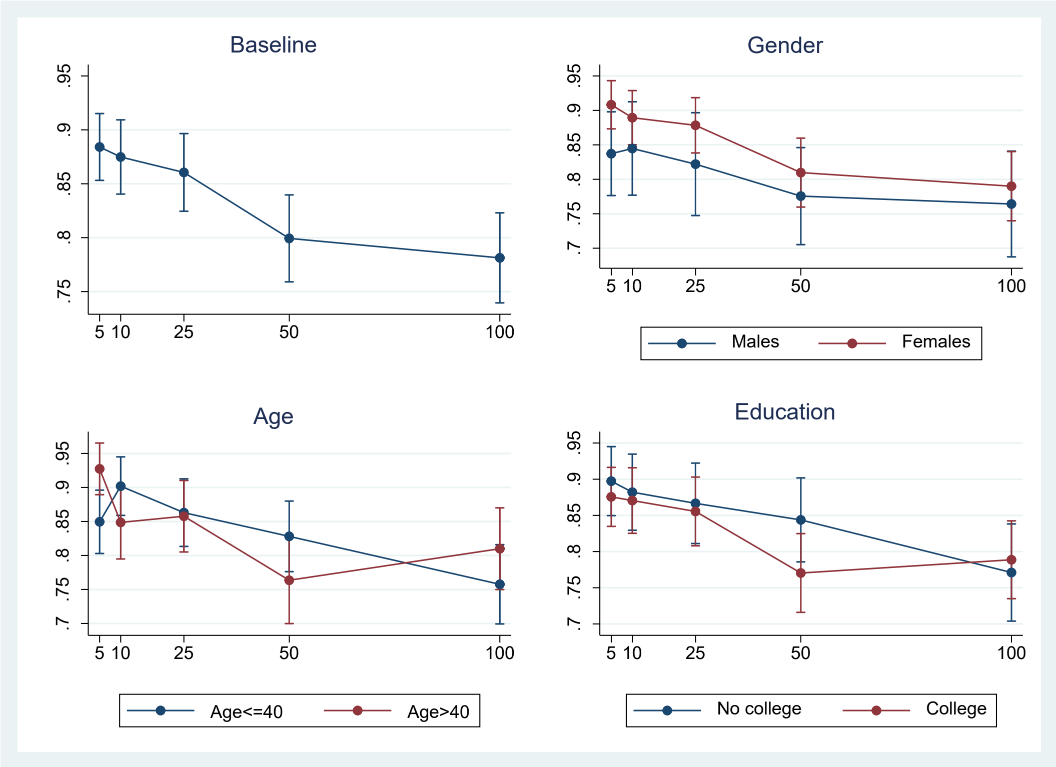
Note. Each figure plots the predicted change in hours and associated 95% confidence intervals from OLS regressions of the change in weekly hours on the wealth shock dummies, controlling for country dummies and socioeconomic variables (gender, age, education, family size, disposable income). The figures distinguish between part-time and fulltime workers (working less or more than 20 hours), income groups (below or above median disposable income), levels of debt-income ratio (below or above one), and employment status (self-employed vs. employed) across the lottery prizes. We compute the predicted change in hours from OLS regressions with full interaction of the lottery prize and the group dummies.

Figure 7. Search intensity, by lottery prize



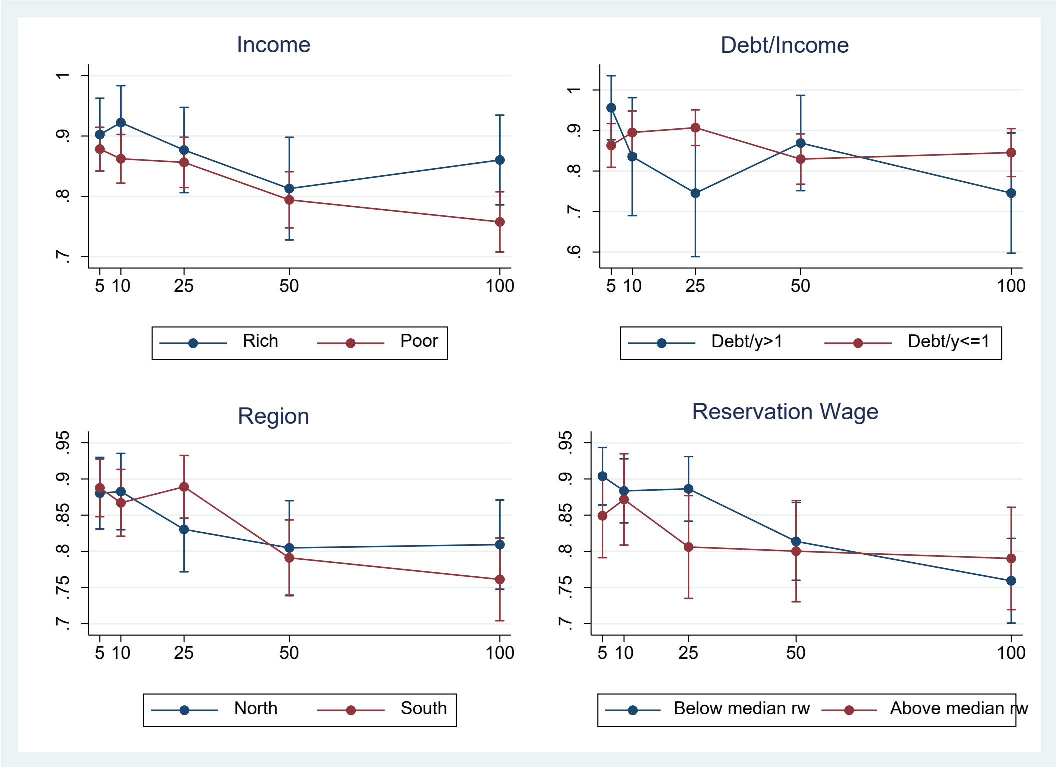
Note. The histogram uses the sample of non-working respondents for the six outcomes of the survey question on the intention to look for a job after receiving a hypothetical lottery. We compute averages using sample weights.

Figure 8. Search intensity: baseline estimates and effects of gender, age and education



Note. Each figure plots the predicted search intensity and associated 95% confidence intervals from logit regressions of search intensity on the lottery prize dummies, controlling for country dummies and socioeconomic variables (gender, age, education, family size, disposable income). Search intensity is a dummy defined in the sample of non-employed individuals, equal to zero if respondents intend to stop search or search less, and one otherwise. The upper left graph is based on the logit regression of column 3 of Table 6. The other figures report the search intensity for different groups defined by gender, age (younger or older than 45 years) and education (college vs. non-college) across the lottery prizes. We compute the predicted search intensity from logit regressions with full interaction of the lottery prize dummies and the group dummies.

Figure 9. Search intensity: effects of income, debt exposure, region and reservation wage



Note. Each figure plots the predicted search intensity and associated 95% confidence intervals from logit regressions of search intensity on the lottery prize dummies, controlling for country dummies and socioeconomic variables (gender, age, education, family size, disposable income). Search intensity is a dummy defined in the sample of non-employed individuals, equal to zero if respondents intend to stop search or search less, and one otherwise. The figures report search intensity of different groups defined by income (below or above median disposable income), debt-income ratio (below or above one), region (Southern vs. Northern Europe) and self-reported reservation wage from the May 2022 survey (below or above median) across the lottery prizes. We compute predicted search intensity from logit regressions with full interaction of the lottery prize and the group dummies.

Appendix A

A1. The Consumer Expectations Survey

The ECB's Consumer Expectations Survey (CES) is a new online high frequency panel survey of euro area consumer expectations and behavior. Building on recent international experiences and advances in survey methodology and design the CES was launched in pilot phase in January 2020. The CES has several important and innovative features that help facilitate rich analysis of economic shocks and their transmission via the household sector. Below we provide a summary of these main features – see Georgarakos and Kenny (2022) for a more detailed description of the CES and ECB (2021) for a first evaluation of the survey.

The CES covers the six largest euro area economies (Belgium, Germany, Italy, France, Spain, and the Netherlands) with a sample size of approximately 10,000 consumers during the period covered by our analysis. In this paper, we use mostly data from a special-purpose survey that was fielded in June 2022. The sample is comprised of anonymized individual-level responses from approximately 2,000 survey participants from each of the four largest euro area countries (Germany, Italy, France, Spain) and 1,000 in each of the two smaller countries (Belgium, the Netherlands). Three out of four participants in the four largest euro area countries were recruited via random dialing while the remaining are drawn from existing samples. The survey provides sample weights that we use to make descriptive statistics representative of the adult population in each country.

The large sample size helps ensure the survey's overall representativeness of population structures at both the euro area and component country levels. Respondents are invited to answer online questionnaires every month and must leave the panel between 18 and 24 months after joining. Each respondent completes a background questionnaire upon entry into the panel. This provides a range of important background information that changes very little month by month (e.g., education, family situation, household annual income, measures of financial literacy). More time-sensitive information is collected in a series of monthly, quarterly and ad hoc topical questionnaires. Detailed questions about household consumption expenditures are asked every quarter, while questions on consumption and asset choices in response to wealth shock scenarios like the one we utilize in the present paper can be asked in ad hoc special-purpose modules. The survey's online nature is particularly important for allowing the questionnaires to reflect evolving economic developments. For example, it was possible to field the survey experiment in June 2022.

Last, the CES is an incentivized survey with respondents receiving a gratuity with a relatively modest monetary value in recognition for their participation. These incentives signal the important value of the data supplied by respondents and strengthen the CES's overall quality by promoting high overall survey response rates, strong panel retention and minimal skipping of individual questions by participants.

A2. The experimental design

In June 2022 we asked respondents in the CES to report how they would change their work and search efforts after receiving a lottery prize. The question randomly assigns five different lottery prizes (<Amount>: 5, 10, 25, 50 and 100 thousand euro).

To the currently employed we ask: *Imagine you win a lottery prize of <Amount> today. What would be your plans for working over the next 12 months?*

The coding of responses is:

(1) Reduce my hours worked;

(2) Continue to work exactly the same number of hours;

(3) Increase my hours worked;

(4) Stop working (by either resigning or taking unpaid leave).

As a follow up question, we ask: *You said before you will choose to reduce / increase your hours worked per week. By how many hours would you choose to reduce / increase your work per week over the next 12 months?*

The coding of responses is: 0 hours; 1 to 2; 3 to 5; 6 to 10; 11 or more.

To all unemployed we ask: *Imagine you win a lottery prize of <Amount> today. How actively would you look for a job over the next 12 months?*

The coding of responses is:

(1) I am looking for a job, and would then look for a job more actively than before;

(2) I am looking for a job, and would then continue to look for a job exactly as before;

(3) I am looking for a job, but would then look for a job less actively than before;

(4) I am looking for a job, but would then stop looking;

(5) I am not looking for a job, and would not start looking for a job;

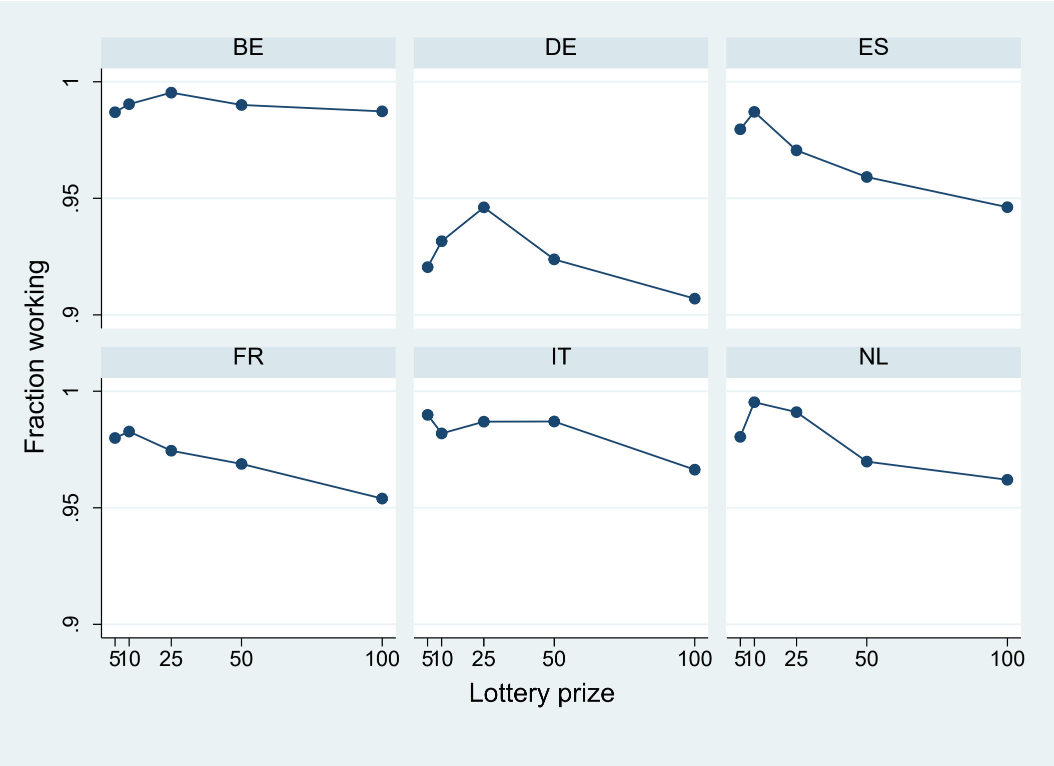
(6) I am not looking for a job, but would then start looking for a job.

A3. Reservation wage

The question asked to those not working is: Imagine that someone offered you a full-time job in a position that you would be happy to accept. What is the lowest annual net income (i.e., after tax and compulsory deductions) that you would accept in order to take up that job offer? Please consider all possible income from this job, including any overtime pay, tips, bonuses and profit-sharing benefits (unless they would be part of your pension arrangements).

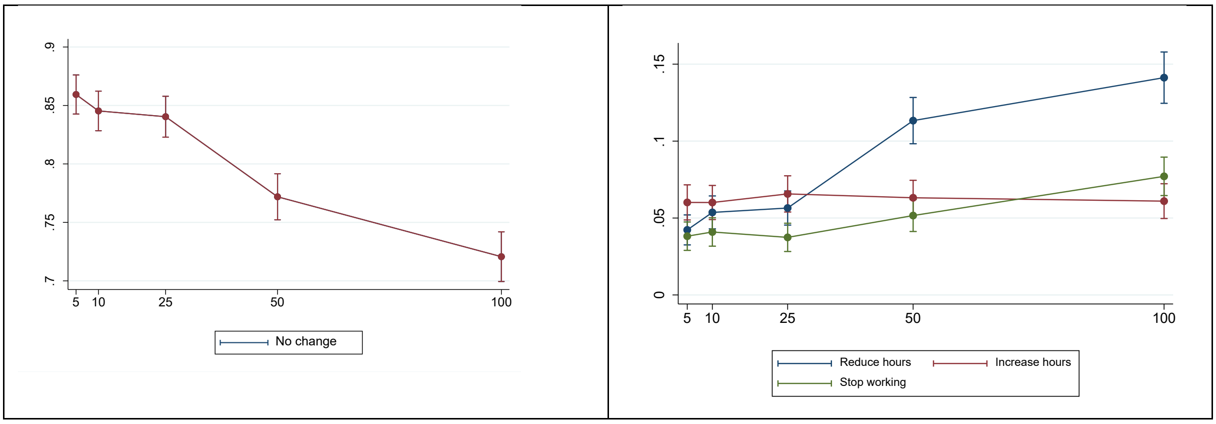
Appendix B. Additional figures and results

Figure B1. The probability of working, by lottery prize and country



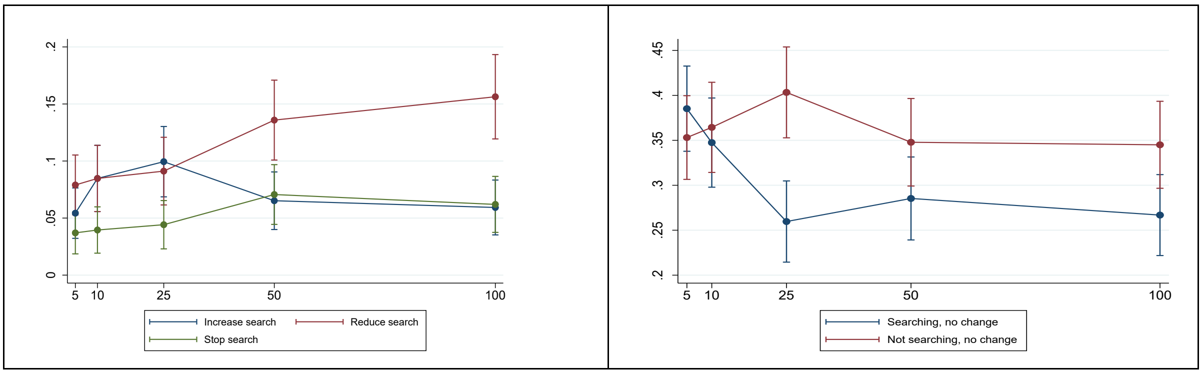
Note. The graph plots the fraction of those working who intend to continue working after receiving the hypothetical lottery in the countries of our survey experiment (Belgium, Germany, Spain, France, Italy and the Netherlands). We compute averages using sample weights.

Figure B2. Multinomial logit for change in hours and employment status



Note. The figures plot the predicted probabilities of change in hours and employment status using a multinomial logit.

Figure B3. Multinomial logit for search behavior



Note. The figures plot the predicted probabilities of search behavior using a multinomial logit. The baseline omitted outcome is “I am not looking for a job, and would not start looking for a job”.

Table B1. Probability of working

	Males	Females	Young	Old
€10,000 prize	0.0046	-0.0141	-0.0056	-0.0006
	(0.0095)	(0.0139)	(0.0120)	(0.0110)
€25,000 prize	0.0209	-0.0206	0.0007	0.0015
	(0.0110)*	(0.0137)	(0.0126)	(0.0113)
€50,000 prize	-0.0019	-0.0315	-0.0139	-0.0151
	(0.0092)	(0.0132)**	(0.0117)	(0.0104)
€100,000 prize	-0.0187	-0.0545	-0.0211	-0.0429
	(0.0086)**	(0.0126)***	(0.0115)*	(0.0097)***
N	4,440	3,911	3,372	4,979

Note. The table reports the effects of lottery prizes on the probability of working from logit regressions, splitting the sample by gender and age (less or more than 40 years old), controlling for country dummies and socioeconomic variables (gender, education, family size, disposable income, self-employment). Standard errors are reported in parenthesis. One star indicates significance at the 10%, two stars at the 5%, three stars at the 1%.

Table B2. Change in hours worked

	Males	Females	Young	Old
€10,000 prize	0.0724	-0.0768	0.0516	-0.0512
	(0.1205)	(0.1537)	(0.1635)	(0.1173)
€25,000 prize	0.0644	-0.2442	0.0646	-0.1597
	(0.1216)	(0.1545)	(0.1645)	(0.1182)
€50,000 prize	-0.2870	-0.7275	-0.1917	-0.6868
	(0.1200)**	(0.1548)***	(0.1629)	(0.1177)***
€100,000 prize	-0.5998	-0.8587	-0.5308	-0.8422
	(0.1224)***	(0.1559)***	(0.1653)***	(0.1195)***
N	4,258	3,682	3,213	4,727

Note. The table reports marginal effects from OLS regressions of lottery prizes on change in hours, splitting the sample by gender and age (less or more than 40 years old), controlling for country dummies and socioeconomic variables (gender, education, family size, disposable income). Standard errors are reported in parenthesis. One star indicates significance at the 10%, two stars at the 5%, three stars at the 1%.

Table B3. Search intensity: sample splits by gender and age

	Males	Females	Young	Old
€10,000 prize	0.0148	-0.0237	0.0676	-0.0937
	(0.0530)	(0.0356)	(0.0411)	(0.0454)**
€25,000 prize	-0.0165	-0.0404	0.0160	-0.0906
	(0.0527)	(0.0346)	(0.0378)	(0.0458)**
€50,000 prize	-0.0637	-0.1021	-0.0227	-0.1706
	(0.0468)	(0.0325)***	(0.0349)	(0.0427)***
€100,000 prize	-0.0750	-0.1172	-0.0799	-0.1397
	(0.0477)	(0.0317)***	(0.0327)**	(0.0443)***
N	610	1,249	1,002	857

Note. The table reports marginal effects of lottery prizes on search intensity from logit regressions, splitting the sample by gender and age (less or more than 40 years old), controlling for country dummies and socioeconomic variables (gender, education, family size, disposable income). One star indicates significance at the 10%, two stars at the 5%, three stars at the 1%.