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Labor supply response to windfall gains

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Abstract

Using a large survey of euro area consumers, we conduct an experiment in which respondents report how they would adjust their labor market participation, hours worked, and job search effort (if not employed) in response to randomly assigned windfall gain scenarios. Windfall gains reduce labor supply, but only when the gains are substantial. At the extensive margin, gains of €25,000 or less have no effects, while gains between €50,000 and €100,000 reduce the probability of working by 1.5 to 3.5 percentage points. At the intensive margin, small gains produce no impact, while gains above €50,000 lead to a reduction of approximately one hour of work per week. The effects among women and workers near retirement are stronger. The share of non-employed respondents who stop or reduce job search intensity declines by 1 percentage point for each €10,000 in windfall gain, with the strongest effects observed among older individuals receiving €100,000.

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

JEL: E24, D10, J22, J68

None-technical summary

The impact of wealth or unearned income shocks on labor supply has long been a central question in labor economics. From a policy perspective, understanding the magnitude of such effects is crucial. A common criticism of transfer programs is that they may discourage work or job search. Moreover, the aggregate demand effects of fiscal stimulus programs could be weakened if transfers induce individuals to consume more leisure and hence to earn less. These considerations are relevant for recent fiscal interventions, such as the one-time bonuses and transfers introduced during the COVID-19 pandemic and the recent energy crisis. They are also central to the evaluation of universal basic income (UBI) programs, implemented in various forms by governments on both sides of the Atlantic and in parts of Asia. Labor supply responses to wealth shocks are also central to the design of policies that directly affect wealth. One prominent example is the taxation of inheritances, which can significantly alter the size of what is typically a large, but infrequent, wealth shock. Another is the implementation of wealth taxes, as often proposed in the U.S. and other developed countries, or, in countries that already have one, the effects of modifying their progressivity or repealing them altogether.

In this paper we study the labor supply responses to both more common, smaller wealth or unearned income shocks, such as those typically associated with transfer programs, as well as less frequent and larger shocks such as those associated with inheritances. To do so, we design a survey experiment using a large-scale, population-representative survey in which respondents report how they would change their labor market participation, hours worked, and job search intensity (if unemployed) in response to randomly assigned windfall gains ranging from €5,000 to €100,000. Because the shocks are randomly assigned, they are by construction orthogonal to respondents' observed and unobserved characteristics, allowing us to estimate the causal impact of wealth shocks on labor supply and to explore heterogeneity across demographic groups (e.g., by age, gender, or education). In this way we contribute to the literature on the labor supply effect of windfall gains, as well as the growing literature employing survey experiments based on real-life scenarios.

Our experimental results indicate that windfall gains reduce labor supply, but only when the gains are substantial. For amounts of €25,000 or below, the effects are statistically indistinguishable from zero. In contrast, larger gains (ranging between €50,000 and €100,000) reduce the likelihood of working by 1.5 to 3.5 percentage points (off an 84% baseline employment rate). At the intensive margin, small gains have no effect on hours worked, while prizes above €50,000 lead to a reduction of about one hour worked per week. Women, individuals nearing retirement and those living in countries with more flexible labor markets respond more strongly to windfall gains. Among the non-employed, job search intensity declines by roughly 1 percentage point for each €10,000 gain, with larger effects among older recipients of large windfalls. These results suggest that only relatively large wealth shocks generate economically sizable labor supply responses, while smaller transfers or bonuses – such as those typically observed in policy settings – have minimal to no disincentive effects. The non-linear response of labor supply to wealth shocks that we identify is consistent with the presence of labor market frictions and adjustment costs, which may inhibit behavioral changes unless the shock is sufficiently large. Alternatively, it may reflect behavioral biases, such as bounded rationality or mental accounting.

Overall, our findings suggest that only relatively large shocks (e.g., unanticipated inheritances) trigger economically meaningful labor supply responses, while shocks within the range of typical transfers or bonuses result in small or negligible disincentive effects on labor supply. Given the scale of typical UBI-style programs as currently discussed, our estimated responses imply that such programs would overall have quite limited labor supply disincentives effects. Our estimates also suggest that one can dismiss the idea that stimulus packages are ineffective in raising consumption because they end up mainly financing leisure rather than spending.

1. Introduction

The impact of wealth or unearned income shocks on labor supply has long been a central question in labor economics, as it helps distinguish between uncompensated and compensated labor supply responses to wage changes.[1] From a policy perspective, understanding the magnitude of the income effect on labor supply is crucial. A common criticism of transfer programs is that they may discourage work or job search. Moreover, the aggregate demand effects of fiscal stimulus programs could be weakened if transfers induce individuals to consume more leisure and hence to earn less. These considerations are relevant for recent fiscal interventions, such as the one-time bonuses and transfers introduced during the COVID-19 pandemic and the recent energy crisis. They are also central to the evaluation of universal basic income (UBI) programs, implemented in various forms by governments on both sides of the Atlantic and in parts of Asia.

Labor supply responses to wealth shocks are also central to the design of policies that directly affect wealth. One prominent example is the taxation of inheritances, which can significantly alter the size of what is typically a large, but infrequent, wealth shock. Another is the implementation of wealth taxes, as often proposed in the U.S. and other developed countries, or, in countries that already have one, the effects of modifying their progressivity or repealing them altogether. In this paper we aim to study the labor supply responses to both more common, smaller prizes, such as those typically associated with transfer programs, as well as less frequent and larger shocks such as those associated with inheritances.

From an empirical perspective, researchers face three challenges. The first is the difficulty of isolating truly exogenous changes in wealth. Early studies estimated relevant elasticities using variation in unearned income (such as income from capital or a spouse) from non-experimental data (Blundell and MaCurdy, 2000). However, these sources of unearned income may be correlated with preferences or other unobserved characteristics that also influence labor supply decisions. Subsequent work has focused on settings where exogenous variation is more credible such as among inheritance recipients (Holtz-Eakin et al., 1993; Joulfanian and Wilhelm, 1994; Bø et al., 2019), beneficiaries of government windfall payments (Bibler et al., 2023; Powell, 2020), and lottery prize winners (Imbens et al., 2001; Cesarini et al., 2017; Picchio et al., 2018; Golosov et al., 2024). One limitation of these approaches is that the

[1] We will use the terms "wealth shocks" and "unearned income shocks" interchangeably.

evidence comes from specific population sub-groups that may not be representative of the general population.

The second empirical challenge is that real-world labor supply responses may be dampened by factors such as inattention, lack of salience, or frictions including labor adjustment costs or the illiquidity of the specific wealth change. These frictions become less relevant when wealth shocks are large. However, such shocks (like large lottery winnings or inheritances) are relatively rare in available data.

The third challenge is that, although the theoretical framework focuses on hours worked, most empirical evidence relies on earnings. The response of earnings may differ from scaled hours responses in the presence of non-linear wage schedules induced by tax progressivity, overtime premia, or penalties associated with part-time work. Additionally, labor supply responses to wealth shocks can occur on both the extensive and intensive margins, including adjustment in the job search effort among the non-employed.

Against this background, we design a survey experiment that addresses all three empirical challenges at once. We conduct a large-scale, population-representative survey in which respondents report how they would change their labor market participation, hours worked, and job search intensity (if unemployed) in response to randomly assigned windfall gains ranging from €5,000 to €100,000. Because the shocks are randomly assigned, they are by construction orthogonal to respondents' observed and unobserved characteristics, allowing us to estimate the causal impact of wealth shocks on labor supply and to explore heterogeneity across demographic groups (e.g., by age, gender, or education). Unlike studies based on lottery prizes or inheritance recipients, our approach is based on a representative sample of the population. A further innovation of our design is the random variation in the size of the windfall gain, which enables us to test whether responses are heterogeneous with respect to the *size* of the shock. This is a key distinction: in the absence of frictions, the labor supply response to wealth shocks should be independent of the shock size. However, in the presence of labor market frictions or adjustment costs, individuals may respond only to shocks large enough to overcome the frictions. A final key innovation of our approach is that we focus on hours worked rather than earnings, allowing us to abstract from potential non-linearities in the wage schedule. Moreover, in models with labor market frictions, the unemployed face a trade-off between leisure and time spent searching for a job. This implies that wealth shocks may not only reduce hours worked among the employed, but also reduce job search intensity among the non-employed, a combination of intensive and extensive margin responses which our design allows us to analyze separately (see also Coibion et al., 2020). More broadly, our study contributes to a much-debated policy issue: many researchers have argued that programs resembling the windfall gains in our experiment can reduce labor supply, encourage informal work, and discourage job search activities among recipients.

We find that windfall gains reduce labor supply, but only when the gains are substantial. For amounts of €25,000 or below, the effects are statistically indistinguishable from zero. In contrast, larger gains (ranging between €50,000 and €100,000) reduce the likelihood of working by 1.5 to 3.5 percentage points (off an 84% baseline employment rate). At the intensive margin, small gains have no effect on hours worked, while prizes above €50,000 lead to a reduction of about one hour worked per week. Women, individuals nearing retirement and those living in countries with more flexible labor markets respond more strongly to windfall gains. Among the non-employed, job search intensity declines by roughly 1 percentage point for each €10,000 gain, with larger effects among older recipients of large windfalls. These results suggest that only relatively large wealth shocks generate economically sizable labor supply responses, while smaller transfers or bonuses – such as those typically observed in policy settings – have minimal to no disincentive effects. The non-linear response of labor supply to wealth shocks that we identify is consistent with the presence of labor market frictions and adjustment costs, which may inhibit behavioral changes unless the shock is sufficiently large. Alternatively, it may reflect behavioral biases, such as bounded rationality or mental accounting.

In addition to contributing to the literature on the labor supply effect of windfall gains, our paper adds to the growing literature employing survey experiments based on real-life scenarios. Several chapters in the *Handbook of Economic Expectations* (Bachmann et al., 2023) as well as the comprehensive review by Stantcheva (2023), document the widespread use of this approach across various fields, such as education, labor, health, and macro-finance. Bernheim et al. (2021) point out that scenario questions are especially useful when the treatment is correlated with individual decisions, as with wealth shocks, and rare, as is the case for large windfall gains. While the literature recognizes potential biases in respondents' answers to scenario questions, such as social desirability and survey-demand effects, or reluctance to disclose sensitive information, it also notes that when biases are randomly distributed across experimental groups, the design still permits valid causal inference and yields meaningful insights.

The paper is organized as follows. Section 2 provides an overview of the data, while Section 3 outlines the empirical framework and discusses the identification challenges. In Section 4 we present evidence on the causal effects of wealth shocks on employment probabilities (the extensive margin), and hours worked (the intensive margin), comparing our findings with existing literature. Section 5 presents the results on search intensity. Section 6 concludes.

2. The survey experiment

To examine the labor supply effects of windfall gains, we use the ECB's Consumer Expectations Survey (CES), a high-frequency panel survey capturing euro area consumer expectations and behaviors. The CES was launched in 2020, initially covering the six largest euro area economies: Belgium, Germany, Italy, France, Spain, and the Netherlands. The sample consists of anonymized individual-level responses from approximately 2,000 survey participants in each of the four largest euro area countries (Germany, Italy, France, and Spain) and 1,000 participants in each of the two smaller countries (Belgium and the Netherlands), yielding a total sample size of about 10,000 consumers.

In this study, we draw data from a special-purpose survey conducted in June 2022, combining it with background information and other data collected through the regular CES modules. After asking respondents to report their labor market status, the survey experiment proceeds with a series of three questions. Respondents are randomly assigned to one of five hypothetical lottery winnings of varying amounts (€5,000, €10,000, €25,000, €50,000, €100,000). Those who report being employed are then 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 responses are to reduce the hours worked, maintain the same number of hours, increase hours worked, or stop working entirely (by either resigning or taking unpaid leave). Following this, employed respondents (excluding those who reported that they would stop working) are asked to indicate how many more or fewer hours they would work per week over the next 12 months, with responses ranging 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 are given a set of qualitative response options. Those who are actively seeking a job indicate whether they would search more actively, less actively, or stop looking altogether. Respondents who are not currently looking for a job are asked whether they would start looking or not. The Appendix provides the exact wording of the questions and details of the experiment's design.

The survey questions were designed to capture labor supply responses to both more common changes (smaller prizes) and less frequent, larger ones. The hypothetical windfall gains range from relatively small (€5,000) to very large (€100,000), and these amounts are randomized across respondents. Smaller prize amounts are intended to simulate the typical size of temporary income support policies. For example, in Italy, the basic income support program introduced in 2019 ("reddito di cittadinanza") provides up to €750 per month for 18 months to individuals who are unemployed or out of the labor force.[2] A prize between €10,000 and €20,000 is roughly equivalent to this program if extended for one or two years. Larger prize amounts may reflect windfalls such as bequests or gifts received on special occasions (with the corresponding tax implications), or severance payments. For example, in Spain severance payments can be up to 20 days' pay per year of service, while in France it can be up to one-third of monthly salary per year of service for employees with over 10 years of tenure. The range of prize amounts included in the survey experiment also enables direct comparisons with prior studies based on actual lottery outcomes.

In experimental settings, it is standard practice to use a 'baseline' group for comparisons. In our experiment the group assigned a hypothetical €5,000 prize serves as this baseline – the smallest windfall amount considered. Accordingly, in the empirical analysis we estimate the effects of larger gains relative to this reference amount. When designing the survey, we considered using even smaller prize amounts (€500 or €1,000), but decided that it would be implausible to expect meaningful labor supply responses to one-time gains that – at least for

[2] During the pandemic, several countries implemented similar support schemes. In Germany, the short-time work allowance was extended up to 28 months until 30 June 2022 (from 12 months). In France, the government relaxed eligibility criteria of the partial-activity allowance scheme. In Spain, furloughed workers received 70% of their base salary for the first six months, with the rate decreasing to 50% for subsequent months. The Netherlands introduced various type of subsidies during the COVID-19 outbreak. In Belgium the 2021 protection bonus amounted to €780 for low-wage workers, with no formal limits on the duration of support.

most individuals - are negligible.[3] 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.

Prizes are randomly assigned across five groups of respondents. By design, this ensures that the resulting windfall gains are exogenous and orthogonal to both observed and unobserved individual characteristics. This setup allows us to estimate the causal effects of unanticipated windfall gains on labor supply, capturing three key dimensions of labor supply decisions. First, we assess the extensive margin—whether employed individuals choose to exit the labor force entirely. Second, we examine the intensive margin, measuring changes in the number of hours worked in response to the prize. Third, we explore the impact of wealth shocks on job search behavior, focusing on both the intensity and likelihood of job search among those currently not employed.

Our approach offers several advantages over prior literature. Random assignment of the lottery prizes enables a clean identification of the causal effect of exogenous wealth shocks, and allows us to investigate how the size of the shock influences behavior. Importantly, we use weekly hours worked as our outcome for the intensive margin, whereas most previous studies rely on earnings data and assume proportionality between hours and earnings—an assumption that may not hold in practice, particularly given that overtime wage premia and part-time wage penalties may drive a wedge between the two. Additionally, our survey experiment captures the search response to wealth shocks—an often-overlooked dimension in the existing literature. The use of a large, representative sample also allows us to investigate heterogeneous effects across demographic groups, providing deeper insights into how different segments of the population respond to unexpected income gains.

Before moving to the empirical analysis, it is important to acknowledge some potential limitations of our research design. First, survey-based studies on self-reported behavior may capture intentions rather than actual choices (Forster and Neugebauer, 2024). While intentions can be informative, they do not always translate into realized behavior, which could lead to

[3] We avoided eliciting responses to very small windfall gains also because we wanted respondents to engage with the scenario questions in a realistic manner and felt that too small prizes would trigger noisy responses. For similar reasons, 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).

discrepancies between reported and actual labor supply responses.[4] A second limitation of the direct survey questions used in this paper is that responses may be affected by differences in the wording of the questions and by framing effects. Crossley et al. (2025) compare two methods for eliciting the Marginal Propensity to Consume (MPC) in surveys: a direct question and a filtered question.[5] They find that differences in question wording lead to substantially different MPC distributions. In particular, direct questions tend to yield significantly higher MPC estimates than filtered methods. A third limitation is that survey questions that try to elicit behavioral responses may not be fully understood or interpreted in a uniform way by all respondents.

A final limitation is that we measure the labor supply response to a transitory, one-time unearned income shock, similar in spirit to Powell (2020).[6] From a life-cycle perspective, a rational consumer facing such a shock would smooth the consumption of leisure over the remaining horizon, implying that the immediate labor supply response may be relatively modest. In particular, a rational consumer would behave as if a one-time windfall gain of size Q were equivalent to an annual windfall of $\frac{r}{1+r}\left(1-\frac{1}{(1+r)^{T-t+1}}\right)^{-1}Q$ received every year until retirement, where r is the interest rate and $T-t$ the remaining number of working periods. We thus need additional assumptions to compute the Marginal Propensity to Earn (MPE) out of lifetime income. We discuss these assumptions and the formula we use to compute the MPE in Section 4, where we also compare our estimated MPE with estimates from the existing literature.

One important interpretative issue is the possibility that respondents perceive the windfall gain as taxable, pushing them into a higher tax bracket. We assume that individuals interpret the hypothetical windfall gain as an after-tax change in wealth. This means that their reported labor supply response reflects the perceived net gain, inclusive of any tax effect. This assumption is realistic for both small and large shocks. Smaller gains are unlikely to trigger "bracket creep" or significant changes in tax liability. For larger prizes, respondents may equate

[4] We are not aware of any work that compares the approach used in this paper (of estimating "hypothetical labor supply responses") with actual behavioral responses ("revealed-preference estimates") for the *same* respondents. See Parker and Souleles (2019) for an exercise of this type related to the marginal propensity to consume (MPC).

[5] A filtered question has two steps: respondents are first asked whether a certain windfall would lead them to increase their spending, decrease spending or keep spending the same; then, they are asked how much they would spend out of the windfall.

[6] Moreover, our analysis does not capture general equilibrium effects (e.g., associated with impacts on aggregate demand that can arise if spending responds to a wealth shock).

them with events like receiving an inheritance, for which many countries typically offer substantial tax exemptions especially for the range of wealth shocks that we consider. In such cases, the perceived after-tax value would closely align with the nominal amount presented in the survey.[7]

3. Empirical framework

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

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

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 (such as the market wage rate and 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. The parameter of interest is β, which measures the causal effect of unearned income (or wealth) on hours of work.

Equation (1) closely mirrors the specification used in much of the life-cycle labor supply literature, where hours worked are modelled as a linear function of wealth.[8] This functional form implies that the effect of a wealth shock on labor supply is constant – i.e., independent of the size of the shock. If there are frictions in the labor market or if the response to windfall gains depends on the perceived size or framing of the shock, as in models with bounded rationality or mental accounting, then hours worked could vary with the size of the shock.[9] In the analysis below we allow the labor supply responses to depend on the size of the shock.

[7] One indication that differences in marginal tax rates are unlikely to bias our estimates is that the labor supply effects do not vary systematically across income groups in our regressions. This suggests that respondents are not adjusting their behavior based on tax considerations tied to their income level, reinforcing the assumption that the windfall is perceived as an after-tax gain. On the other hand, it may be problematic to extrapolate the estimated responses to settings with different nonlinearities than those induced by, say, progressive taxation.

[8] See, e.g., Ziliak and Kniesner (1999), MaCurdy (1981), Blundell and Walker (1986) and Pistaferri (2003).

[9] The literature has focused on various types of labor market frictions that may limit ability to adjusting working hours freely (see Blundell at al., 2008, for an overview). For example, many workers cannot make marginal adjustments to their hours; instead, they face discrete choice, such as moving from part-time to full-time (and *vice versa*), often requiring a job change to do so. In some models, jobs are offered as fixed bundles of hours and wages, either due to technological constraints in production or institutional features of the labor market. In other papers, constraints arise in setting where firms possess monopsonistic power. Additionally, in certain contexts workers must meet minimum weekly hours to qualify for specific benefits, such as current health insurance coverage or

In principle, if the size of the shock correlates with constraints on working hours or unobserved beliefs, it could induce biases rendering the estimated effect inconsistent. For instance, if small windfall gains come from transfer programs targeting the poor - who are more likely to face frictions in adjusting their desired working hours or exhibit behavioral biases - this could lead to smaller observed labor supply responses. However, these concerns do not apply in our set up. The experimental design ensures that the shocks are exogenous and orthogonal to respondents' preferences, beliefs, or labor market constraints.[10]

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 that people differ in their unobserved attitudes for hard work. Those with stronger attitudes for hard work will tend to work longer 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 may be a positive correlation between current hours and Q_{it} not because of a causal effect running from higher Q_{it} to longer hours of work, but because people with stronger unobserved attitudes for hard work accumulate more wealth *and* work longer hours.

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 the case if $cov(Q_{it}, v_{it}) \neq 0$, where v_{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):

future unemployment insurance. Finally, it is possible that frictions related to the staggering nature of collective bargaining agreements can lead to a delay in actual labor supply responses, since hours schedules can only be renegotiated at fixed time intervals. All these institutional and structural frictions can shape labor supply responses, particularly at the intensive margin.

[10] In our survey setting, inattention or lack of salience are unlikely to be concerns, as the question explicitly references a wealth shock. In principle, this leaves labor market frictions—such as constraints on adjusting hours or the distinction between full- and part-time employment—as potentially the most relevant factors for explaining (low) labor supply responses in our context. On the other hand, we do not want to claim that direct survey questions can be used to fully resolve identification issues (i.e., separating frictions in adjusting hours from behavioral or informational biases), since – as noted above – survey questions may not be fully understood or interpreted in a uniform way by all respondents.

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

The second equality follows from the assumption that $\Delta Q_{it} = P_{it}$, where P_{it} is the *randomly* assigned windfall gain. Thanks to the randomization, P_{it} is by design independent of any unobserved variable that might affect the labor supply decision. Moreover, 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 4 we estimate logit regressions for the probability of continuing to work after the windfall gain assignment, i.e., $Prob(\Delta h_{it} \geq 0)$.

Table 1 presents summary statistics for the key variables used in the empirical analysis. Means and standard deviations are calculated using sample weights. We exclude retired individuals and 538 respondents (approximately 5% of the sample) who completed the survey in under 2.5 minutes, well below the expected completion time of around 10 minutes for the full module. The final sample includes 9,438 working and 1,860 non-working respondents.[11] The non-working group consists of individuals who are not retired and are either actively seeking employment or of working age but not currently searching.

Among the employees, across all prize groups, 81% report that they would continue working the same number of hours, while, 5% indicate they would stop working, 8.1% say they would reduce their hours, and 6.1% report they would increase them. On average, the intended change in weekly hours across all prize groups is –0.19.

Among non-working respondents, 31% say they would continue searching at the same intensity, while 36.2% indicate they would neither work nor search. In terms of changes in search behavior, 7.2% would search more actively, 9.6% would start searching, 10.9% would reduce their search effort, and 5.1% would stop searching altogether. As we will show, these patterns become more informative when analyzed by prize amount rather than across the overall sample.

To check if the randomization is properly implemented, we provide statistics showing that the sample is balanced across the groups receiving the hypothetical prize amounts. We also run regressions of the probability of being part of a particular randomized sub-sample. Table 2 presents sample means for key socio-economic variables across the randomly assigned lottery

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

prizes. In terms of sample size, the five sub-samples range from 1,853 to 1,925 for the employed, and between 354 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.[12] 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 respondent characteristics (the χ^2 statistic is 37 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%).

4. Labor supply responses

4.1. The extensive margin: probability of employment

We begin the empirical analysis by presenting descriptive statistics and regressions for the extensive margin, specifically the probability of continuing to work following the experiment. Figure 1 illustrates the proportion of respondents who would stop working, reduce their hours, or increase their hours, as a function of the assigned lottery prize. The omitted category is "work the same," which includes the largest fraction of respondents (around 80%). Approximately 6% of respondents express an intention to work more, with this fraction remaining unchanged across different prize sizes. In contrast, the proportion of respondents who plan to work less or stop working entirely increases with the size of the lottery prize.

In the upper-left graph of Figure 2, we combine the fractions of respondents who intend to continue working—whether by working less, the same, or more—and plot it against the prize amount. The figure shows that about 97% of respondents would continue working for small prizes (up to €25,000), but this fraction drops to 94% for prizes between €25,000 and €100,000. Figure B1 in the Appendix further reveals that the negative employment effect at higher prize levels is approximately 3% across all countries, except for Belgium, where the effect remains flat.

Table 3 reports the marginal effects from a logit regression for the extensive margin. We define a dummy variable that equals one for respondents who intend to continue working after receiving the lottery prize, and zero otherwise. In the baseline regression presented in column

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

(1), we include only two controls: the lottery prize (measured in thousands of euros) and country dummies. The prize enters linearly and has a small effect on employment: a €1,000 increase in unearned income reduces the probability of continuing to work by 0.04%. This implies that receiving the largest prize of €100,000 would reduce the likelihood of working by 4 percentage points. To benchmark this number, note from Table 1 that the share of people in our sample who work is 84% $\left(\frac{9438}{9438+1860}\right)$. 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 randomly assigned wealth shocks.[13] 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 of Table 3 we report the coefficients of a linear probability model, with almost identical results.

Given the large and representative nature of our sample, we are able to explore heterogeneity in responses. We evaluate the marginal effects of wealth shocks on employment across different group pairings and present the results in graphical form in Figures 3 and 4. For comparison, the upper-left graph in Figure 3 plots the estimated probabilities and associated 95% confidence intervals derived from the baseline logit model in column (3) of Table 3. The only significant effects relative to the baseline prize appear for respondents exposed to €100,000 wealth shocks, with the effect of the €50,000 shock being significant at the 10% level, as seen in Table 3.

In the upper-right graph of Figure 3, we expand the model from column (3) of Table 3 by adding an interaction term for gender 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. However, for the €25,000 prize, female employment rates are 2.5 percentage points lower than those of males, with the effect of the €50,000 prize being significant at the 10% level. These findings suggest that women are somewhat more responsive to shocks, consistent with previous literature indicating that women tend to exhibit larger labor supply elasticities than men in response to wealth shocks (Keane, 2011).

[13] The statistical test that the prize coefficients are equal is rejected at the 1% level, with a χ^2 statistic of 32.8.

The other two graphs of Figure 3 explore additional dimensions of heterogeneity and are constructed in a similar way. The bottom-left graph considers age effects, interacting the prize dummies with indicators for older (over 40 years old) and younger workers (40 or younger). The graph shows that for the largest wealth shock the labor supply of older workers is more responsive than that of younger ones (a 4 percentage points higher decline in the employment rate), even though the marginal effect is not statistically different from zero at the 5% level. This finding supports the idea that workers closer to retirement tend to respond to economic incentives, as they have less time to adjust labor supply and a shorter horizon over which to smooth the shock. In contrast, the lower-left graph shows no significant differences when interacting the prize dummies with college education. In Figure 4, we explore heterogeneity in responses to wealth shocks by interacting the wealth shock dummies with employment status (part-time vs. full-time workers), income level (below vs. median) and indebtedness (debt/income ratio below vs. above one). We find that part-time workers (defined as those working less than 20 hours per week) respond much more to the largest wealth shock than full-time workers (with a differential effect of 10 percentage points, and significant at the 5% level). Another group showing a significant marginal difference is workers with low debt. In response to the largest prize, they report a 5 percentage points higher probability of exiting the labor force compared to their highly indebted counterparts. We find no significant difference in the intention to continue to work based on income level.[14]

While regressions with interaction terms between the prize dummies and group indicators allow for testing differential effects across groups, they impose the restrictions that the effects of other covariates are held constant across those groups. As an alternative, we estimate separate logit regressions on subsamples. Table B1 in the Appendix presents these regressions for the two key dimensions in our analysis (gender and age). Consistent with the patterns observed in Figure 3, the results show that prizes of €50,000 and above, the estimated marginal effects are larger (in absolute value) for women and for older workers.

In the main analysis we categorize individuals in the "continue working" category if they report that they intend to work fewer hours, more hours, or maintain their current working

[14] We also explore other dimensions of heterogeneity. We interact the lottery prizes with different levels of financial sophistication, measured by the number of financial literacy questions answered correctly, an indicator that may capture the ability to understand the hypothetical lottery scenario. Reassuringly, we find no difference across this dimension. We also interact the prize dummies with a dummy for single individuals without children (or just singles) and find no differential effects between singles and other household types.

hours. One concern with this aggregation is that it may obscure heterogeneity across theses different responses. To address this, we estimate a multinomial logit model distinguishing among four labor supply outcomes: increase hours worked, reduce hours worked, stop working, and continuing to work the same number of hours.

The model includes the same set of covariates used in the baseline specification, and results are presented graphically in Figure B2 of the Appendix. The estimated probability of increasing hours remains flat across all prize levels. In contrast, the probability of reducing hours rises with the size of the wealth shock and becomes statistically significant for the largest prize. Similarly, the likelihood of exiting the labor force increases significantly for prizes exceeding €50,000, corroborating the findings from the binary logit model. These shifts are reflected in the left panel of Figure B2, which shows a decline of approximately 14 percentage points in the share of respondents reporting no change in their employment status (from 86% to 72%).

To summarize the extensive margin results, we find that windfall gains reduce the extensive margin of labor supply for the employed, but only when the gains are sufficiently large. Windfall gains of up to €25,000 do not produce economically meaningful or statistically significant responses, while the probability of continuing to work declines by approximately 3 percentage points for larger wealth shocks. The point estimates suggest that the negative effect of wealth shocks on employment is stronger for women, workers nearing retirement, part-time workers, and less leveraged households.

4.2. The intensive margin: change in hours

The upper-right panel of Figure 2 plots the average change in weekly hours of employed workers. While there is a negative gradient linking the change in hours to the prizes, the effects are not large. Even for the largest prizes (above €25,000) the average reduction is only about one half of an hour per week, compared to a sample mean of 35 hours. The evidence is consistent with a small income effect, or with frictions preventing workers from freely adjusting hours due to institutional, contractual or technological constraints within the firm.

Regression results reported in Table 4 confirm the descriptive evidence. Column (1) presents the baseline OLS regression of changes in weekly hours on the prize variable (measured in thousands of euros) and country fixed effects. The prize coefficient is precisely estimated, but small in magnitude (-0.008), and the estimated response remains unchanged when we include additional controls. In fact, the estimate of Column 2 implies that a €100,000 prize leads to a reduction of 0.8 hours per week, or approximately 48 minutes.

In the last column of Table 4 we allow for non-linear effects by replacing the prize variable with prize category dummies. A joint test rejects the null hypothesis that prize coefficients are equal at the 1% level, indicating nonlinearity in the response. We find no significant effect on hours worked for prizes up to €25,000. For larger wealth shocks the reduction in weekly hours is -0.49 for a €50,000 prize and -0.72 for a €100,000 prize. Relative to the 35-hour average workweek, this corresponds to reductions of 1.4% and 2.1%, respectively.

We next examine heterogeneity at the intensive margin, presenting the results graphically, consistent with the approach used for the extensive margin. The upper-left panel of Figure 5 replicates the OLS estimates from column (3) of Table 4, illustrating the estimated change in hours worked across different prize levels, along with 95% confidence intervals. The remaining panels in Figure 5 reveal greater responsiveness to prizes by gender and age, but not by education level. For example, at the €50,000 prize level, the estimated reduction in hours worked is -0.78 for women compared to -0.28 for men. Older workers exhibit a more pronounced response to larger prize shocks than younger workers, particularly at the €100,000 prize, where the effects are -0.80 and -0.42 hours, respectively. Additional results in Appendix Table B2 report regression results on hours worked, disaggregated by age and gender. We find that for prize levels of €50,000 and above, the estimated effects are larger in absolute terms for women and older individuals, as in Figure 5. As we shall see, while short-run MPE are larger for older workers than younger workers, the two groups display very similar MPE out of lifetime income once differences in time horizons are accounted for.

Figure 6 shows that differences in the change in hours worked across income levels, employment status (part-time vs. full-time) and levels of indebtedness are not statistically significant across the full range of prize amounts. In contrast, among the self-employed—who typically have greater flexibility in their work schedules—the estimated effect of large prizes is more pronounced (at the €100,000 prize level, -1.1 for the self-employed, compared to -0.6 for employees), although the difference is not statistically significant at the 5% level.

We also investigate cross-country heterogeneity in the responsiveness of working hours to wealth shocks. To this end, we estimate OLS regressions of changes in weekly hours on prize dummies separately for each of the six countries in our sample. The results indicate that in countries with more flexible labor markets (as proxied by the prevalence of part-time employment), the reduction in hours worked in response to windfall gains is greater than in countries with more rigid labor markets. For instance, in the Netherlands, where part-time work is more common, the reduction in weekly hours is -1.5, compared to -0.5 in Italy.[15] These results are summarized graphically in Figure 7.

The survey questions pertain to the individual respondent rather than the household, and as such, our estimates may omit potential intra-household spillover effects. For example, spouses may adjust their labor supply in response to the partner's wealth shock. Golosov et al. (2024) estimate that spousal earnings' responses amount to approximately one-third of the winner's effect. If the variable of interest is household labor supply, our estimates may thus understate the overall effect of the windfall gain.[16]

In summary, our analysis of the intensive margin reveals a non-linear relationship between hours worked and wealth shocks: the response is flat for shocks up to €25,000, and modest (less than one hour per week) for larger prize levels. Consistent with the findings at the extensive margin, heterogeneity analysis indicates stronger responses among women and workers approaching retirement age, likely reflecting greater labor supply elasticities and shorter planning horizons, respectively.

It is important to note that our estimates do not incorporate general equilibrium effects. In particular, to the extent that lottery winnings are spent in the market, they may generate positive labor demand effects that could partially or fully offset the observed reductions in labor supply (see Jones and Marinescu, 2022). Accordingly, our estimates are likely providing an upper bound to the true effects of wealth shocks on employment and working hours.

4.3. Comparison with previous studies

To compare our results with the existing literature, we conclude this section by estimating the effect of hypothetical €10,000 and €100,000 wealth shocks on annual earnings. We construct these estimates using the subsample of respondents who were randomly assigned

[15] The incidence of part-time employment is 34.2% in the Netherlands, 21.1% in Germany, 17.1% in Belgium, 11.7% in Spain, 12.6% in France and 16.3% in Italy. Source: Incidence of part-time employment based on OECD-harmonized definition in 2023. OEWCD Data Explorer, https://data-explorer.oecd.org/, last updated on July 24, 2024.

[16] In this case we would expect labor supply decisions to be made "jointly" by the two spouses. However, when we re-estimate our specification using a subsample of single individuals, we find no statistically significant differences compared to the broader sample that includes multi-earner households.

these two prizes, merging data on actual earnings and hours worked available in the May 2022 wave of the CES with data from the June 2022 experimental module on changes in employment status and hours worked. The resulting sub-sample includes 1,348 individuals with complete data for the €100,000 shock and 1,358 for the €10,000 shock.

In our calculations, we make three assumptions: (a) individuals who report that they would stop working experience a complete loss of earnings, (b) hourly wages remain constant for those adjusting their hours, and (c) employed individuals work an average of 40 weeks per year. Based on these assumptions, Table 5 reports an average earnings reduction of €2,465 in response to a €100,000 shock, equivalent to 2.5% of the prize amount. Of this reduction, about 2% is due to the reduction in employment (the extensive margin) and 0.5% to the reduction in hours worked (the intensive margin).

Table 5 further reveals that the reduction in earnings is larger for women than for men (2.7% vs. 2.3%), and for individuals closer to retirement compared to younger respondents (3.1% vs. 1.5%). These patterns are consistent with the heterogeneity estimates presented in Sections 4.1 and 4.2. In all cases, the response at the extensive margin (changes in employment status) is approximately four times larger than that of the intensive margin (adjustments in hours worked).

The table also reports the estimated earnings impact of a smaller wealth shock (€10,000), intended to approximate the scale of a typical universal basic income (UBI)–style transfer. In line with the observed non-linear relationship between wealth shocks and labor supply, the total decline in earnings for this smaller prize is modest—approximately €90, or less than 1% of the shock value. Given the negligible change in hours worked for small shocks, this small average earnings reduction is entirely attributable to the extensive margin response.

How do our results compare with those in the literature? Table 6 reports findings from several representative studies, distinguishing between short-run and long-run responses. In comparing the different studies one should consider that they differ in methods, samples and earnings concepts, as explained in the note to Table 6. The first row reports our own results. The short-run marginal propensities to earn (MPE) is taken from Table 5 (the column showing the total drop in earnings for a €10,000 prize). To calculate the implied MPE with respect to lifetime income, we multiply the short-run MPE by the average remaining working life assuming a retirement age of 65 years.[17] Our estimate of the implied lifetime MPE is -0.189: a one-time wealth shock of €10,000 would reduce lifetime income by €1,890.[18]

Since our analysis explicitly references a lottery prize, we begin by comparing our estimates with those from studies that examine a similar source of wealth shocks (but actual, instead of hypothetical lottery winnings) in Sweden, the Netherlands, and the U.S.. Reassuringly, our estimates fall in the ballpark of these studies, which generally report modest labor supply responses of recipients, even for large lottery prizes. This reinforces the validity of our approach. Given the limited access to administrative datasets that include both wealth shocks and labor supply outcomes, our scalable and flexible method offers a valuable alternative for researchers examining similar questions.

Cesarini et al. (2017), using Swedish lottery data, estimate labor supply effects up to 10 years after the shock, distinguishing between extensive and intensive margins, and providing estimates for both short-run and Marginal Propensities to Earn (MPE) out of lifetime income. They find that the response is near-immediate, limited in magnitude and quite stable over time: they estimate a short-run MPE of -€110 for a €10,000 lottery prize, and MPE out of lifetime income of -0.18. Similar patterns emerge in the Netherlands, where studies based on lottery data also report small responses. In the U.S., earlier work by Imbens et al. (2001) found an MPE of approximately -0.11.[19]

[17] To compute the MPE with respect to lifetime income we consider an intertemporal model with consumption and leisure in the utility function and assume that the discount rate equals the interest rate. The MPE is defined as: $MPE = \frac{\partial}{\partial Q} \sum_{s=t}^{T} \frac{y_s}{(1+r)^{s-t}}$, which simplifies to: $MPE \approx (T-t)\frac{\partial y_t}{\partial Q}$, i.e., the product of the short-term MPE effect and the remaining working life, if we assume no discounting and a stable effect of wealth on labor supply (as found by Cesarini et al., 2017). Since the average respondent in our sample is close to 44 years old (see Table 1), and assuming retirement at age 65, the average remaining work life is approximately 21 years. We thus estimate that a one-time wealth shock of €10,000 would reduce lifetime income by €90×21=€1,890, or 18.9% of the shock would be allocated to leisure. This implies that the remaining 81.1% of the wealth shock would be consumed.

[18] Computing MPE for different age groups also clarifies that the shorter time horizon of older individuals is offset by their higher immediate earnings response. We use separate estimates of the labor supply response to a €10,000 windfall, reported in Table 5 (–0.382 for individuals under 40, and –1.23 for those aged 40 and above). The average age in the younger group is 31.3, and 53.84 in the older group, implying an MPE for the young of 0.128, and an MPE for the older group of 0.137, showing that the implied lifetime labor supply responses are quite similar across age groups.

[19] Imbens et al (2001) find that for every $1 of annual lottery prize, annual earnings drop by about $0.10. Given the structure of the payments, the present value of the total lottery prize is roughly 90% of the "headline" amount due to discounting and the 20-year payment schedule (see their footnote 20). Hence, to get the lifetime MPE, we need to adjust the annual estimate upward by about 10% (i.e., the Lifetime MPE=Annual MPE×(1/0.9)), which is approximately 0.11.

Recent evidence from Golosov et al. (2024), based on administrative data and an event-study design exploiting the timing of lottery wins, yields a larger MPE of –0.52. This may partly reflect the substantial average windfall in their sample (about $180,000). For comparison, applying our results from the bottom panel of Table 5—which indicate significant nonlinearities—to a hypothetical €100,000 windfall gives an implied lifetime MPE of –0.02465 × 21 = –0.52, closely matching their estimate. Nevertheless, our main analysis focuses on a €10,000 windfall, which we regard as a more realistic policy benchmark and one that better reflects the scale of temporary support programs providing one-off gains to individuals.

A different approach is to use inheritances as a source of unearned income shocks. Joulfaian and Wilhelm (1994), drawing on data from the Michigan Panel Study of Income Dynamics (PSID) and Federal Estate Tax returns, find that inheritances have only a modest effect on labor supply. This may be due in part to the PSID's limited ability to capture large inheritance transfers.[20] A limitation of this approach is that inheritances are often at least partially anticipated, meaning the transfer may already be incorporated into recipients' expectations, planning and behavior, in line with standard life-cycle models. Moreover, the decision to leave a bequest may correlate with unobserved individual characteristics, such as workers' effort or risk aversion. As discussed above, our survey experiment is robust to such concerns.[21]

A final set of papers leverages experimental or quasi-experimental variation from specific government transfer programs. Vivelt et al. (2025) study the labor supply effects of an experiment involving 1,000 low-income individuals who were randomly assigned to receive unconditional monthly payments of $1,000 for three years. In this low-income sample, the transfer reduced earnings by 17% of the amount transferred and lowered labor force participation by 3.9 percentage points.

Bibler et al. (2023) estimate the effects of transfers on labor market activity by exploiting the timing and variation in the Alaska Permanent Fund Dividend, while Powell (2020) studies

[20] Holtz-Eakin et al. (1993) analyze tax-return data to study labor force behavior before and after the receipt of inheritances. They find that individuals receiving inheritances of approximately $150,000 are nearly four times more likely to exit the labor force compared to those receiving less than $25,000. Their results suggest that large inheritances have a substantial negative effect on labor supply. Bø et al. (2019), using comprehensive administrative data from the entire Norwegian population, document significant reductions in labor supply, though only among recipients of large inheritances.

[21] Other studies have examined the impact of inheritances on retirement decisions. Brown et al. (2010), using data from the Health and Retirement Study, show that inheritances (particularly when unanticipated) increase the likelihood of retirement, with the effect size rising alongside the inheritance amount. For example, receiving an inheritance of $100,000 increases the probability of early retirement by approximately five percentage points.

labor supply responses to unearned transitory income using the differential timing of the 2008 tax rebates in the U.S.[22] Both studies report larger labor supply effects from unearned income shocks than found in other studies (short run effects of -0.17 and -0.28, respectively).[23] It remains unclear whether these larger effects are driven by differences in the population studied or to the specific characteristics of the transfer programs studied.

5. Search intensity

A novel aspect of our survey is that we can study also the effect of wealth shocks on search behavior. The experiment described in this section focuses on individuals in the CES who are "not employed". Unlike the conventional definition of unemployment, we adopt a broader classification. We exclude retired individuals but include those of working age (18-64 years) who are classified as out of the labor force, such as potentially discouraged workers and individuals not actively looking for a job. This is motivated by the possibility that wealth shocks may prompt individuals to initiate job search, as we explain below. The sample for our analysis includes 1,860 individuals: unemployed actively searching for work, unemployed interested in having a job but not actively looking, individuals in education or training, those caring for children or other dependents, and those engaged in housework.

Table 1 reveals that the sample of individuals classified as "not employed" is more skewed towards women, younger, lower-income, and less-educated respondents compared to the sample of employed individuals. Table 2 shows that the characteristics of the five randomized sub-samples are well balanced across the lottery prize distributions in our experiment. In Figure 8, we present histograms depicting the six possible outcomes for the search behavior question. Relative to the baseline €5,000 prize, we observe an increase in the proportion of respondents who intend to reduce or stop searching after receiving the prize, alongside a corresponding decrease in the proportion of those who plan to maintain or reduce their search effort. In contrast, the proportion of individuals not actively searching and those intending to start searching remain relatively stable across the prize distribution (notably, the latter is not zero).

[22] The Alaska Permanent Fund in the United States is the closest existing program resembling a Universal Basic Income program. On average, the annual payment is around $1,600, though it is not fixed or guaranteed. For the average respondent in our sample—assumed to be 44 years old with retirement at 65—this would amount to approximately $33,600 over their remaining working life.

[23] See the notes to Table 6 for details on how we calculate the implied MPE in the Bibler et al. (2023) case.

Here, “search intensity” is defined as a dummy variable that takes the value of one if respondents report that they would search more actively (if currently looking for work) or that they would begin to start looking for work (if currently not looking for work), and zero otherwise. The figure illustrates that search intensity declines by approximately 10 percentage points across the prize distribution (from 88% to 78%).

Table 7 presents the marginal effects from logit regressions on search intensity. In the linear specifications of columns (1) and (2), the effect of the lottery prize (measured in thousands of euros) is negative and statistically significant. The marginal effect suggests that search intensity decreases by 11 percentage points (from a baseline of 84% in the total sample) for the €100,000 prize, even after expanding the specification to include demographic variables (column 2).[24]

Distinguishing between the different prize levels in column (3) reveals that the disincentive effect of wealth shocks is negative across all prize levels, with a statistically significant effect being estimated for the two largest prizes (-8.6 and -10 percentage points, respectively). In the final column of Table 7, we report the OLS coefficients from a linear probability model for search intensity, which yield nearly identical results.[25]

As with the intensive and extensive margin labor responses to the lottery prizes, Figures 9 and 10 present the marginal effects for different subgroups. We find some evidence that older individuals tend to reduce search intensity more than younger individuals in response to relatively large prizes (e.g., €50,000). We observe no significant differences in the effects by gender, education, income, or indebtedness.[26] For search intensity, we further distinguish non-employed individuals by their self-reported reservation wage (above or below the median), as recorded in May 2022. This allows us to assess whether individuals with higher reservation

[24] The income effects on search effort that we estimate are related to Chetty’s (2004) estimate of the elasticity of unemployment duration with respect to a 1% increase in UI income through a lump-sum grant (the windfall gain we randomize among job seekers). However, we cannot directly compare our estimate with Chetty (2004) because his elasticity captures both supply-side forces (the change in search effort) and demand-side forces (the effect of increased effort on the job offer rate), whereas our analysis only captures the former. Additionally, the questions we use to elicit changes in search effort are qualitative in nature.

[25] As with the intensive and extensive margins, the assumption that the prize coefficients are equal is rejected at the 5% level.

[26] In Table B3 of the Appendix we split 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. The results indicate that for prizes of €50,000 and above, the effects of the prizes on search intensity are larger (in absolute value) for females and older workers.

wages are more responsive to wealth shocks. However, we find no statistically significant difference in the effects between the two groups.

In the Appendix, we examine whether the search intensity indicator conceals heterogeneity in responses by employing a multinomial logit model for six distinct outcomes: increase search, reduce search, stop search, start search, search the same, and not searching or changing strategy. We use the same set of covariates and present the results graphically in Figure B3. The relationship between the prize and the probabilities of not searching, stopping the search, or increasing search effort is relatively flat. In contrast, the probabilities of searching the same or reducing search intensity decline with the prize, which is consistent with the results from the logit regressions.

6. Conclusions

A classic question in labor economics is how labor supply responds to wealth shocks. Isolating the wealth effects from other confounding factors is important in many contexts, such as assessing the labor supply response to cash transfers and the effectiveness of fiscal policy. However, identifying these effects is challenging. First, one must isolate genuine variation in wealth or income that is uncorrelated with workers' labor market status, wages, and preferences. Moreover, the wealth shocks must be sufficiently large to overcome informational frictions or adjustment costs in working hours. Finally, labor supply adjustment can occur along both the extensive and intensive margins, including changes in the search effort of the non-employed.

Labor economists have employed various approaches to study labor supply responses to wealth shocks, including changes in capital income, the income of a spouse, and quasi-natural experiments such as the receipt of inheritances or lottery winnings. Most previous studies focus on earnings as the outcome variable, as separate data on wages, hours worked and time spent on job search activities (for the non-employed) are typically unavailable. Additionally, these studies typically estimate linear or log-linear relationships between wealth shocks and labor supply indicators, which does not allow for testing whether the effects vary by the size of the income shock. We implement a novel approach that addresses all these challenges. We design and analyze a survey experiment within the CES, a large panel of individuals representative of the national populations of the six largest euro area countries. In our experiment, respondents report how their labor market participation, hours worked, and search effort (if not employed) would change in response to randomly assigned lottery prizes of varying size, which serve as proxies for unexpected windfall gains.

At the extensive margin, we find that wealth shocks reduce employment, but only when the shocks are sufficiently large. There is no effect for prizes of €25,000 or less, but the probability of employment decreases by 1.5 to 3.5 percentage points for prizes ranging from €50,000 to €100,000. At the intensive margin, we observe again no effect for smaller prizes, and very modest effects (less than one hour per week) for prizes above €50,000. We also examine heterogeneity in responses, finding that women and workers closer to retirement are more responsive to wealth shocks than men or younger individuals. These findings, which are for a representative sample of euro area countries also align with other studies utilizing actual lottery data and thus more selected samples.

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 decreases by approximately one percentage point for each €10,000 prize, with a stronger effect observed among older individuals receiving the largest hypothetical windfall gain.

Overall, our findings suggest that only relatively large shocks (e.g., unanticipated inheritances) trigger economically meaningful labor supply responses, while shocks within the range of typical transfers or bonuses result in small or negligible disincentive effects on labor supply. Given the scale of typical UBI-style programs as currently discussed, our estimated responses imply that such programs would overall have quite limited labor supply disincentives effects. Our estimates also suggest that one can dismiss the idea that stimulus packages are ineffective in raising consumption because they end up mainly financing leisure rather than spending.

The fact that the labor supply responses increase with the size of the wealth shocks is consistent with the presence of labor market frictions and adjustment costs (or behavioral biases). In real-world contexts, wealth shocks comparable to the largest hypothetical lottery prizes in our research design capture phenomena like the receipt of inheritances. One important debate in public economics is whether and how much to tax these large transfers of wealth. Besides the tax revenue aspects, taxing inheritance has two advantages: an increase in equity (taxing inheritances reduces inequality) and a reduction in inefficiency (since people work less or put less effort when the tax is absent, what is known as the "Carnegie conjecture"). Our findings suggest that while labor supply responses to large prizes are negative and statistically significant, they appear modest. Hence, our evidence aligns with the view that eliminating inheritance or wealth taxes would likely have only small effects on employment rates and hours worked for the typical employee.

The research design employed in this study could be extended in many directions. Since existing literature has primarily focused on positive wealth shocks, it would be valuable to test for asymmetric effects. This could be done by eliciting labor supply and job search responses to hypothetical *negative* wealth shocks, such as those resulting from declines in retirement wealth due to stock market downturns, a wealth tax, pension reforms, or a housing market crash. Moreover, it would be useful to explore the role of added worker effects or peer effects on the individual labor supply responses, as well as the labor supply of spouses to household level wealth shocks and the distinction between before- and after-tax wealth changes.

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Table 1. Descriptive statistics

Sample of working individuals	Mean	Standard deviation	Observations
Work more	0.061	0.240	9,438
Work the same	0.807	0.394	9,438
Work less	0.081	0.273	9,438
Stop working	0.050	0.218	9,438
Change in hours	-0.196	2.741	8,967
Female	0.476	0.499	9,431
Age	43.372	11.045	9,438
Family size	2.807	1.255	9,438
College	0.619	0.486	9,438
Disposable income	37.191	22.871	9,438
Self-employed	0.128	0.334	8,356
€5,000 prize	0.196	0.397	9,438
€10,000 prize	0.204	0.403	9,438
€25,000 prize	0.197	0.398	9,438
€50,000 prize	0.204	0.403	9,438
€100,000 prize	0.199	0.399	9,438
Sample of non-working individuals			
Search more	0.072	0.259	1,860
Search the same	0.310	0.463	1,860
Search less	0.109	0.312	1,860
Stop searching	0.051	0.219	1,860
Not working or searching	0.362	0.481	1,860
Start searching	0.096	0.294	1,860
Female	0.672	0.470	1,859
Age	39.445	13.787	1,860
Family size	3.023	1.24	1,860
College	0.383	0.486	1,860
Disposable income	24.282	17.121	1,860
€5,000 prize	0.217	0.412	1,860
€10,000 prize	0.190	0.393	1,860
€25,000 prize	0.195	0.396	1,860
€50,000 prize	0.198	0.398	1,860
€100,000 prize	0.199	0.400	1,860

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

Table 2. Descriptive statistics, by lottery prize

	Female	Age	Family size	College	Disposable income	Self-employed	Obs.
Working							
€5,000 prize	0.48	43.43	2.82	0.64	36,931	0.13	1,853
€10,000 prize	0.48	43.11	2.82	0.63	37,499	0.13	1,923
€25,000 prize	0.48	43.30	2.82	0.61	37,537	0.12	1,859
€50,000 prize	0.46	43.55	2.81	0.61	37,221	0.13	1,925
€100,000 prize	0.47	43.47	2.78	0.60	36,761	0.13	1,878
Not working							
€5,000 prize	0.65	38.90	3.07	0.37	24,757	-.-	405
€10,000 prize	0.69	40.03	3.01	0.39	23,320	-.-	354
€25,000 prize	0.71	39.77	3.02	0.39	24,844	-.-	362
€50,000 prize	0.64	39.48	2.98	0.38	23,676	-.-	368
€100,000 prize	0.68	39.14	3.02	0.39	24,733	-.-	371

Note: Data are drawn from the June 2022 wave of the Consumer Expectations Survey (CES). The table reports the means of selected socioeconomic characteristics, separately for working and non-working individuals, for each randomized sub-sample of the survey experiment. All statistics are computed 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 (in 1,000 euros)	-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 final column). All regressions include country fixed effects. One star indicates significance at the 10% level, two stars at the 5% level, and three stars at the 1% level.

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

	Baseline OLS	Adding demographics	Adding prize dummies
Prize (in 1,000 euros)	-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)***
N	8,967	7,940	7,940

Note: All regressions are estimated using OLS and include country fixed effects. One star indicates significance at the 10% level, two stars at the 5% level, and three stars at the 1% level.

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

€10,000 prize	Total drop in earnings (%)	Drop due to the extensive margin (%)	Drop due to the intensive margin (%)	Number of observations
Females	-1.066	-1.147	0.080	613
Males	-0.766	-0.947	0.181	745
Age<=40	-0.382	-0.833	0.450	526
Age>40	-1.230	-1.166	-0.063	832
College	-0.919	-1.142	0.223	853
No college	-0.872	-0.861	-0.011	505
Total sample	-0.902	-1.037	0.136	1,358

€100,000 prize	Total drop in earnings (%)	Drop due to the extensive margin (%)	Drop due to the intensive margin (%)	Number of observations
Females	-2.701	-2.157	-0.544	625
Males	-2.264	-1.890	-0.373	722
Age<=40	-1.479	-1.261	-0.218	543
Age>40	-3.130	-2.520	-0.611	805
College	-2.612	-2.068	-0.544	827
No college	-2.231	-1.924	-0.307	521
Total sample	-2.465	-2.013	-0.452	1,348

Note. The percentage drop in earnings is computed from responses to questions on employment and hours, combining the effect of a €10,000 (or €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 but will continue to work. The total drop in earnings is calculated as $\Delta y = EM + IM$, where $EM = -y \times \mathbf{1}\{SW = 1\}$ is the extensive margin response, $IM = w \times \Delta h \times 40 \times \mathbf{1}\{SW = 0\}$ is the intensive margin response, and y, w, Δh, $\mathbf{1}\{SW = 0\}$ and $\mathbf{1}\{SW = 1\}$ are current earnings, the current hourly wage rate, the reported change in hours, an indicator for those who report they will continue to work, and indicators for those who report they will continue or stop working, respectively. Results are expressed as a percentage of the windfall gain.

Table 6. Summary of literature

Study	Source of variation (country)	Short-run MPE estimate (95% C.I.)	Notes	Implied Lifetime MPE
This paper (2025)	Hypothetical windfall gain (6 EU countries)	-0.009 (-0.013 to -0.005)	From Table 5	-0.19
Cesarini et al. (2017)	Lottery prize (Sweden)	-0.011 (-0.015 to -0.007)	Effect on pre-tax earnings in the 1st year post-lottery win (extrapolation from Figure 1)	-0.18
Picchio et al. (2018)	Lottery prize (Netherlands)	-0.012 (-0.003 to 0.002)	Effect on earnings in the 1st year post-lottery win (Table 4, row 1, column T=1)	-0.24
Golosov et al. (2024)	Lottery prize (US)	-0.021 (-0.023 to -0.019)	Effect on earnings in the 1st and 2nd year post-lottery win (extrapolation from Figure B.5)	-0.52
Imbens et al. (2001)	Lottery prize (US)	-0.06 (-0.08 to -0.04)	Effect on earnings in the 1st year post-lottery win (Table 4, Average estimate of year 1 earnings across specifications)	-0.11
Joulfaian and Wilhelm (1994)	Inheritances (US)	-0.008 (-0.014 to -0.002)	Effect on family earnings 1 year after inheritance (Table 7, col. 3 evaluated at heirs' means, Table 1)	-0.18
Powell (2020)	2008 tax rebate (US)	-0.28 (-0.378 to -0.182)	Effect on earnings in the first 4 months after receiving tax rebate (Table 3, Panel A)	NA
Bibler et al. (2023)	Alaska Permanent Fund payments (US)	-0.17	Authors' calculation based on reported hours responses and CPS data	NA

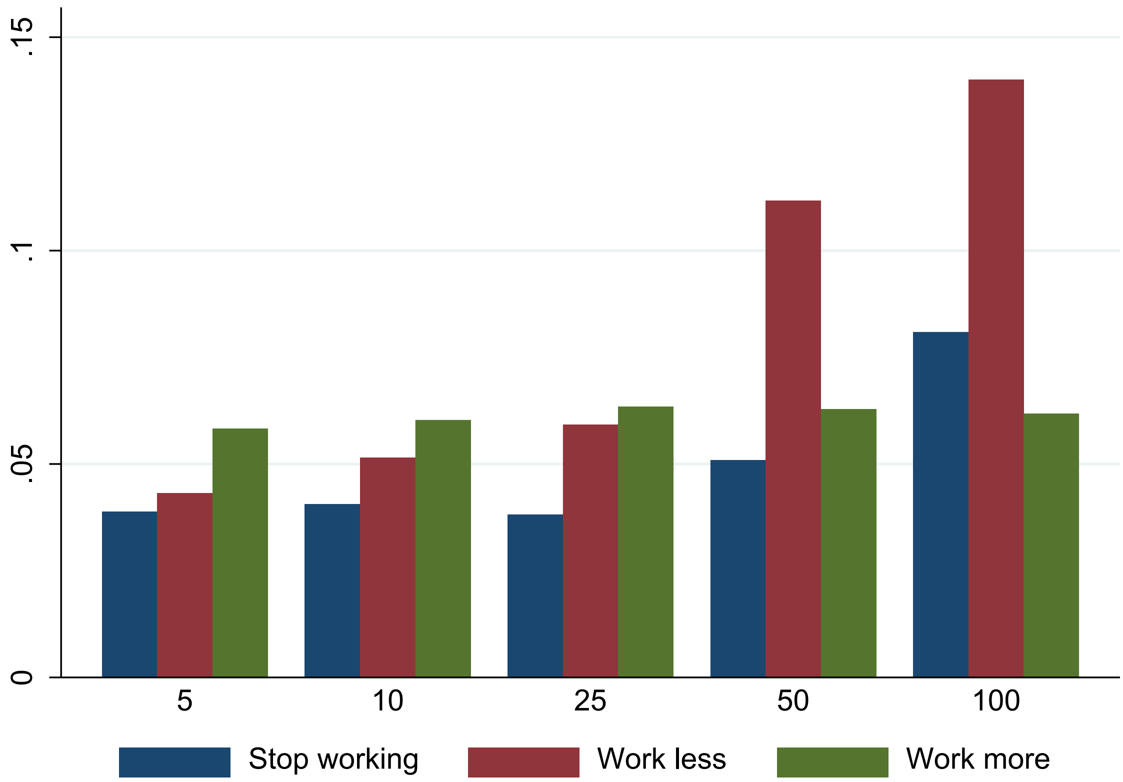
Note. The implied Lifetime Marginal Propensity to Earn (MPE) is calculated as (Short run MPE)×(65-Sample average age), except for Golosov et al. (2024), where we use the one reported by the authors, and Imbens et al. (2001), since individuals receive a lottery win over a 20 year period (see our footnote 19). Studies differ in the earnings concept used. Cesarini et al. (2017) and Golosov et al. (2024) consider individual pretax labor earnings, Picchio et al. (2018) individual labor earnings across the different jobs held by a worker during the year, Imbens et al. (2001) individual social security earnings, Joulfaian and Wilhelm (2004) and Powell (2020) use household labor earnings, and Bibler et al. (2023) individual weekly hours. To calculate the effect in the Bibler et al. (2023) case, we convert the effect of the wealth shock (Q) on weekly hours ($\frac{\partial H_{weeks}}{\partial Q}$) that they report into an MPE (effect of wealth shocks on annual earnings) in the following way. Their estimates are obtained separately for men $\left(\frac{\partial H_{weeks,M}}{\partial Q} = 0.44\right)$ and women $\left(\frac{\partial H_{weeks,F}}{\partial Q} = -1.10\right)$. Note that the MPE for the whole population can be written as: $\frac{\partial Y}{\partial Q} = \pi_M \times \overline{weeks_M} \times \overline{w_{hour,M}} \times \frac{\partial H_{weeks,M}}{\partial Q} + \pi_F \times \overline{weeks_F} \times \overline{w_{hour,F}} \times \frac{\partial H_{weeks,F}}{\partial Q}$, where π_M (π_F) is employment share accounted by men (women), and $\overline{weeks_g}$ and and $\overline{w_{hour,g}}$ are average weeks worked during the year and average hourly wage for gender g, respectively. We use CPS data for Alaska (1994-2016, people aged 20-55 as in their paper) to obtain estimates for average weeks worked during the year, the average hourly wage, and the share of employment of men and women to complete to computation.

Table 7. Effect of wealth shocks on search intensity

	Baseline Logit	Logit with demographics	Logit with prize dummies	OLS with prize dummies
Prize (in 1,000 euros)	-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

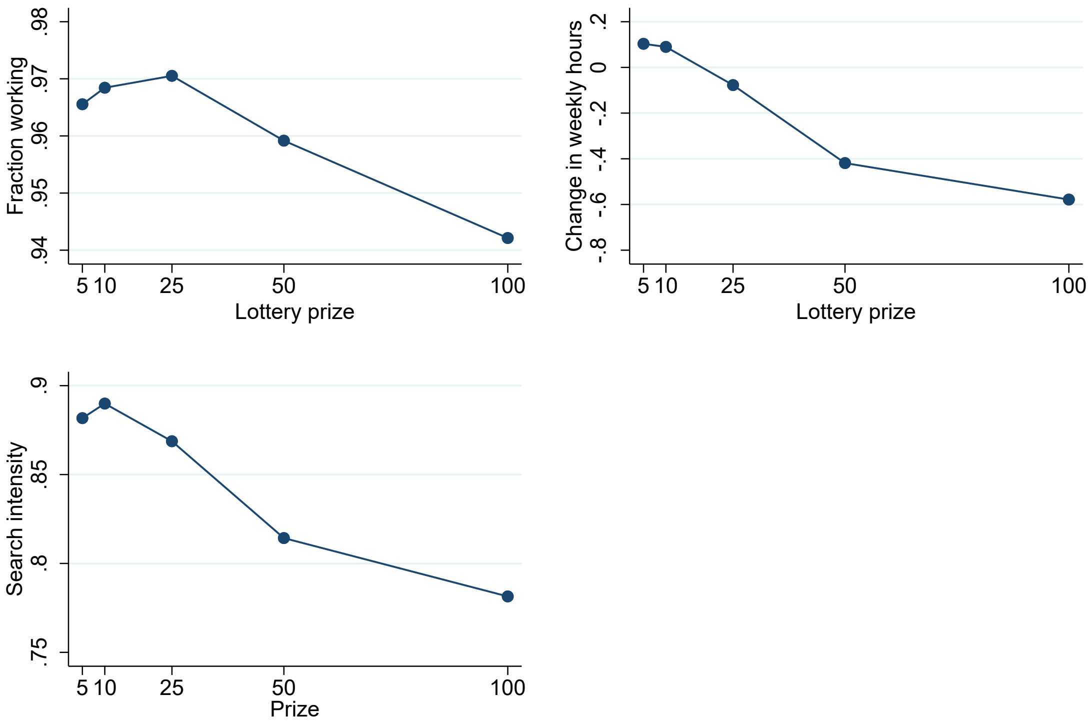
Note: The table reports marginal effects from logit regressions (OLS in the final column). All regressions include country fixed effects. One star indicates significance at the 10% level, two stars at the 5% level, and three stars at the 1% level.

Figure 1. Change in working status, by lottery prize



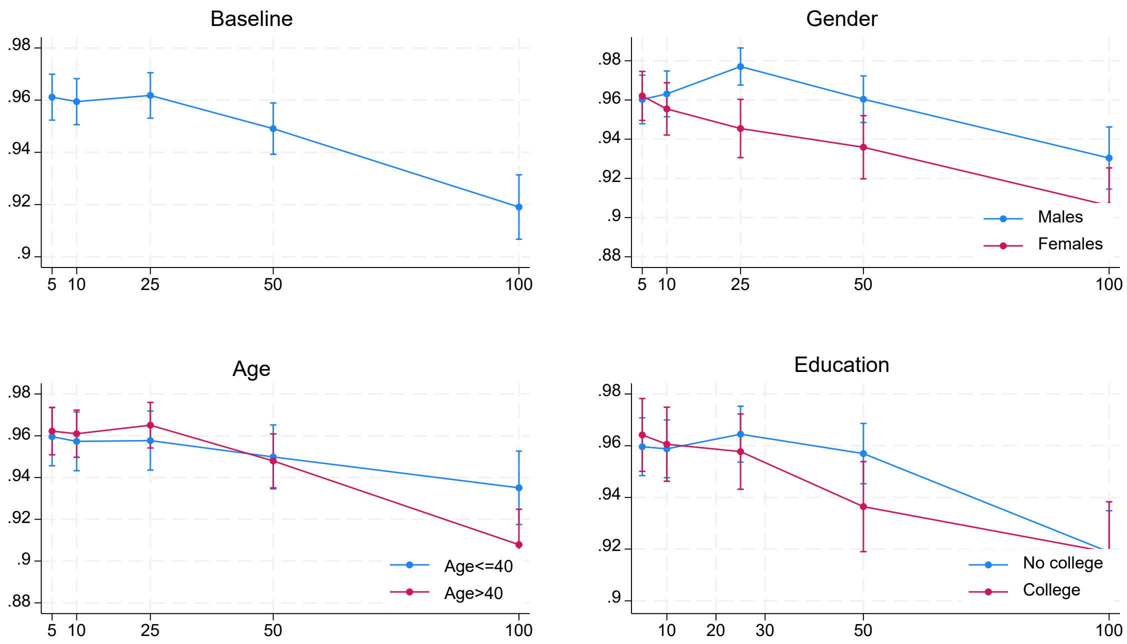
Note: The histogram plots the fraction of working respondents who, after receiving the randomly assigned lottery prize, report that they would stop working, work less, or work more. Averages are computed using sample weights.

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



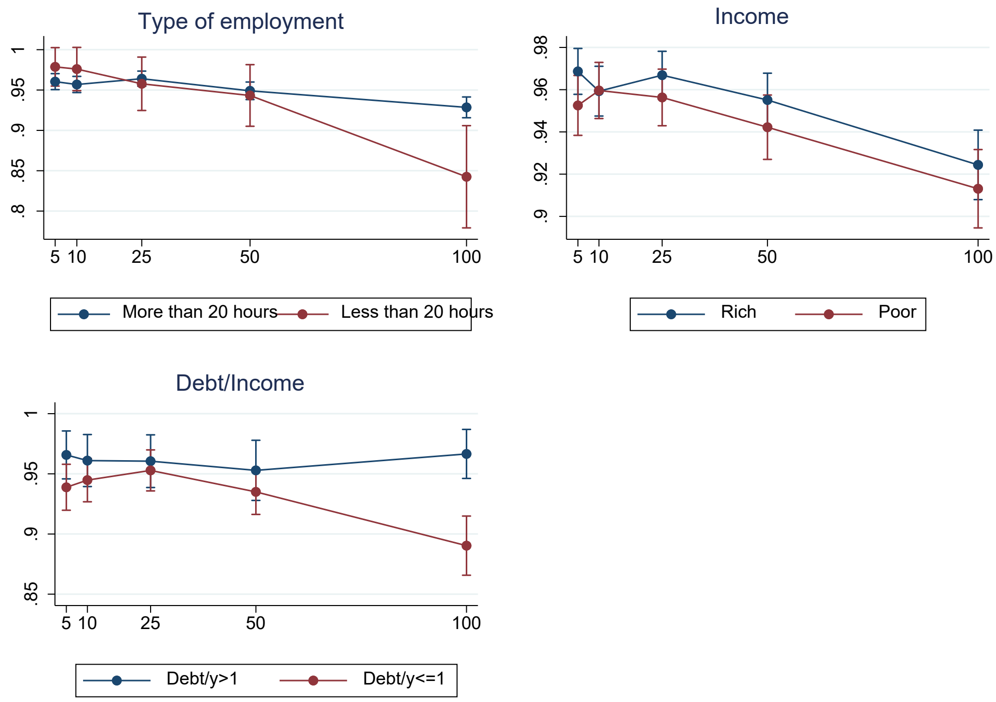
Note: The upper-left graph plots the fraction of working individuals who intend to continue working after receiving the randomly assigned prize (in thousands of euros). The upper-right graph shows the change in weekly hours worked for those employed after receiving the randomly assigned prize. The bottom graph plots search intensity, defined as a dummy variable in the sample of non-employed individuals, equal to zero if respondents intend to stop searching or search less, and one otherwise, following receipt of the randomly assigned prize. Averages are computed using sample weights.

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



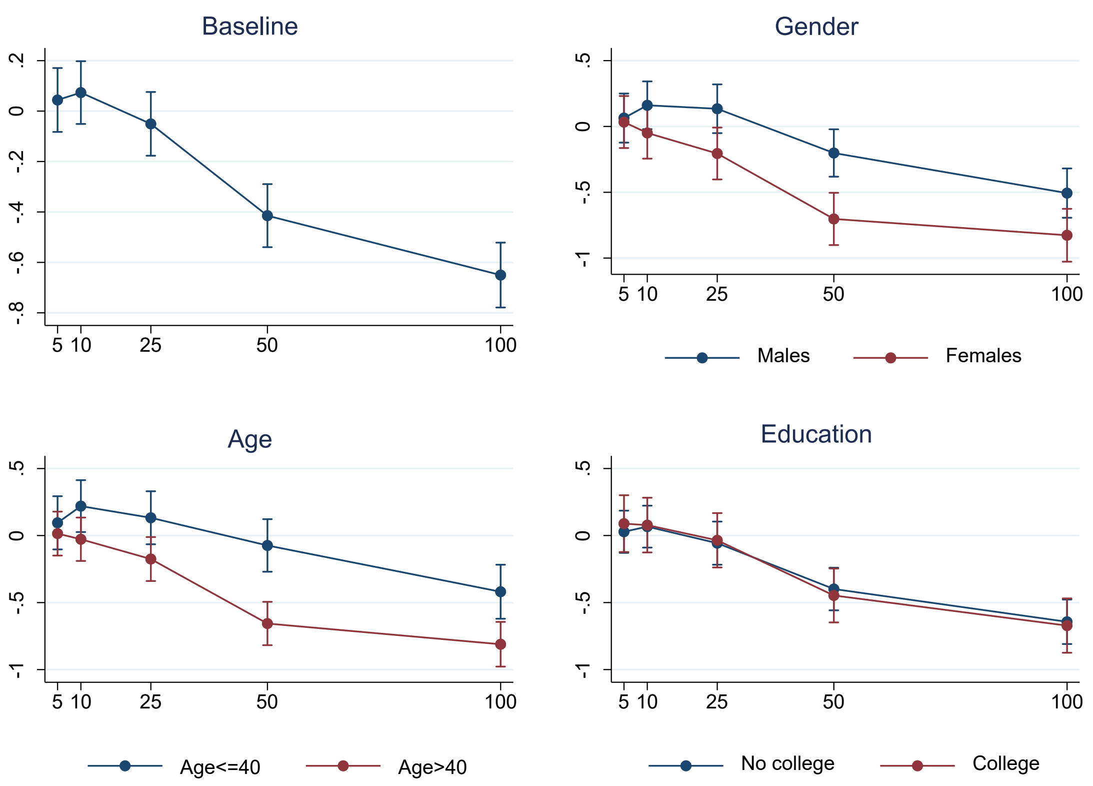
Note: Each figure plots the estimated probability of working along with the associated 95% confidence intervals from logit regressions, where the probability of working is regressed on wealth shock dummies, controlling for country dummies and socioeconomic variables (gender, age, education, family size, disposable income). The upper-left graph is based on the regression from column 3 of Table 3. The other figures report equivalent probability effects for 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 between the lottery prize dummies and the group dummies.

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



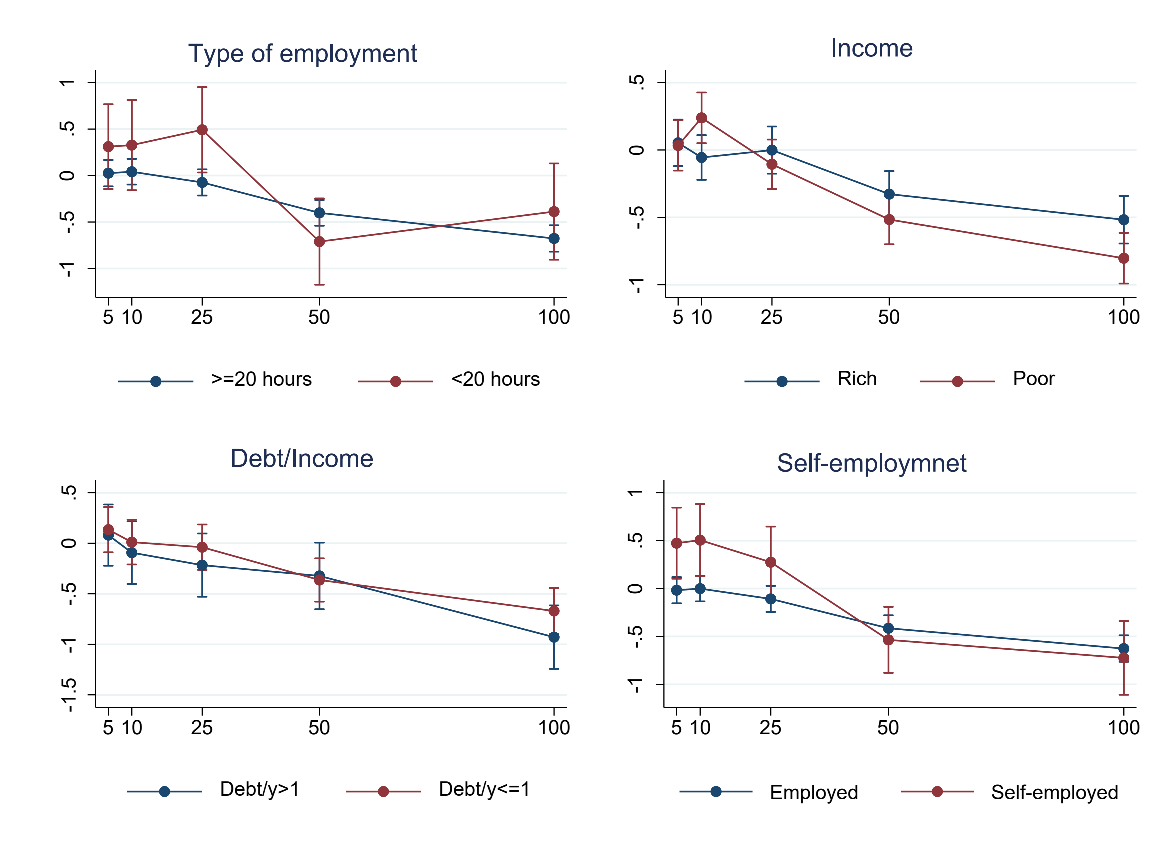
Note: Each figure plots the predicted probability of working along with the associated 95% confidence intervals from logit regressions, where the probability of working is regressed on wealth shock dummies, controlling for country dummies and socioeconomic variables (gender, age, education, family size,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

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



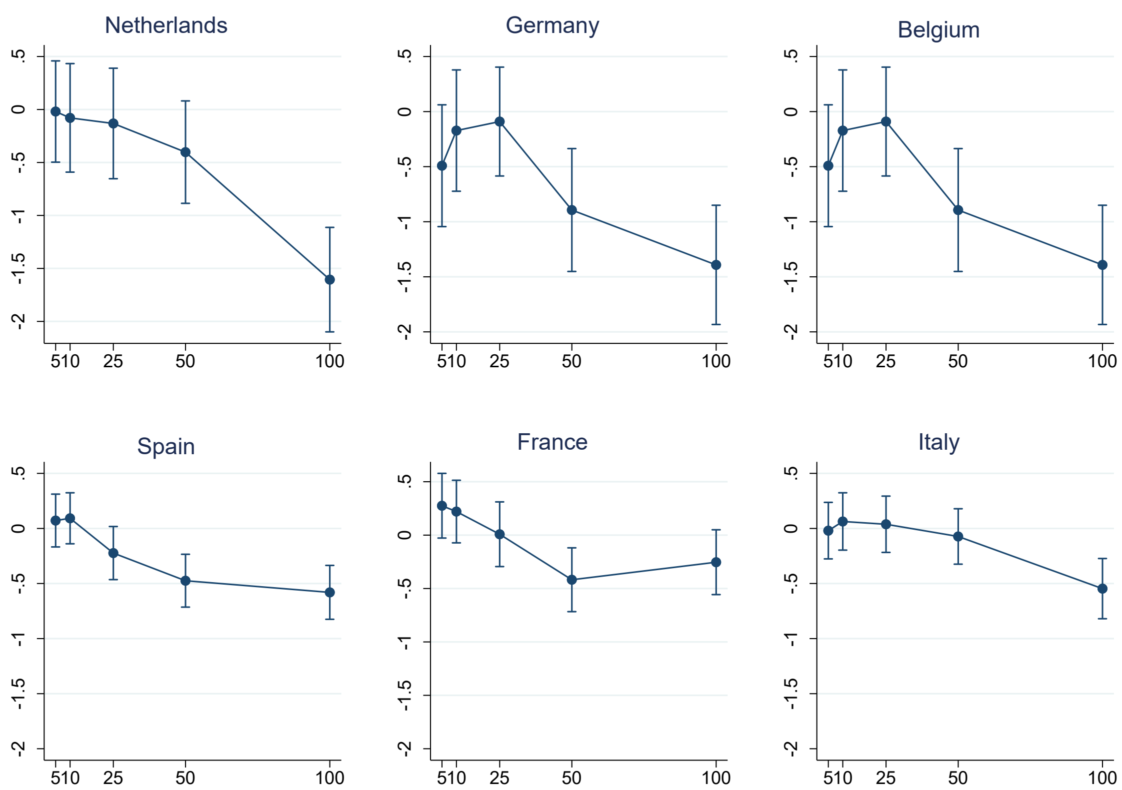
Note: Each figure plots the predicted change in hours, along with the associated 95% confidence intervals, from OLS regressions of the change in weekly hours on the wealth shock dummies, controlling for country dummies and socioeconomic variables (gender, age, education, family size, disposable income).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

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



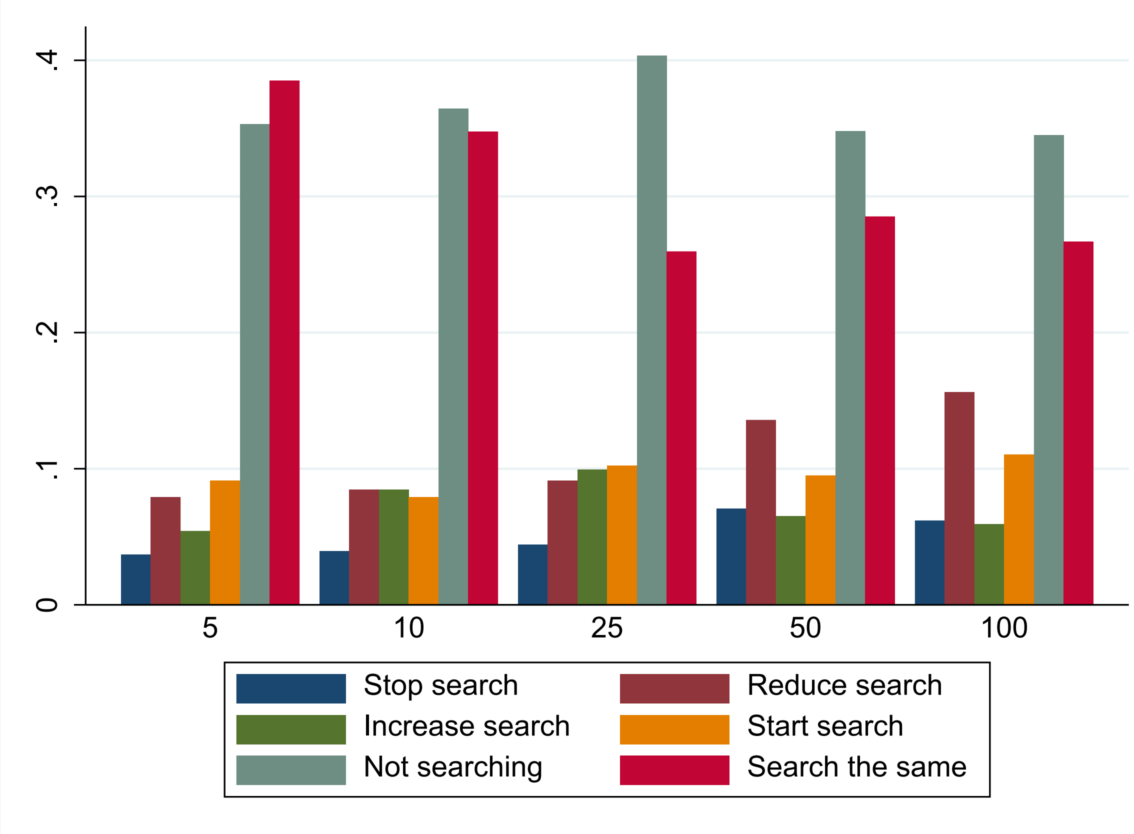
Note: Each figure plots the predicted change in hours, along with the associated 95% confidence intervals, from OLS regressions of the change in weekly hours on the wealth shock dummies, controlling for country dummies and socioeconomic variables (gender, age, education, family size, disposable income).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

Figure 7. Change in hours: country heterogeneity



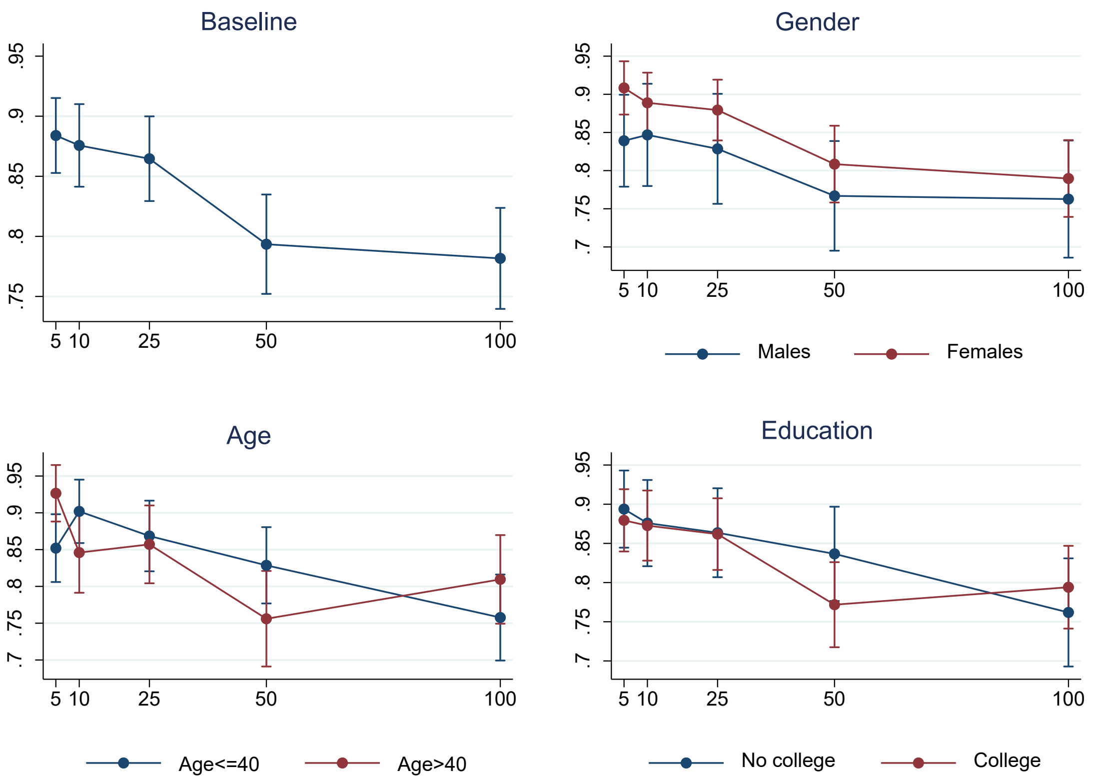
Note: Each figure plots, for each of the six countries of the CES sample, the predicted change in hours, along with the associated 95% confidence intervals, from OLS regressions of the change in weekly hours on the wealth shock dummies, controlling for country dummies and socioeconomic variables (gender, age, education, family size, disposable income). The predicted change in hours is computed from OLS regressions with full interaction between the lottery prize and group dummies.

Figure 8. Search intensity, by lottery prize



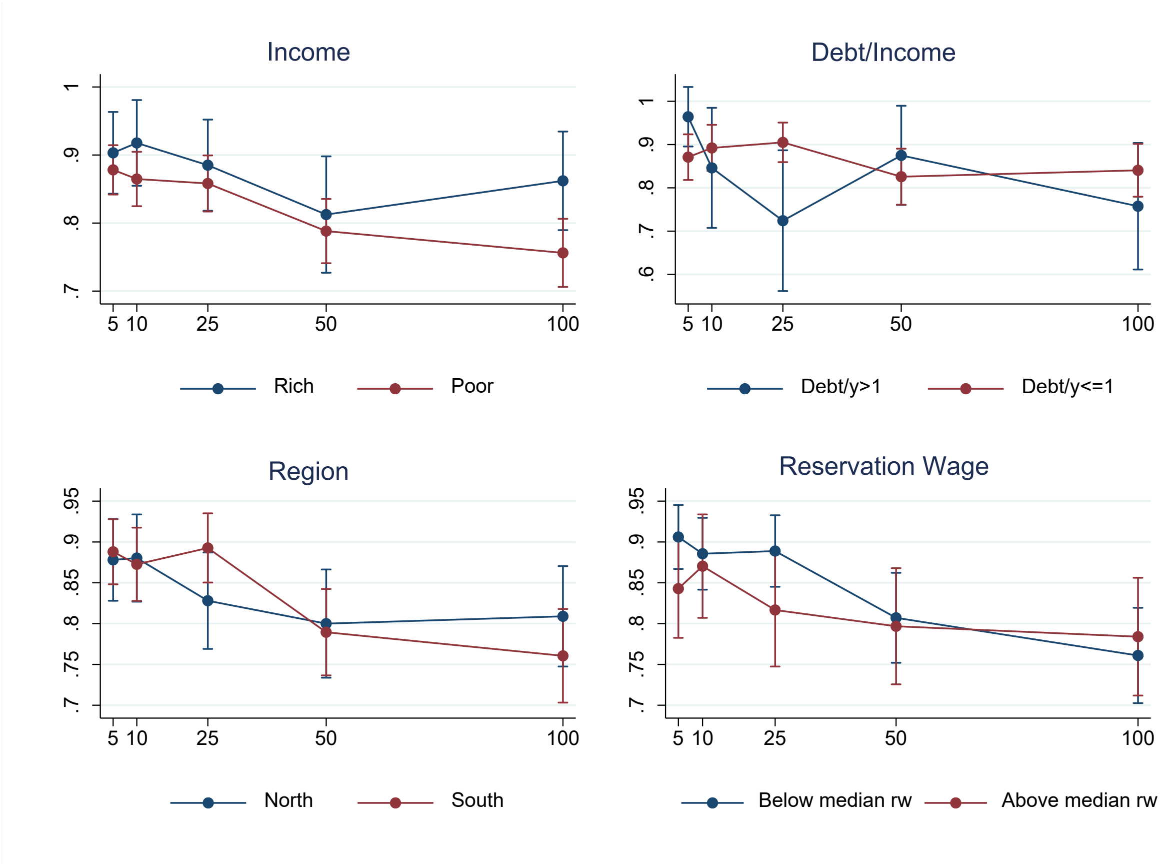
Note: The histogram uses the sample of non-working respondents to display the six outcomes of the survey question on the intention to search for a job after receiving the randomly assigned lottery prize. Averages are computed using sample weights.

Figure 9. Search intensity: baseline estimates and effects by 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 defined as a dummy in the sample of non-employed individuals, equal to zero if respondents intend to stop searching or search less, and one otherwise. The upper-left graph is based on the logit regression in column 3 of Table 6. The other figures display 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. The predicted search intensity is computed from logit regressions with full interaction between the lottery prize dummies and the group dummies.

Figure 10. Search intensity: effects by income, debt exposure, 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 defined as a dummy in the sample of non-employed individuals, equal to zero if respondents intend to stop searching or search less, and one otherwise. The figures report search intensity for different groups defined by income (below or above median disposable income), debt-to-income ratio (below or above one), and self-reported reservation wage from the May 2022 survey (below or above median) across the lottery prizes. Predicted search intensity is computed from logit regressions with full interaction between the lottery prize dummies and the group dummies.

Appendix A

A1. The Consumer Expectations Survey

The ECB's Consumer Expectations Survey (CES) is a high-frequency online panel survey designed to track consumer expectations and behavior across the euro area. Launched in pilot phase in January 2020, the CES builds on recent advancements in international survey methodologies and design. It includes several key features that enable in-depth analysis of economic shocks and their transmission through the household sector. For a more detailed description of the CES, refer to Georgarakos and Kenny (2022), and for an initial evaluation of the survey, see ECB (2021).

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 analyzed in this paper. The primary dataset used here comes from a special-purpose survey conducted in June 2022, which includes anonymized individual-level responses from roughly 2,000 participants each from the four largest euro area countries (Germany, Italy, France, and Spain) and 1,000 participants from each of the two smaller countries (Belgium and the Netherlands). In the four largest euro area countries, three out of four participants were recruited via random dialing, while the remaining participants were drawn from existing samples. The survey provides sample weights, which we use to ensure that descriptive statistics are representative of the adult population in each country.

The large sample size of the CES ensures that the survey is highly representative of the population structure at both the euro area and country levels. Respondents are invited to complete online questionnaires each month and remain in the panel for a period of 18 to 24 months after joining. Upon entry, each respondent fills out a background questionnaire, providing essential information that remains relatively stable over time, such as education level, family situation, household income, and financial literacy. More dynamic, time-sensitive data is collected through monthly, quarterly, and ad hoc topical questionnaires. For example, detailed questions on household consumption expenditures are asked quarterly, while questions on consumption and asset choices in response to wealth shock scenarios—like the one used in this paper—are included in special-purpose modules.

The online nature of the CES allows the survey to remain responsive to ongoing economic developments. This flexibility was key in enabling the fielding of the survey experiment in June 2022. Additionally, the CES is an incentivized survey, with participants receiving a modest monetary gratuity for their participation. These incentives not only recognize the value of the data provided by respondents but also enhance the quality of the survey by promoting higher response rates, panel retention, and minimal missing responses.

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 non-working 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;

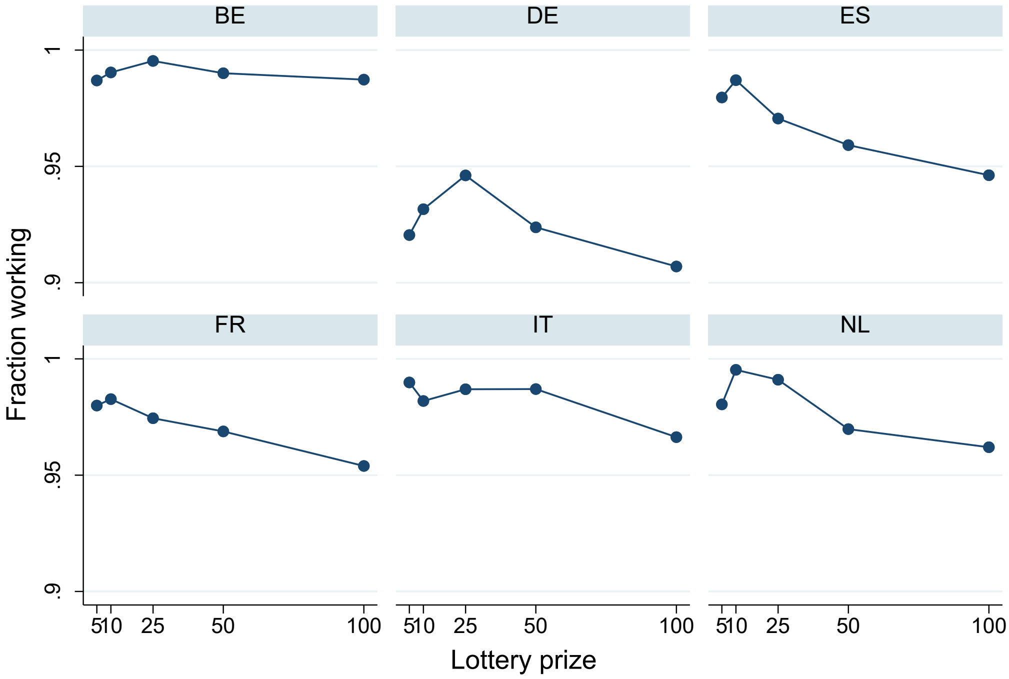
(6) I am not looking for a job, but would then start looking for a job.

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).

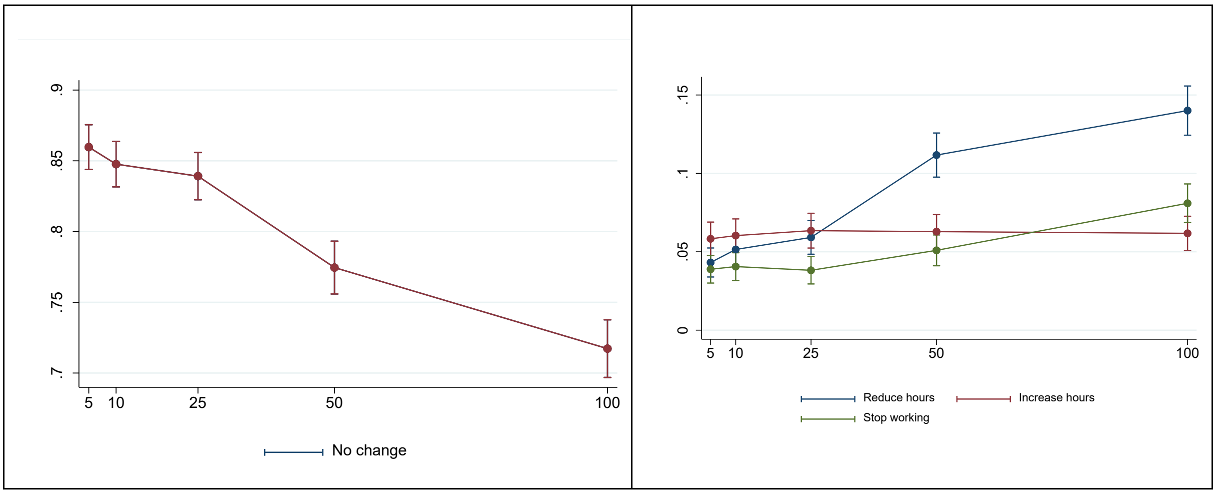
Appendix B. Additional figures and results

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



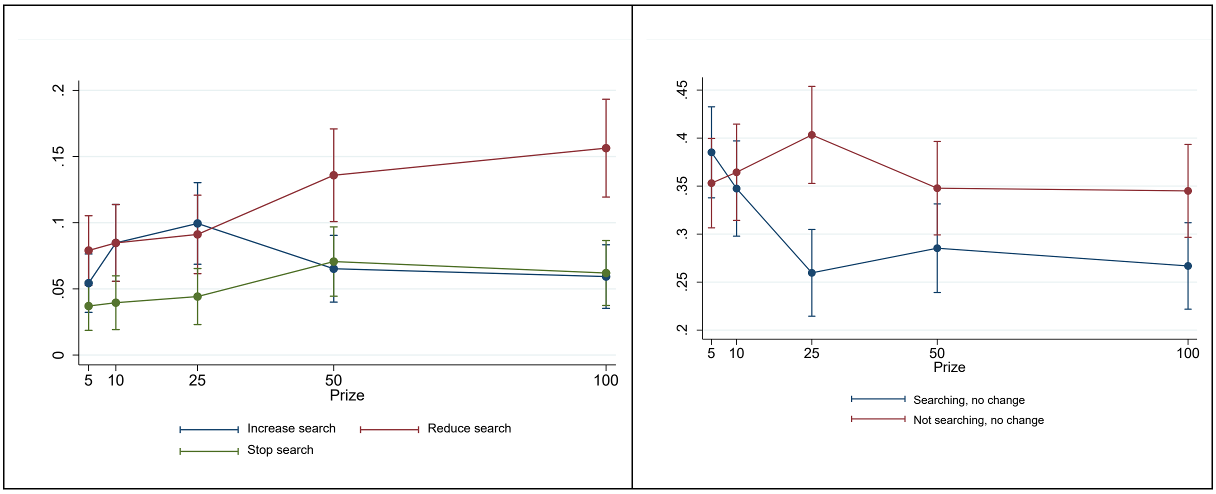
Note. The graphs plot the proportion of individuals currently employed who intend to continue working after receiving the randomly assigned lottery prize, across the countries included in our survey experiment (Belgium, Germany, Spain, France, Italy, and the Netherlands). Averages are computed using sample weights.

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



Note. The figures display the predicted probabilities of changes in hours worked and employment status, estimated using a multinomial logit model.

Figure B3. Multinomial logit for search behavior



Note. The figures plot the predicted probabilities of search behavior, estimated using a multinomial logit model. 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: Sample splits by gender and age

	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, with the sample split by gender and age (less than or more than 40 years old). All regressions control for country dummies and socioeconomic variables (gender, education, family size, disposable income, self-employment). Standard errors are reported in parentheses. One star indicates significance at the 10%, two stars at the 5%, and three stars at the 1%.

Table B2. Change in hours worked: Sample splits by gender and age

	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 the change in hours worked, with the sample split by gender and age (less than or more than 40 years old). All regressions control for country dummies and socioeconomic variables (gender, education, family size, disposable income). Standard errors are reported in parentheses. One star indicates significance at the 10%, two stars at the 5%, and 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, with the sample split by gender and age (less than or more than 40 years old). All regressions control for country dummies and socioeconomic variables (gender, education, family size, disposable income). One star indicates significance at the 10%, two stars at the 5%, and three stars at the 1%.

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