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Do Windfall Gains Affect Labour Supply? Evidence from the European Household Panel

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Abstract: We investigate whether workers adjust hours worked in response to windfall gains using data from the European Household Panel. The results suggest that unexpected variation in income has a negative (although small) effect on working hours. In particular, after receiving an unanticipated windfall gain, individuals are more likely to drop out of the labour force and the effects become larger as the size of windfall increases. Furthermore, the empirical findings show that the impact of windfall gains on labour supply: (i) is more important for young and old individuals, (ii) is mostly negative for married individuals with young children, (iii) but can be positive for single individuals at the age of around 40 years.

Keywords: windfall gains, working hours.
JEL classification: D12, J22.

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1. Introduction

What is the effect of windfall gains on economic behaviour? A popular belief presumes that the majority of people would quit work if they won a lottery. But do windfall gains have an impact on individuals' working hours? According to the life-cycle model, a relaxation or tightening of the consumer's intertemporal budget constraint can lead both to changes in consumption and to changes in labour supply. Windfall gains represent an unanticipated increase in non-earned income and by reducing an agent's marginal utility of wealth they therefore reduce her incentive to work.

In this paper, we analyze the linkages between windfall gains and working hours using data from the European Community Household Panel Longitudinal Users' Database. We show that an unanticipated rise in wealth reduces working hours in accordance with the life-cycle model, although the effect is, in general, small. The impact of windfall gains is stronger at the external margin, that is, individuals adjust their labour supply primarily by dropping out of the labour force, rather than by reducing their work hours conditional on working.

We also look whether "size matters" with respect to the effects of windfall gains on working hours. We assess how households respond to small, medium or large windfall gains. We find that the effects become stronger as the size of windfall increases. In particular, men receiving a windfall of 50,000 EUR or more, on average reduce labour supply by 1.3 hours per week, which is equivalent to a 3.4% reduction in working hours.

Finally, analysing the effects of windfall gains along various personal characteristics, we find that: (i) at younger and older ages, the effect of windfall gains on labour supply is the most negative; (ii) for married people and people with young children, the windfall gain leads to a stronger decrease in working hours and (iii) for single individuals at the age of around 40, the effect can be positive. A potential explanation for the latter empirical finding is in the effect of windfall gains on reducing liquidity constraints in capital markets. By doing so, windfall gains may encourage people to set up their own business, become self-employed and increase their working hours.

This paper contributes to the literature in following ways. This is the first paper that analyses effects of windfall gains on working hours using data for a set of European countries. Furthermore, because we include 15 countries in our analysis, the sample of people for which we observe windfall gains is large, offering a further empirical advantage to our approach. With the panel data set, we observe a rich set of personal characteristics of individuals. This gives us an opportunity to better understand the ways that participation and working-hours decisions differ between individuals.

The remainder of the paper is structured as follows. Section 2 reviews the existing literature on the effects of unexpected variation in income. Section 3 describes the data. Section 4 presents the theoretical and the econometric approach and Section 5 discusses the empirical results. Section 6 concludes.

2. A brief review of the literature

The launch of the pan-European lottery, *Euromillions*, in 2004 induced many people to fantasize about what they would do if they actually won. Notable wins include prizes of around 180 Million EUR which, therefore, reveals the extraordinary importance that a lottery may play in people's life and behaviour.

A vast literature has explored the reaction of consumption and savings to exogenous changes in income. An early example is Bodkin (1959), who used an unexpected National Service Life Insurance dividend paid to veterans of the World War II in 1950. Similarly, Brickman et al. (1978) focused on how the income effect affects consumption. More recent examples include Imbens et al. (2001), who look at the differences among major-prize winners of the Megabucks Lottery in Massachusetts between 1984 and 1988, and Kuhn et al. (2008), who analyze the differences in winnings in the Dutch postcode lottery.[1]

Unexpected variation in income may also affect the level of happiness of individuals.[2] Whereas some surveys suggest that money indeed makes people happy (Gardner and Oswald, 2001), others find only a weak link between unexpected wealth variation and happiness (Myers, 1992; Argyle, 2001; Nettle, 2005; Layard, 2005).[3]

Another dimension of the effects of exogenous changes in income refers to fiscal policy and, in particular, the effectiveness of temporary fiscal measures.[4] In fact, understanding the effect of unearned income on labour supply is also of great importance for policy makers, as it is at least part of what is needed to evaluate such programs (Joshi et al., 1996; Kuhn et al., 2008). For instance, Petrongolo and Pissarides (2008) find that strict employment protection legislation characterizes well the dynamics of unemployment in France, while fixed-term contracts contribute significantly to the dynamics of unemployment in Spain. Manning (2009) shows that changes in the welfare support for the unemployed can impact on the labour market, by reducing their search activity.

[1] Some recent studies have also used exogenous variation to analyze neighbourhood and peer effects on individuals (Sacerdote, 2001; Katz et al., 2001; Kling et al., 2005; Ludwig et al., 2001; Kuhn et al., 2008).
[2] For discussions of this question, see, for example, Easterlin (1974) and Martin (1995).
[3] Lindahl (2005) shows that higher income from a monetary lottery prize generates good health.
[4] For a revision of the major developments in labour market theory and their policy implications, see, for instance, Manning (1995).

In addition to the potential effects of income shocks on consumption and savings or on the level of happiness, a popular belief presumes that the majority of people would quit work if they won a lottery. But do individuals who win continue to work, and if so, why? While the literature on the empirical and theoretical inter-temporal substitution effects in labour supply is well established (Heckman and MaCurdy, 1980; Altonji, 1986), the research on the effects of capital gains is still somewhat insipient (Henley, 2004), despite the fact that lottery winnings are a source of exogenous variation in income (Altonji, 1986).

In the US, Kaplan (1988) show that the level of education and the type of profession can help explain the percentages of winners who choose to continue to work.[5] Holtz-Eakin et al. (1993) and Imbens et al. (2001) find that windfall gains lead to a reduction in working hours or even a withdrawal from the labour force. In contrast, Joulfaian and Wilhelm (1994) suggest at most a small (although significant) effect for married women and men. Hirschfeld and Field (2000) use the proposition of work centrality, that is, the degree of importance that working has in one's life at any given time to explain why lotteries may have a limited impact.

In Europe, Blanchflower and Oswald (1998), Taylor (2001), using UK data, and Lindh and Ohlsson (1996), based on evidence for Sweden, report a positive effect of windfall gains (inheritance and lottery wins) on the probability of entering self-employment. Henley (2004) analyzes the impact of both windfall financial gains and house price shocks on hours worked, and suggests that there are significant substitution effects, in particular, in response to house price shocks.

3. Data and descriptive statistics

3.1 Data

The data is obtained from the European Community Household Panel Longitudinal Users' Database (ECHP henceforth). This is a large panel data set that contains household-level and person-level information over time, covering eight survey years from 1994 to 2001.[6] The data includes 15 EU countries: Germany, Denmark, The Netherlands, Belgium, Luxembourg, France, United Kingdom, Ireland, Italy, Greece, Spain, Portugal, Austria,

[5] Note that the education level can also be a proxy for a worker's skill. In this context, Portela (2001) proposes an index of skill that takes into account different dimensions, namely, schooling, labor market experience and unobservable ability.

[6] Azmat et al. (2006) also use the European Community Household Panel Survey, but in the context of analyzing the large gender gap in unemployment rates. Notably, the authors show that interactions between the differences in human capital accumulation by gender and labor market institutions play a major role. In a similar context, Joshi et al. (2007) argue that women's education and experience rather than a movement towards equal treatment play a special role in gender pay differences. Mumford and Smith (2007, 2009) find that the gender earnings gap can also be largely explained by the workplace in which the employee works.

Finland and Sweden. It is an unbalanced panel with a maximum length of 8 years for each individual.

In what follows, the analysis is done at the individual level, rather than at the level of households, with age restricted to 25-60 years. This age band is chosen to avoid complications that arise due to education and retirement choices. The data on incomes and wages are converted using PPP in order to allow for comparisons across countries and over time.

The question of interest relates to the effects of unanticipated windfall gains on labour supply. Working hours are described by the ECHP variable PE005: *Total number of hours working per week (in main + additional jobs)*. In the data, this variable is only available for employed workers. However, we set hours worked to zero for all unemployed individuals and those out of the labour force.

The variable that measures windfall gains is the ECHP variable HF017: *Inherit, receive gift or lottery winnings worth 2000 EURO or more*. It is the response to a following survey question: *"During (… year prior to the survey …), did anyone in the household inherit any property or capital, or receive a gift or lottery winnings, worth 2000 EURO or more?"*. Observations for which the information on the windfall receipt is missing are discarded.

One major drawback of this variable is that it does not provide information about the exact amount of the windfall gain. However, it can be complemented by the variable HF018: *Amount of the inheritance, gift or lottery winnings*. This variable offers three brackets for the windfall gains: *less than 10,000 EURO, more than 10,000 EURO but less than 50,000 EURO* and *50,000 EURO or more*. We label the three brackets for windfall gains as "small", "medium" and "large", respectively.

These two variables hence give information on the size of windfall gains received by individuals. Nevertheless, given that they are reported in categorical terms, one cannot convert them into PPP terms. As a result, they are not perfectly comparable across countries and over time. Another weakness is that both variables are reported at the household level. Consequently, there is no way to identify which household member was the actual recipient of the windfall gain.[7]

[7] It should be noted, however, that an indicator for a windfall gain is, to some degree, a personal characteristic. For example, in cases where individuals change households (i.e. get married) and they receive windfall gains only after they have moved to a new household, they are recorded as recipients of windfall gains together with their partner. Naturally, individuals from the initial household have not received any windfall gains. Should the individual move households again with a new partner, for example, then he would still be recorded as a recipient of windfall gains, but his new partner would not.

It is important to emphasise that the variable measuring windfall gains is recorded for the "year prior to the survey".[8] Notwithstanding this, we did not decide to adjust the timing of the variable. First, a substantial fraction of the data (that is, 19% of person-year observations) would be lost by lagging the windfall gains variable by one period. Second, leaving the variable as it is, we can be sure that at the time of the interview in the time period *t*, an individual knows whether she has received windfall gains or not. On the contrary, if we lagged windfall gains variable by one period, to *t-1*, we would not know for sure whether at the time of the interview at *t-1* the individual had already received the windfall gains or not.[9] Furthermore, in practice individuals take a bit of time before they react to new economic information. Therefore, it seems more appropriate not to lag the windfall gains variable back by one period.

In Table 1, we report the number of *individuals* in the sample and the number of times they received windfall gains. Only those individuals who were observed at least twice are included. To ease discussion, we label people that have received windfall gains as "winners" and the rest as "non-winners". There are 100,289 individuals in the sample, and most of them (88.4%) never received any inheritance, gift or lottery winnings of more than 2000 EUR. In addition, 8,824 individuals (or a fraction of 8.8%) received windfall gains only once, and about 2% of individuals received windfall gains twice.

[PLACE TABLE 1 HERE.]

For the purpose of the analysis, the most important group is the one with 8,824 individuals who received windfall gains only once, as in the regression analysis it is not straightforward to deal with individuals who received windfall gains more than once. Most of the empirical analysis will therefore be based on that group. Compared to similar research done by other authors, this is quite a large sample and represents one of the advantages of using the ECHP dataset.[10]

[8] Similarly, income variables are also recorded for "year prior to the survey". On the other hand, net monthly wage and other variables are recorded for "the time of the interview".

[9] How much information the individual possesses at the time of the interview of course depends on the relative timings of windfall gains and survey interview, but on average there is a 50% chance that the individual had already received the windfall gains.

[10] For instance, Imbens et al. (2001) have about 237 winners, Joulfaian and Wilhelm (1994) have 439 heirs in their sample, Holtz-Eakin (1993) have 2,700 married couples and 1632 individuals in their sample, and Henley (2004) has around 5,400 men and women included.

In Table 2, we report the number of individuals by size of windfall gains received. There are 4,172 (48.8%) observed individuals with small windfall gains, 3,353 (39.2%) with medium windfall gains, and 1,023 (12.0%) individuals with large windfall gains.

[PLACE TABLE 2 HERE.]

3.2 Descriptive statistics

In this sub-section, we analyse differences in personal characteristics between winners and non-winners prior to the receipt of windfall gains, and differences among winners of windfall gains of different sizes (i.e. *small* versus *large* winners). We also compare the means of variables *before* and *after* the receipt of windfall gains.

Table 3 reports the means and number of observations for selected variables, comparing winners, (columns (1) and (2)) and non-winners (columns (3) and (4)). Column (5) reports the *p*-value of the test for differences in means between winners and non-winners. The reported statistics refer to one year *before* the receipt of windfall, which, on average, corresponds to a third year in the sample for winners. Therefore, for non-winners we report the means of the variables in the third year in the sample.

Among the 18 variables reported, only three (the number of children in the household, the percentage of women and the percentage of those who are married) have differences that are not statistically significant.[11] Otherwise, winners tend to be older and they live in slightly smaller households, but for these two variable differences are small. For the rest of the variables, the differences are large and important.

Winners are more educated; the share of individuals with post secondary education is 29% for winners and 18% for non-winners; winners are 7 percentage points more likely to be employed than non-winners. According to income variables, winners have higher incomes and wages even *before* windfall gains. By all measures of income (total income, income from working and non-work income), winners are better off than non-winners: the personal total income of winners is about 29% higher and hourly wage[12] is 13% higher. Higher income is

[11] Interestingly, Joshi et al. (1996) show that the presence of children reduces full-time emplyment among women. Similarly, Joshi (1998) highlights the impact of child-rearing on women's time use.

[12] Hourly wage is a measure of offered wages in the labour market. Reported data is in purchasing power parity units in order to be comparable across countries. Hourly wage is calculated from net monthly wage given in the data, divided by weekly working hours times 4.33 to correct for the average number of weeks in one month. All hourly wages lower than 1 euro or higher than 100 euros are put to missing. Wages of people who do not work or wages otherwise missing are then imputed. For those individuals of which wage information is available in some periods but not in others, the average wage of the individual is imputed in other periods. Other wages are

partly a consequence of the fact that winners, on average, work more hours per week and they are more likely to be employed. They are also more educated and thus have higher hourly wage. However, another potential reason for the difference in incomes lays also in the fact that our measure of windfall gains includes gifts and inheritances. It can then be the case that people from better family backgrounds are more likely to receive (large) gifts or inheritances, which is reflected in our data. Family background is of course a fixed effect and will eventually drop out of the analysis when data will be analysed using our econometric methodology.

The observed differences between winners and non-winners from Table 3 could of course reflect simply differences across countries. If there was a country with above average number of winners, and also with above average incomes, this would make winners, in a spurious fashion, appear to have higher incomes in the full sample. Data show that in most countries, between 87% and 96% of the sample is comprised of non-winners. However, four countries (Denmark, the Netherlands, Finland and Belgium) have a lower percentage of non-winners, but when we checked differences in means after excluding these four countries, the magnitudes and conclusions were similar. Therefore, we conclude that the differences reported in Table 3 reflect genuine differences between winners and non-winners.

[PLACE TABLE 3 HERE.]

In Table 4, we turn to comparisons of personal characteristics among winners of small, medium and large windfall gains. We report means and number of observations one period prior to the receipt of windfall. Columns (7) – (9) report *p*-values from testing the null hypothesis of no differences in means between groups.

No statistically significant differences between winners of windfall gains of different sizes are found for household size, number of adults, number of children in household, percentage of females, marital status, and employment status. On the other hand, there are statistically significant differences in age and education: the group with small windfall gains is significantly younger than the other two groups (i.e. 41.4 years compared to 42.5 and 42.8 years for medium and large windfall gains groups, respectively); the group of large winners is also more educated (37% of large winners have education beyond the secondary level, while only 27% of small winners and 28% of medium winners have education of such level).

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imputed using a regression equation separately for men and women using age, age squared, married dummy, two education dummies and wave and country dummies as regressors.

There are also large and highly significant differences in incomes between the three groups; the larger the windfall gains, the higher the income. Such differences in incomes and education can again be explained with family characteristics. If people with higher education and household incomes tend to be from families of better background, then this may be reflected in higher inheritances or gifts. However, this will be controlled for by fixed effects in our estimation.

[PLACE TABLE 4 HERE.]

Finally, in Table 5, we compare the means of personal characteristics before and after the receipt of windfall gains. "Before" stands for one period prior to windfall and "after" stands for one period after the windfall. Intuitively, we would expect non-work income to increase from the period before to the period after the receipt of windfall gains. However, this is not necessarily the case, because, strictly speaking, windfall gains bring a one-off increase in non-work income that lasts only for one period. Nevertheless, it is possible that individuals save or invest part of their unanticipated gains and start earning interest, which may increase their non-work income also in subsequent periods. According to the life-cycle theory of labour supply, the receipt of an unexpected windfall should also reduce working hours and employment of the winners.

Consider first the top panel of Table 5, where differences for the whole sample are reported. Only two variables are (marginally) significantly different between the two periods: total household income is slightly higher after the receipt of windfall gains at a 10% significance level and household non-work income is higher at a 6% significance level and personal hourly wage is higher at 7% significance. Weekly hours worked show no difference in the two periods. Looking at the group with small windfall gains, changes in none of the variables are statistically significant from one period to another, except for the hourly wage, which tends to be higher after the receipt of windfall gains. The percentage of employed people and weekly working hours both slightly decrease, but the differences are not significantly different from zero. In the case of individuals who received medium windfall gains, there is a statistically significant rise in the household income from working, in the unearned household income and in the personal unearned income. Interestingly, the share of employed people and weekly working hours show a slight increase, although the differences are not significant. Finally, for the group with large windfall gains, household total income (at a 1% significance level), household income from working (at a 9% significance level) and

personal total income (at a 9% significance level) all rise from one period to another. Employment and working hours slightly decrease, but the differences are not statistically significant.

[PLACE TABLE 5 HERE.]

3.3 Non-work income and working hours over time

In this sub-section, we show the evolution of unearned income and working hours over time. From the previous analysis, windfall gains do not seem to have strong effects on income or on labour supply, since differences over time, before and after the windfall gains, are mostly not statistically significant. Hence, one could ask whether the windfall gains variable is a correct measure. For this reason, Figure 1 depicts the average (household and personal) non-work income over time. The time period "0" refers to a time of windfall gains receipt. Since the maximum number of periods for an individual in the sample is eight, the graph is plotted only for five years prior and five years after the receipt of windfall gains. Moving further away from the point of receipt would make the sample size become very small. From Figure 1, it can be seen that the variable windfall gains is meaningful and informative. Indeed there is a positive blip in both household and personal non-work income at the time of receipt. After that, non-work income returns to its upward trend.

[PLACE FIGURE 1 HERE.]

Figure 2 displays household income over time by size of windfall gains. Due to limitations in the sample size, we put the large windfall gains and the medium windfall gains groups into a single category. Non-work household income of the medium/large group is, in general, higher than for the small group. The discrete jump in income in the period the windfall gains are received is still visible for both groups, and, as expected, is larger for the group that receives medium/large gains.

[PLACE FIGURE 2 HERE.]

Next, we turn to the evolution of weekly working hours (Figure 3 and Figure 4). Figure 3 shows that the positive trend in average weekly working hours is reversed after the receipt of windfall gains. Similar information is conveyed by Figure 4, where we split the

sample between those who receive small windfall gains and those who receive either medium or large windfall gains. Whereas the evolution of working hours for the small group seems to be more or less unchanged, the downward trend after windfall gains for medium/large group is more apparent. This is consistent with the hypothesis that, after receiving windfall gains, individuals adjust their labour supply downwards. Of course, this is a very crude method of relating working hours to windfall gains and in the analysis that follows we will proceed with the regression analysis.

[PLACE FIGURE 3 HERE.]

[PLACE FIGURE 4 HERE.]

4. Theory and econometric approach

4.1 The impact of windfalls on working hours: A theoretical illustration

Consider a representative consumer who chooses consumption, C_t, and leisure hours, L_t, in order to maximize lifetime utility

$$\sum_{i=0}^{T}(1+\rho)^{-t}U(C_t, L_t) \tag{1}$$

subject to the intertemporal budget constraint

$$A_0 + \sum_{i=0}^{T} R_t N_t W_t = \sum_{i=0}^{T} R_t C_t \tag{2}$$

where U represents the utility function in time period t that is separable in consumption and leisure, N_t denotes hours worked equal to L^* (a fixed time endowment) minus L_t, A_0 refers to initial assets, W_t is the hourly wage rate, R_t is the discount rate, $\prod_{i=1}^{t} 1/(1+r_i)$, where r is the real rate of interest, and ρ is the rate of time preference.

Following MaCurdy (1981), we assume that U has the following form for individual i at time t

$$U_i(C_{it}, L_{it}) = \alpha_{1it} C_{it}^{\omega_1} - \alpha_{2it} N_{it}^{\omega_2} \tag{3}$$

where α_1 and α_2 are 'taste-shifters' which depend on consumer *i*'s preferences at *t*, $0 < \omega_1 < 1$ and $\omega_2 > 1$.

If we consider an interior optimum (that is, for $N_{it} > 0$), the logarithm of the labour supply function for a given marginal utility of wealth can be expressed as

$$\log N_{it} = (\omega_2 - 1)^{-1}(\log \lambda_{it} - \log \alpha_{2it} - \log \omega_2 + \log(R_t(1+\rho)^t) + \log W_{it}). \quad (4)$$

where λ denotes the marginal utility of wealth.

We assume that 'tastes' for work are randomly distributed according to the relationship $\log \alpha_{2it} = \gamma X_{it} + \sigma_i + u_{it}^*$ where X_{it} denotes the set of observable determinants of consumer's tastes, σ_i represents the unobserved permanent component of consumer's characteristics and u_{it}^* a time-varying random component with zero mean.

Assuming a constant real interest rate, replacing the distribution for 'tastes for work' in equation (4) and using approximation $\log(1+x) \approx x$, we can simplify the labour supply function as

$$\log N_{it} = -\delta(\sigma_i + \log \omega_2) + \delta(\rho - r)t + \delta \log \lambda_{it} + \delta \log W_{it} + \delta\gamma X_{it} + u_{it} \quad (5)$$

where $\delta = (\omega_2 - 1)^{-1}$, and $u_{it} = \delta u_{it}^*$.

Following Altonji (1986) and Joulfaian and Wilhelm (1994), we assume that the marginal utility of wealth evolves as

$$\log \lambda_{it} = \log \lambda_{it-1} + a + \phi_{it} \quad (6)$$

where ϕ_{it} represents the forecast error of the marginal utility for next period and *a* is a parameter determined by the discount factor, the interest rates, and the distribution of the forecast error. We approximate λ_{it-1} by

$$\log \lambda_{it-1} = \xi Z_i + \theta \log(E_{t-1}(G_i)) + \varepsilon_i \quad (7)$$

where Z represents the family background characteristics and the effect of the expected lifetime wage profile on the marginal utility, $E_{t-1}[G_i]$ denotes the expected present value of the capital gain (loss), including for example potential inheritance and other windfall gains, and ε_i captures any individual unobserved time invariant heterogeneity in marginal utility of wealth. Combining equations (6) and (7) and plugging into equation (5), we obtain the following labour supply representation:

$$\log N_{it} = \delta(\varepsilon_i - \sigma_i) + \delta\xi Z_i + \delta\theta \log(E_{t-1}(G_i)) - \delta(a + \log\omega_2) + \delta(\rho - r)t + \\ + \delta \log W_{it} + \delta\gamma X_{it} + \delta\phi_{it} + u_{it}. \quad (8)$$

It is clear from the first and the second term on the RHS of (8) that that labour supply response should be estimated using fixed effects estimation. Thus one eliminates the need to explicitly control for family background and also removes any potential biases due to ε_i.

When the capital gain is fully unanticipated (that is, $E_{t-1}[G_i]=0$), capital gains affect labour supply *only* via the forecast error, ϕ_{it}. Assuming that the forecast error is a proportion κ of the actual capital gain, that is, $\phi_{it} = \kappa G_{it}$, where $\kappa < 0$, then labour supply response will be $\delta\kappa$, which is negative.

However, when the capital gain is fully anticipated (that is, $E_{t-1}(G_i) = G_i$ and $\phi_{it} = 0$), then capital gains will exert their effects on labour supply by $\delta\theta$. Given that marginal utility would have lowered before the time period in question, there would be no further adjustment at the time of inheritance. Therefore, the unanticipated windfall gains reduce the marginal utility of wealth, and thus reduce labour supply.

4.2 The impact of windfalls on working hours: the econometric specification

Despite the large literature concerned with estimating the impact of unearned income on labour supply, the use of an exogenous measure of income variation is not consensual. As a result, different approaches have been considered, namely: (i) the capital income or spousal-labour earnings as variables measuring unearned income (Imbens et al., 2001); (ii) experimental data with exogenous components of unearned income (Rees, 1974; Pencavel, 1986); and (iii) natural experiments in which large amounts of money were allocated using distribution rules that were independent of preferences and other determinants of economic behaviour (Bodkin, 1959; Kreinin, 1961; Holtz-Eakin et al., 1993).

We start by looking at whether the windfall gain affects the probability of being employed, and estimate the following linear probability model

$$\text{Prob}(E_{it} = 1) = c_0 + c_{0i} + c_1 Windfall_{it} + c_2 W_{it} + c_3 X_{it} + \varepsilon_{it} \quad (9)$$

for $i = 1, \ldots, N$, $t = 1, \ldots, T$, where E_{it} is a dummy variable that takes the value of 1 if individual i is employed or 0 otherwise, $Windfall_{it}$ is our variable of interest and takes the value of 1 if the household has received a windfall gain or 0 otherwise, W_{it} denotes the hourly wage, $\boldsymbol{X_{it}}$ represents a set of controls for age, civil status and family characteristics, c_{0i} is individual fixed effect and ε_{it} is an i.i.d. error term.

In order to assess the effect of unexpected capital gains on working hours, we estimate the empirical counter-part of Equation (8) as described by

$$H_{it} = c_0 + c_{0i} + c_1 Windfall_{it} + c_2 W_{it} + c_3 X_{it} + \varepsilon_{it} \quad (10)$$

for $i = 1, \ldots, N$, $t = 1, \ldots, T$, where H_{it} stands for weekly working hours of household i in year t.

Taking into account that the impact of windfalls on labour supply differs for different amounts of unanticipated gains, we also disaggregate the *Windfall* dummy into three different categories: (i) *Small Windfall*, in the case of capital gains between 2,000 and 10,000 EUR; (ii) *Medium Windfall*, for capital gains between 10,000 and 50,000 EUR; and (iii) *Large Windfall*, when the capital gain exceeds 50,000 EUR. Then, we consider the model:

$$\begin{aligned} H_{it} = {} & c_0 + c_{0i} + c_1^1 Small\ Windfall_{it} + c_1^2 Medium\ Windfall_{it} + c_1^3 Large\ Windfall_{it} + \\ & + c_2 W_{it} + c_3 X_{it} + \varepsilon_{it} \end{aligned} \quad (11)$$

for $i = 1, \ldots, N$, $t = 1, \ldots, T$.

Finally, we look at whether the effect of the windfall varies with different personal characteristics. Therefore, we interact the regressors with the *Windfall* dummy and estimate the following model:

$$H_{it} = c_0 + c_{0i} + c_1 Windfall_{it} + c_2 W_{it} \times (1 + Windfall_{it}) + c_3 X_{it} \times (1 + Windfall_{it}) + \varepsilon_{it} \quad (12)$$

for $i = 1, \ldots, N, \ t = 1, \ldots, T$.

The estimation of the above models is complicated by the potential endogeneity of the wage term on the right-hand side.[13] Altonji (1986) emphasizes that current labour supply depends on all past and expected future wage rates and that it is important to control for permanent differences in wages across individuals.

Consequently, we assess the robustness of the results using both the fixed effects (FE) estimator and the fixed effects instrumental variable (FEIV) estimator. In the IV regressions, we follow Joulfaian and Wilhelm (1994) and Henley (2004) and instrument log hourly wages using conventional earnings-function control variables, namely, two dummies for education, interactions between education dummies and a quadratic in age, as well as country-year dummies.

5. Empirical results

5.1 The effects of windfall gains on working hours

In this and subsequent sub-sections, we analyse the effect of windfall gains on working hours. According to the empirical specification of the theoretical model presented above, we use the fixed effects estimation, thus controlling for family background and other time-invariant personal characteristics. Windfall gains are measured using a dummy variable that takes a value of 1 in the period of windfall receipt and after, and 0 in periods prior to windfall gains. This is in line with the life-cycle model of labour supply where after an unanticipated shock in personal wealth, an individual adjusts her whole labour-supply profile.

In all specifications we include the following set of regressors: the dummy variable for the windfall gain, age, age squared, a dummy for married status and two dummy variables indicating whether there are any children aged 0-6 or 7-15 in the household. We focus on three main specifications, each of them being estimated for the full sample (Table 6), and then separately for men (Table 7) and for women (Table 8).

[PLACE TABLE 6 HERE.]

The first specification (column (1)) analyses the effects of windfall gains on the probability of being employed. According to the theory, after receiving unanticipated windfall

[13] Pencavel (1986) also highlights the endogeneity of nonwage income. In the context of our framework we consider windfall gains as unanticipated and exogenous.

gains, individuals are more likely to drop out of the labour force and use windfall gains to enjoy more leisure. Such behaviour is reported in Holtz-Eakin et al. (1993), who find a negative effect of unanticipated inheritances on participation in the labour market. As a dependent variable we use a dummy variable indicating whether or not an individual is employed.[14] Normally, probit specification would be used to analyse this; however, due to inconsistency of probit regression in settings with fixed effects, we use a linear probability model instead.[15]

The second specification (column (2)) uses working hours per week as a dependent variable. In this case we include all individuals who ever received windfall gains no matter whether they participate in the labour force in any particular period or not. That is, working hours can take any positive value, but they can also be zero. The second specification thus covers both external and internal margins of adjustment of labour supply to windfall gains[16]. In addition to the standard controls on the right hand side, this specification also includes a measure of hourly wage. As the hourly wage is computed from monthly wages and weekly working hours, it is endogenous. Consequently, we also report the results from an instrumental variables estimation (column (3)). Here we overcome the endogeneity problem by using two dummies for education, interactions of education dummies with quartic in age, as well as country-year dummies as instruments for hourly wage.

Finally, in the third specification (column (4)), we express working hours and wages in logs. As a consequence, only person-year observations with positive working hours and positive wages are included. This specification is closest to the theoretical approach based on the interior solution of the life-cycle optimisation problem derived in section 4.1. From an econometric perspective, however, one should note that a potential problem in this context stems from the fact that when receiving windfall gains individuals may decide to reduce their working effort either by reducing working hours *or* by dropping out of the labour force, which can generate a selection bias problem. We present the results both from the fixed effect setting (column (4)) and the instrumental variable estimation with fixed effects (column (5)).

Table 6 summarizes the findings for the effects of windfall gains on working hours using the whole sample. The empirical evidence is not supportive of theoretical prediction of the life-cycle model that an unanticipated rise in wealth reduces an individual's working hours

[14] In our sample, about 25% of people change their employment status at least once.

[15] In all cases in the paper where we estimated the linear probability model we also checked the results using logit specification with fixed effects. Results were very similar with the same conclusions.

[16] Due to the number of zeroes on the left hand side, we estimated this specification also using the Tobit with fixed effects estimator from Honore (1992). The results were again very similar and conclusions would be the same.

via a reduction in the marginal utility of wealth, in particular, the coefficients of the windfall gains dummy are not statistically significant. On the other hand, most coefficients of the other control variables have the expected signs and magnitudes and are statistically significant: (i) age has a nonlinear, inverted "U" shaped effect on labour supply; (ii) being married tends to increase labour supply; and (iii) having children reduces it. Only hourly wage has a surprising negative effect on working hours, which is reduced after using instrumental variables estimation, but it nevertheless remains negative and significant.[17]

Table 7 reports the results for the sample consisting of men. Again, the coefficients of the windfall gains dummy are not statistically significant. Nevertheless, they are negative, which is in accordance with the theoretical formulation of the life-cycle model. Other controls have coefficients of sensible signs and magnitudes and, in particular, one can see that being married increases men's labour supply.

[PLACE TABLE 7 HERE.]

Table 8 shows the results for the sample consisting of women. Again, in all five specifications, the effects of windfall gains are not statistically significant and are close to zero. These findings are therefore in line with Imbens et al. (2001), who show that the reaction of people to non-earned income does not differ significantly between men and women. Interestingly and in contrast with the results for men, there is an indication that being married reduces women's labour supply.

[PLACE TABLE 8 HERE.]

So far we have found no supportive evidence that the receipt of unanticipated windfall gains has a significant and negative impact on labour supply. This finding however could either reflect that these effects are non-existent, or that they are very small and not well captured in the data. In fact, other researchers have reported that unanticipated windfall gains (inheritances, financial wealth, housing prices) have, at most, a small impact on labour supply, which in many cases are only marginally statistically significant (Holtz-Eakin, 1993;

[17] This is perhaps due to the income effect being stronger than the substitution effect, although empirically this remains an unresolved issue. All regressions reported in the chapter have also been run using net monthly wage instead. In this case, the coefficient on the wage variable was always positive in both the OLS and instrumental variables specifications. However, the coefficients on the other variables and the conclusions regarding the effects of windfall gains were very similar to the results from the specifications which included the hourly wage.

Joulfaian and Wilhelm, 1994; Henley, 2004). Another possible explanation for the small and not statistically significant results may lay in the fact that the windfall gains dummy used so far does not contain enough information. This is because it simply indicates whether an individual has received a windfall gain or not, no matter what the size of the gain was. Therefore, in the next sub-section, we split the windfall dummy into three groups: small, medium and large.

5.2 The effects of small, medium and large windfall gains

We now introduce into the regression three dummies representing the size of windfall gains that individuals receive: small (less than 10,000 EURO), medium (more than 10,000 EURO but less than 50,000 EURO) and large (50,000 EURO or more). The benchmark for comparison is the time before the windfall gains are received. For example, the small windfall gains dummy tells us by how much working hours decrease (or increase), on average, due to the windfall gain in comparison to the situation where the windfall gain has not yet been received. According to the theory, the higher the unanticipated windfall gain, the stronger the effect on the marginal utility of wealth and the more negative we expect the effect on labour supply to be. Therefore, we expect the effect of the large windfall gains dummy to be negative and largest in absolute value.

We report the results separately for the whole sample, for men and for women, in Table 9, Table 10 and Table 11, respectively.

Column (1) of Table 9 suggests that windfall gains have a negative effect on the probability of being employed. Despite not being statistically significant for small and medium windfall gains, the coefficient associated with large windfall gains is negative and statistically significant. This lends some empirical support to the idea that after receiving large windfall gains, individuals are more likely to drop out of the labour force. As for the other specifications (columns (2) - (5)), the results are not statistically significant, although large windfall gains tend to have the most negative impact on labour supply.

[PLACE TABLE 9 HERE.]

Table 10 displays the results for the sample of men. In all five specifications, not only is the coefficient of large windfall gains the most negative, but it is also statistically significant in all cases. Column (1) indicates that receiving large unanticipated windfall gains induces some men to leave the labour force. Similarly, in specifications with working hours

on the left hand side (columns (2) – (5)) there is a statistically significant and negative effect of large windfall gains on working hours.

Column (2) captures both external and internal margins of adjustment: on average, receiving an unanticipated windfall gain of 50,000 EUR or more reduces the labour supply of men by 1.3 hours per week. Since average working hours for men in the sample are equal to 39.2 hours per week, this represents on average a 3.4% reduction in working hours. In column (4), where only the internal margin is considered, the evidence suggests that the large windfall gains reduce working hours by 2.1%. Since only the adjustment of working hours conditional on working is taken into account, the effect is plausibly smaller.

[PLACE TABLE 10 HERE.]

The results for women in Table 11, on the other hand, are not supportive of the idea that windfall gains reduce labour supply. None of the coefficients on windfall gains dummies are statistically significant, and many of them are nonnegative. In light of the fact that women are usually considered as being less attached to the labour market than men, this result is surprising. One would indeed expect the effect of windfall gains to be stronger and more negative for women. For instance, Henley (2004) finds a significant adjustment in hours worked to unanticipated financial gains for both men and women, but the largest impact occurs for women. In addition, the author shows that while men seem to make a (positive) adjustment in hours to housing losses but not a (negative) adjustment to gains, for women the reverse is true. On the other hand, Imbens et al. (2001) estimate the marginal propensity to earn out of unearned income and find that it does not differ significantly between men and women. Joulfaian and Wilhelm (1994) also show that the hours' reduction by married women is of the same order of magnitude as men's.

[PLACE TABLE 11 HERE.]

A potential reason why the effects do not come through very strongly in the analysis above is due to heterogeneity in the effects of windfall gains. The effects of windfall gains may possibly depend on personal characteristics in an important way, so that the impact cancels out across different individuals. For example, an old worker may retire from the labour market after receiving the windfall gain, whereas a young employed worker may use it as a starting capital for a new business, become self-employed and increase his labour

supply.[18] In order to assess the potential heterogeneity in the effects of windfall gains, in the next sub-section we interact the windfall gains dummy with several personal characteristics.

5.3 The effects of windfall gains and interactions

In order to see whether the effects of unanticipated positive wealth shocks differ with respect to personal characteristics, we interact the windfall gains dummy with the other regressors. As discussed above, if the effects of windfall gains depend on personal characteristics and if, in addition, they cancel each other out across individuals, then this would explain why in the previous regressions the effects were small and often not statistically significant.

In Table 12 we report the results for the whole sample. Note that the coefficient in front of the windfall gain dummy alone simply represents the effect of windfall gains when all other controls are set to zero. In most cases, the coefficients of the interaction terms are statistically significant. Column (1) displays the results for the probability of being employed. Looking at the interactions, age has a "U" shaped curve effect: at younger and older ages, the effect of windfall gains on participation is the most negative. This is in line with evidence reported by Holtz-Eakin (1993) and Imbens et al. (2001).

Being married also makes the negative effect of windfall gains on participation stronger. Thus, married people are more likely to reduce their labour supply. One possible explanation for this is that married people have less to worry about their income situation, as they have a partner who usually earns an income. Such behaviour can also be explained with a social multiplier (Glaeser et al., 2003). If people like to spend leisure in groups, then they are more likely to consume leisure when they have someone to spend the leisure with.

In Columns (2) and (3) where total working hours are used as a dependent variable, results are similar: (i) there is an indication of a non-linear effect of age; (ii) being married makes the effect of windfall gains more negative; and (iii) similarly, having children of age 0-6 leads to a larger decrease in working hours, indicating that parents of young children do not drop out of the labour force after receiving windfall gains, but they seek shorter working hours. Columns (4) and (5) show the results for the sample with positive hours worked. They confirm that being married and having small children makes the effect of windfall gains more negative.

[18] Lindh and Ohlsson (1996) and Taylor (2001) find empirical evidence of such behaviour. The authors argue that windfall gains can contribute to the relaxation of the liquidity constraints in capital markets and they find evidence that windfall gains increase the probability of becoming self-employed.

[PLACE TABLE 12 HERE.]

Table 13 reports the empirical findings for the sample of men. In Columns (1), (2) and (3), one can see that if they are of younger or older age, have young children or are married, then windfall gains reduce the probability of being employed. However, when we take away the adjustment along the external margin (columns (4) and (5)), the effects largely become not statistically significant, except for the effects of having young children.

[PLACE TABLE 13 HERE.]

Table 14 provides similar findings for women. In Column (1), where the probability of being employed is explored, there is a "U" shaped effect of age and a statistically significant negative effect of being married. The coefficients on the interactions of children dummies with windfall gains are not statistically significant. In the regressions with working hours on the left hand side (columns (2) and (3)) the results show that women with young children tend to reduce working hours after the receipt of windfall gains. Columns (4) and (5) also confirm this finding.

[PLACE TABLE 14 HERE.]

In order to obtain a better understanding of the heterogeneity in the effects of windfall gains and how they depend on personal characteristics, Table 15 reports the predicted effects of windfall gains on labour supply by various types of individuals. We compute the effects of windfall gains for 8 hypothetical types of individuals. We start by choosing four different age groups: 25, 30, 40 or 55 years. We assume that: (i) individuals of age 25 can only be single and have no children; (ii) individuals of age 30 are either single with no children, or married with one child of age 0-6, (iii) individuals of age 40 can be single without children, married without children, or married with one child of age 0-6 and one child of age 7-15; (iv) individuals of age 55 can either be single or married, but they do not have any young children.

In those specifications where hourly wage is one of the regressors, predicted effects are computed at the mean wage in the sample. Specification (1) represents effects from participation regressions, specification (2) reports the FE IV regressions with working hours

per week on the left hand side,[19] and specification (3) reports effects from FE IV regressions with log working hours as the dependent variable. In brackets we also report p-values from the Wald test of whether the computed predicted effects are statistically different from zero.

For young single people who have no children (first row of Table 15), receiving windfall gains reduces the probability of participating in the labour force. This can be seen, for example, in column (1), where the coefficient is -0.021. A possible explanation for this finding is that after winning an unanticipated windfall young people may decide to prolong their education and finance it with the money they have won. However, as specification (3) suggests, conditional on being employed, windfall gains *increase* the labour supply of young people, perhaps inducing young people to become self-employed and work more.

For individuals of age 30 and with no children, there is a positive effect of windfall gains on the probability of participating in the labour market and also on working hours conditional on working. On the other hand, for individuals of the same age who are married and have children of young age, the effects of windfall gains on labour supply are negative, with effects being strongly negative for both men and women.

In the case of individuals aged 40 with no spouse and no children, there is a *positive* effect of windfall gains on labour supply. Weekly working hours, on average, increase by 2.152 hours (specification (2)) or, conditional on working, for 0.028 log hours (specification (3)). This piece of evidence can again be related with the rise in probability of becoming self-employed as discussed in Lindh and Ohlsson (1996) and Taylor (2001). Interestingly, however, these effects decrease and end up being not statistically significant for individuals of age 40 who are married, especially if they have young children.

We also find support in our data for the behaviour suggested by Lindh and Ohlsson (1996) and Taylor (2001). The results are reported in the Appendix (Tables A.1 and A.2). We find that winning windfall gains increases the probability of becoming self-employed for men. Including interaction terms supports the story that men aged about 40 years have a higher probability of becoming self-employed after winning a windfall gain. However, married men have a higher probability of becoming self-employed compared to single men.

Turning back to the results in Table 15, the effects of windfall gains on the labour supply of married individuals aged 55 tend to be statistically significant and negative. The impact of windfall gains in the employment participation (specification (1)) is equal to -0.028

[19] The results of this specification were also checked using the Honore (1992) estimator, without instruments. The results were very similar and conclusions would be unchanged.

and the effect on weekly working hours (specification (2)) is equal to -0.966. These general patterns are similar for men and for women.

[PLACE TABLE 15 HERE.]

Summing up, several interesting results emerge when we interact personal characteristics with windfall gains. First, the effects of windfall gains operate both at the external and internal margin, but they tend to be stronger at the external margin. This suggests that after receiving unanticipated windfall gains, people adjust their labour supply mainly by dropping out of the labour force, rather than by reducing their hours worked. Second, there is evidence that for some individuals (e.g., for single middle-aged individuals), effects on working hours can be positive. And third, for young and old people as well as individuals who are married with young children, windfall gains tend to have the most negative impact on labour supply.

6. Conclusion

In this paper, we investigate whether European workers adjust labour supply (that is, labour market participation and working hours) in response to windfall gains. According to the life-cycle model of labour supply, unanticipated gains in non-earned income are expected to have negative effects on labour supply. We use information from the European Household Panel for the 1994 to 2001 period to shed some light on the question of interest.

We find weak evidence that individuals react to windfall gains by reducing their working hours. The effects, however, seem to be small. In addition, individuals seem to adjust their labour supply mostly along the external margin, by dropping out of the labour force, rather than by reducing their working hours while staying in employment. Furthermore, we report that the effects on labour supply are stronger in the case of large windfall gains. The results and conclusions are robust to different specifications and they are not affected by the choice of which measure of wage is used on the right hand side: the hourly wage or the net monthly wage.

Finally, when we allow for heterogeneity of the effects across individuals, the results suggest that the impact of windfall gains on labour supply: (i) is more important for young and old individuals, (ii) is most negative for married individuals with young children, (iii) but can be positive for single individuals aged around 40 years. The last effect can be explained

by the effect of windfall gains on reducing liquidity constraints in capital markets and thus encouraging people to become self-employed.

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List of Tables

Table 1: Number of individuals in the sample and number of times they received windfall gains during the period in the sample.

# of times windfall gains received	Frequency	Percent
0	88,692	88.44
1	8,824	8.80
2	1,957	1.95
3	501	0.50
4	165	0.16
5	82	0.08
6	26	0.03
7	25	0.02
8	17	0.02
Total	100,289	100.00

Source: European Community Household Panel Longitudinal Users' Database. All individuals of age 25-60. Only individuals who are observed for at least two periods are included.

Table 2: Number of individuals who ever received small/medium/large windfall gains.

Size of windfall gains received	Frequency	Percent
small (2000-10,000 EUR)	4,172	48.81
medium (10,000-50,000 EUR)	3,353	39.23
large (more than 50,000 EUR)	1,022	11.96
Total	8,547	100.00

Source: European Community Household Panel Longitudinal Users' Database. All individuals of age 25-60. Only individuals who are observed for at least two periods are included.

Table 3: Comparing personal information for winners and non-winners (prior to receiving windfall gains).

	have received windfall gains		have not received windfall gains		Diff. in means
	Mean	Obs.	Mean	Obs.	p-value
Variable	(1)	(2)	(3)	(4)	(5)
household size	*3.29*	6,674	*3.46*	75,040	0.000
number of adults (>16) in household	*2.45*	6,674	*2.63*	75,040	0.000
number of children (16<) in household	*0.84*	6,674	*0.83*	75,040	0.739
age	*42.01*	6,674	*41.23*	75,040	0.000
female dummy	*0.51*	6,674	*0.51*	75,040	0.484
married dummy	*0.73*	6,664	*0.72*	74,974	0.249
secondary education dummy	*0.38*	6,576	*0.36*	73,598	0.000
post secondary education dummy	*0.29*	6,576	*0.18*	73,598	0.000
employed dummy	*0.77*	6,656	*0.70*	74,998	0.000
household income	*31,186*	6,648	*25,863*	74,584	0.000
household income - from working	*26,758*	6,651	*21,337*	74,598	0.000
household income - unearned income	*1,448*	6,651	*848*	74,598	0.000
personal income	*15,589*	6,674	*12,095*	75,040	0.000
personal income - from working	*13,270*	6,674	*10,222*	75,040	0.000
personal income - unearned income	*690*	6,674	*376*	75,040	0.000
personal hourly wage	*7.68*	6,674	*6.78*	75,040	0.000
total hours working per week	*30.57*	6,497	*28.26*	73,932	0.000

Source: European Community Household Panel Longitudinal Users' Database. All individuals of age 25-60. Winners are observed one period before receiving windfall gains. This approximately corresponds to period 3 in the sample for non-winners.

Table 4: Comparison of personal information among winners by the size of windfall gains received (prior to receiving windfall gains).

	received small windfall gains		received medium windfall gains		received large windfall gains		small vs medium	small vs large	medium vs large
	Mean	Obs.	Mean	Obs.	Mean	Obs.	Difference in means p-value		
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
hh size	*3.30*	3,098	*3.27*	2,579	*3.24*	762	0.358	0.284	0.669
no. of adults in hh	*2.45*	3,098	*2.43*	2,579	*2.44*	762	0.406	0.721	0.852
no. of children in hh	*0.85*	3,098	*0.84*	2,579	*0.80*	762	0.662	0.297	0.470
age	*41.40*	3,098	*42.45*	2,579	*42.77*	762	0.000	0.001	0.428
female dummy	*0.51*	3,098	*0.52*	2,579	*0.52*	762	0.344	0.555	0.974
married dummy	*0.73*	3,095	*0.73*	2,574	*0.71*	761	0.683	0.308	0.207
second. educ. dummy	*0.39*	3,064	*0.37*	2,542	*0.35*	742	0.243	0.029	0.167
post sec. educ. dummy	*0.27*	3,064	*0.28*	2,542	*0.37*	742	0.341	0.000	0.000
employed dummy	*0.77*	3,091	*0.76*	2,573	*0.77*	757	0.463	0.811	0.811
hh income	*28,804*	3,091	*32,185*	2,568	*36,711*	756	0.000	0.000	0.000
hh income - working	*24,958*	3,092	*27,569*	2,570	*31,346*	756	0.000	0.000	0.000
hh income - unearned	*1,386*	3,092	*1,181*	2,570	*2,646*	756	0.077	0.000	0.000
personal income	*14,612*	3,098	*15,987*	2,579	*18,443*	762	0.001	0.000	0.002
pers. income - working	*12,413*	3,098	*13,656*	2,579	*15,717*	762	0.002	0.000	0.006
pers. income - unearned	*665*	3,098	*552*	2,579	*1,280*	762	0.086	0.003	0.000
pers. hourly wage	*7.07*	3,098	*7.98*	2,579	*8.95*	762	0.000	0.000	0.000
weekly hours working	*31.04*	3,016	*30.01*	2,521	*31.22*	736	0.062	0.834	0.166

Source: European Community Household Panel Longitudinal Users' Database. Individuals of age 25-60 that have at some point received windfall gains. Winners are observed one period before receiving windfall gains. Small windfall gains (2000-10,000 EUR), medium windfall gains (10,000-50,000 EUR), large windfall gains (more than 50,000 EUR)

Table 5: Comparing personal information before and after the receipt of windfall gains.

	Before		After		
	Mean	Obs.	Mean	Obs.	Difference in means, p-value
Variable	(1)	(2)	(3)	(4)	(5)
ALL					
employed dummy	*0.77*	6,656	*0.76*	7,079	0.781
hh income	*31,186*	6,648	*31,823*	7,068	0.099
hh income - working	*26,758*	6,651	*27,312*	7,068	0.147
hh income - unearned	*1,448*	6,651	*1,614*	7,068	0.061
personal income	*15,589*	6,674	*15,986*	7,082	0.151
pers. income - working	*13,270*	6,674	*13,592*	7,082	0.228
pers. income - unearned	*690*	6,674	*762*	7,082	0.173
pers. hourly wage	*7.68*	6,674	*7.81*	7.082	0.072
weekly hours working	*30.57*	6,497	*30.56*	6,923	0.966
SMALL WINDFALL GAIN					
employed dummy	*0.77*	3,091	*0.76*	3,444	0.341
hh income	*28,804*	3,091	*28,874*	3,442	0.885
hh income – working	*24,958*	3,092	*24,928*	3,442	0.951
hh income – unearned	*1,386*	3,092	*1,399*	3,442	0.918
personal income	*14,612*	3,098	*14,690*	3,446	0.824
pers. income - working	*12,413*	3,098	*12,478*	3,446	0.847
pers. income - unearned	*665*	3,098	*678*	3,446	0.859
pers. hourly wage	*7.07*	3,098	*7.28*	3,446	0.012
weekly hours working	*31.04*	3,016	*30.57*	3,366	0.362
MEDIUM WINDFALL GAINS					
employed dummy	*0.76*	2,573	*0.78*	2,683	0.261
hh income	*32,185*	2,568	*33,030*	2,675	0.194
hh income - working	*27,569*	2,570	*28,663*	2,675	0.084
hh income - unearned	*1,181*	2,570	*1,430*	2,675	0.035
personal income	*15,987*	2,579	*16,563*	2,684	0.211
pers. income - working	*13,656*	2,579	*14,238*	2,684	0.194
pers. income - unearned	*552*	2,579	*664*	2,684	0.077
pers. hourly wage	*7.98*	2,579	*8.09*	2,684	0.348
weekly hours working	*30.01*	2,521	*30.58*	2,628	0.308
LARGE WINDFALL GAINS					
employed dummy	*0.77*	757	*0.75*	762	0.516
hh income	*36,711*	756	*40,587*	761	0.008
hh income - working	*31,346*	756	*33,858*	761	0.090
hh income - unearned	*2,646*	756	*3,268*	761	0.134
personal income	*18,443*	762	*20,297*	762	0.094
pers. income - working	*15,717*	762	*16,961*	762	0.238
pers. income - unearned	*1,280*	762	*1,497*	762	0.437
pers. hourly wage	*8.95*	762	*9.07*	762	0.691
weekly hours working	*31.22*	736	*31.10*	743	0.912

Source: European Community Household Panel Longitudinal Users' Database. Individuals of age 25-60. Before: one period before receiving windfall gains. After: one period after receiving windfall gains (not in the period when windfall gains were received). Small windfall gains (2000-10,000 EUR), medium windfall gains (10,000-50,000 EUR), large windfall gains (more than 50,000 EUR)

Table 6: Effects of windfall gains on working hours – all.

Dependent variable:	Employment dummy	Working hours per week		Log working hours per week	
	(1)	(2)	(3)	(4)	(5)
	FE	FE	FE IV	FE	FE IV
windfall gains dummy	-0.00424	-0.0618	0.00194	0.00125	0.00236
	(0.00360)	(0.159)	(0.161)	(0.00365)	(0.00375)
hourly wage		-0.831***	-0.441**		
		(0.0262)	(0.203)		
log hourly wage				-0.404***	-0.197***
				(0.00610)	(0.0469)
age	0.0823***	3.876***	3.625***	0.0564***	0.0386***
	(0.00272)	(0.121)	(0.150)	(0.00295)	(0.00464)
age^2	-0.000986***	-0.0452***	-0.0439***	-0.000490***	-0.000391***
	(3.09e-05)	(0.00137)	(0.00142)	(3.40e-05)	(3.88e-05)
married dummy	0.0129*	1.205***	1.157***	0.0146**	0.00932
	(0.00680)	(0.301)	(0.312)	(0.00671)	(0.00708)
children 0-6 in household dummy	-0.0516***	-2.841***	-2.961***	-0.0491***	-0.0534***
	(0.00571)	(0.253)	(0.259)	(0.00560)	(0.00584)
children 7-15 in household dummy	-0.0425***	-2.318***	-2.333***	-0.0293***	-0.0292***
	(0.00519)	(0.230)	(0.233)	(0.00518)	(0.00533)
Constant	-0.841***	-41.45***	-36.29***	2.974***	3.131***
	(0.0589)	(2.615)	(3.089)	(0.0617)	(0.0680)
Observations	54164	53011	52348	40239	39789
Number of individuals	10395	10357	10322	8735	8700
R-squared	0.024	0.049		0.126	
Hausman test[+]			0.000		0.000

Standard errors in parentheses, * significant at 10%; ** significant at 5%; *** significant at 1%. [+] Reports p-value of the Hausman test of endogeneity. In IV regression (log) hourly wage is instrumented using two dummies for education, interactions between education dummies and quartic in age and country-year dummies.

Table 7: Effects of windfall gains on working hours – men.

Dependent variable:	Employment dummy	Working hours per week		Log working hours per week	
	(1)	(2)	(3)	(4)	(5)
	FE	FE	FE IV	FE	FE IV
windfall gains dummy	-0.00493	-0.158	-0.0525	0.00126	0.00130
	(0.00443)	(0.237)	(0.239)	(0.00398)	(0.00408)
hourly wage		-0.879***	-0.812***		
		(0.0360)	(0.218)		
log hourly wage				-0.368***	-0.192***
				(0.00704)	(0.0462)
age	0.0955***	5.188***	5.064***	0.0621***	0.0471***
	(0.00338)	(0.181)	(0.205)	(0.00323)	(0.00490)
age^2	-0.00115***	-0.0602***	-0.0593***	-0.000580***	-0.000495***
	(3.83e-05)	(0.00205)	(0.00208)	(3.69e-05)	(4.23e-05)
married dummy	0.0197**	2.126***	2.050***	0.0349***	0.0293***
	(0.00843)	(0.449)	(0.460)	(0.00748)	(0.00785)
children 0-6 in household dummy	-0.0309***	-1.207***	-1.406***	3.02e-05	-0.00319
	(0.00684)	(0.366)	(0.372)	(0.00602)	(0.00625)
children 7-15 in household dummy	-0.0356***	-1.497***	-1.579***	-0.00605	-0.00580
	(0.00640)	(0.341)	(0.346)	(0.00566)	(0.00582)
Constant	-0.980***	-59.98***	-56.94***	2.959***	3.076***
	(0.0733)	(3.925)	(4.335)	(0.0679)	(0.0738)
Observations	26176	25626	25327	22503	22278
Number of individuals	5087	5073	5061	4691	4679
R-squared	0.044	0.070		0.140	
Hausman test[+]			0.000		0.008

Standard errors in parentheses, * significant at 10%; ** significant at 5%; *** significant at 1%. [+] Reports p-value of the Hausman test of endogeneity. In IV regression (log) hourly wage is instrumented using two dummies for education, interactions between education dummies and quartic in age and country-year dummies.

Table 8: Effects of windfall gains on working hours – women.

Dependent variable:	Employment dummy	Working hours per week		Log working hours per week	
	(1)	(2)	(3)	(4)	(5)
	FE	FE	FE IV	FE	FE IV
windfall gains dummy	-0.00367	0.0201	0.0563	0.000261	0.00366
	(0.00558)	(0.213)	(0.216)	(0.00659)	(0.00687)
hourly wage		-0.759***	-0.0268		
		(0.0385)	(0.330)		
log hourly wage				-0.441***	-0.149**
				(0.0103)	(0.0752)
age	0.0699***	2.651***	2.259***	0.0474***	0.0230***
	(0.00419)	(0.160)	(0.216)	(0.00532)	(0.00763)
age^2	-0.000832***	-0.0314***	-0.0294***	-0.000357***	-0.000232***
	(4.77e-05)	(0.00182)	(0.00195)	(6.21e-05)	(6.81e-05)
married dummy	0.00581	0.179	0.190	-0.0135	-0.0198
	(0.0105)	(0.402)	(0.420)	(0.0118)	(0.0125)
children 0-6 in household dummy	-0.0757***	-4.828***	-4.893***	-0.122***	-0.130***
	(0.00915)	(0.350)	(0.362)	(0.0103)	(0.0109)
children 7-15 in household dummy	-0.0512***	-3.309***	-3.232***	-0.0635***	-0.0643***
	(0.00808)	(0.308)	(0.313)	(0.00932)	(0.00974)
Constant	-0.705***	-23.60***	-16.21***	3.015***	3.245***
	(0.0907)	(3.472)	(4.363)	(0.110)	(0.121)
Observations	27988	27385	27021	17736	17511
Number of individuals	5308	5284	5261	4044	4021
R-squared	0.015	0.036		0.128	
Hausman test[+]			0.003		0.001

Standard errors in parentheses, * significant at 10%; ** significant at 5%; *** significant at 1%. [+] Reports p-value of the Hausman test of endogeneity. In IV regression (log) hourly wage is instrumented using two dummies for education, interactions between education dummies and quartic in age and country-year dummies.

Table 9: Effects of small/medium/large windfall gains on working hours – all.

Dependent variable:	Employment dummy	Working hours per week		Log working hours per week	
	(1)	(2)	(3)	(4)	(5)
	FE	FE	FE IV	FE	FE IV
small windfall gains dummy	-0.00283	-0.132	-0.114	0.00671	0.00599
	(0.00458)	(0.203)	(0.204)	(0.00464)	(0.00476)
medium windfall gains dummy	-0.00597	-0.0102	0.0740	-0.00356	-0.00143
	(0.00494)	(0.218)	(0.221)	(0.00502)	(0.00517)
large windfall gains dummy	-0.0213**	-0.568	-0.406	-0.0137	-0.00931
	(0.00835)	(0.371)	(0.378)	(0.00851)	(0.00882)
hourly wage		-0.830***	-0.427**		
		(0.0262)	(0.204)		
log hourly wage				-0.404***	-0.200***
				(0.00610)	(0.0471)
age	0.0824***	3.885***	3.630***	0.0565***	0.0388***
	(0.00272)	(0.121)	(0.150)	(0.00295)	(0.00464)
age^2	-0.000985***	-0.0452***	-0.0439***	-0.000488***	-0.000391***
	(3.09e-05)	(0.00137)	(0.00142)	(3.40e-05)	(3.88e-05)
married dummy	0.0131*	1.213***	1.159***	0.0148**	0.00942
	(0.00680)	(0.301)	(0.312)	(0.00671)	(0.00708)
children 0-6 in household dummy	-0.0518***	-2.848***	-2.970***	-0.0491***	-0.0534***
	(0.00571)	(0.253)	(0.259)	(0.00560)	(0.00584)
children 7-15 in household dummy	-0.0427***	-2.323***	-2.338***	-0.0294***	-0.0293***
	(0.00519)	(0.230)	(0.233)	(0.00518)	(0.00533)
Constant	-0.848***	-41.78***	-36.56***	2.971***	3.126***
	(0.0587)	(2.609)	(3.085)	(0.0616)	(0.0679)
Observations	54164	53011	52348	40239	39789
Number of individuals	10395	10357	10322	8735	8700
R-squared	0.024	0.049		0.127	
Hausman test[+]			0.000		0.000

Standard errors in parentheses, * significant at 10%; ** significant at 5%; *** significant at 1%. [+] Reports p-value of the Hausman test of endogeneity. In IV regression (log) hourly wage is instrumented using two dummies for education, interactions between education dummies and quartic in age and country-year dummies.

Table 10: Effects of small/medium/large windfall gains on working hours – men.

Dependent variable:	Employment dummy	Working hours per week		Log working hours per week	
	(1)	(2)	(3)	(4)	(5)
	FE	FE	FE IV	FE	FE IV
small windfall gains dummy	-0.00104	-0.177	-0.126	0.00557	0.00517
	(0.00563)	(0.301)	(0.303)	(0.00502)	(0.00515)
medium windfall gains dummy	-0.00617	0.0221	0.111	0.00139	0.00153
	(0.00610)	(0.326)	(0.329)	(0.00552)	(0.00566)
large windfall gains dummy	-0.0306***	-1.337**	-0.966*	-0.0208**	-0.0184*
	(0.0103)	(0.552)	(0.560)	(0.00927)	(0.00953)
hourly wage		-0.878***	-0.795***		
		(0.0360)	(0.219)		
log hourly wage				-0.368***	-0.196***
				(0.00704)	(0.0463)
age	0.0954***	5.191***	5.065***	0.0620***	0.0473***
	(0.00338)	(0.181)	(0.206)	(0.00323)	(0.00490)
age^2	-0.00115***	-0.0601***	-0.0592***	-0.000577***	-0.000495***
	(3.84e-05)	(0.00205)	(0.00209)	(3.69e-05)	(4.23e-05)
married dummy	0.0199**	2.138***	2.055***	0.0350***	0.0295***
	(0.00843)	(0.449)	(0.460)	(0.00748)	(0.00784)
children 0-6 in household dummy	-0.0311***	-1.221***	-1.418***	-6.81e-05	-0.00316
	(0.00684)	(0.366)	(0.372)	(0.00602)	(0.00625)
children 7-15 in household dummy	-0.0357***	-1.505***	-1.586***	-0.00606	-0.00580
	(0.00640)	(0.341)	(0.346)	(0.00566)	(0.00582)
Constant	-0.983***	-60.20***	-57.13***	2.960***	3.075***
	(0.0730)	(3.914)	(4.333)	(0.0677)	(0.0737)
Observations	26176	25626	25327	22503	22278
Number of individuals	5087	5073	5061	4691	4679
R-squared	0.044	0.070		0.141	
Hausman test[+]			0.000		0.034

Standard errors in parentheses, * significant at 10%; ** significant at 5%; *** significant at 1%. [+] Reports p-value of the Hausman test of endogeneity. In IV regression (log) hourly wage is instrumented using two dummies for education, interactions between education dummies and quartic in age and country-year dummies.

Table 11: Effects of small/medium/large windfall gains on working hours – women.

Dependent variable:	Employment dummy	Working hours per week		Log working hours per week	
	(1)	(2)	(3)	(4)	(5)
	FE	FE	FE IV	FE	FE IV
small windfall gains dummy	-0.00442	-0.0920	-0.127	0.00806	0.00690
	(0.00712)	(0.272)	(0.275)	(0.00845)	(0.00877)
medium windfall gains dummy	-0.00583	-0.0449	0.0757	-0.0111	-0.00479
	(0.00765)	(0.291)	(0.297)	(0.00897)	(0.00943)
large windfall gains dummy	-0.0123	0.211	0.183	-0.00496	0.00332
	(0.0129)	(0.495)	(0.508)	(0.0154)	(0.0163)
hourly wage		-0.759***	-0.0251		
		(0.0385)	(0.330)		
log hourly wage				-0.442***	-0.148**
				(0.0103)	(0.0754)
age	0.0702***	2.660***	2.270***	0.0476***	0.0231***
	(0.00419)	(0.160)	(0.215)	(0.00532)	(0.00763)
age^2	-0.000833***	-0.0315***	-0.0294***	-0.000357***	-0.000231***
	(4.77e-05)	(0.00182)	(0.00195)	(6.21e-05)	(6.81e-05)
married dummy	0.00593	0.178	0.192	-0.0135	-0.0199
	(0.0105)	(0.402)	(0.419)	(0.0118)	(0.0126)
children 0-6 in household dummy	-0.0758***	-4.824***	-4.893***	-0.122***	-0.130***
	(0.00915)	(0.350)	(0.363)	(0.0103)	(0.0109)
children 7-15 in household dummy	-0.0513***	-3.308***	-3.232***	-0.0636***	-0.0643***
	(0.00808)	(0.308)	(0.313)	(0.00932)	(0.00974)
Constant	-0.715***	-23.90***	-16.58***	3.009***	3.237***
	(0.0906)	(3.466)	(4.341)	(0.110)	(0.121)
Observations	27988	27385	27021	17736	17511
Number of individuals	5308	5284	5261	4044	4021
R-squared	0.015	0.036		0.129	
Hausman test[+]			0.005		0.004

Standard errors in parentheses, * significant at 10%; ** significant at 5%; *** significant at 1%. [+] Reports p-value of the Hausman test of endogeneity. In IV regression (log) hourly wage is instrumented using two dummies for education, interactions between education dummies and quartic in age and country-year dummies.

Table 12: Effects of windfall gains and interactions – all.

Dependent variable:	Employment dummy	Working hours per week		Log working hours per week	
	(1)	(2)	(3)	(4)	(5)
	FE	FE	FE IV	FE	FE IV
windfall gains dummy	-0.351***	-11.64***	-11.52***	0.0568	-6.97e-05
	(0.0582)	(2.579)	(2.633)	(0.0631)	(0.0670)
hourly wage		-0.912***	-0.158		
		(0.0334)	(0.300)		
interaction of windfall gains with wage		0.117***	-0.187		
		(0.0287)	(0.118)		
log hourly wage				-0.399***	-0.193***
				(0.00714)	(0.0475)
interaction of windfall gains with log wage				-0.00797	0.00363
				(0.00617)	(0.0196)
age	0.0700***	3.371***	2.969***	0.0529***	0.0324***
	(0.00378)	(0.168)	(0.207)	(0.00410)	(0.00569)
interaction of windfall gains with age	0.0186***	0.637***	0.726***	-0.000138	0.00192
	(0.00291)	(0.129)	(0.134)	(0.00318)	(0.00339)
age^2	-0.000843***	-0.0390***	-0.0367***	-0.000440***	-0.000312***
	(4.53e-05)	(0.00201)	(0.00209)	(4.97e-05)	(5.52e-05)
interaction of windfall gains with age^2	-0.000217***	-0.00792***	-0.00869***	-7.41e-06	-3.52e-05
	(3.45e-05)	(0.00153)	(0.00157)	(3.82e-05)	(4.02e-05)
married dummy	0.0398***	2.082***	2.115***	0.0268***	0.0221***
	(0.00790)	(0.350)	(0.361)	(0.00781)	(0.00824)
interaction of windfall gains with married dummy	-0.0436***	-1.505***	-1.619***	-0.0233***	-0.0244***
	(0.00694)	(0.308)	(0.316)	(0.00702)	(0.00724)
children 0-6 in hhold dummy	-0.0425***	-1.978***	-2.251***	-0.0332***	-0.0371***
	(0.00740)	(0.328)	(0.336)	(0.00732)	(0.00760)
interaction of windfall gains with children 0-6 dummy	-0.00801	-1.223***	-0.947***	-0.0247***	-0.0247***
	(0.00783)	(0.347)	(0.358)	(0.00783)	(0.00827)
children 7-15 in hhold dummy	-0.0433***	-2.135***	-2.149***	-0.0303***	-0.0312***
	(0.00676)	(0.299)	(0.304)	(0.00679)	(0.00699)
interaction of windfall gains with children 7-15 dummy	0.00822	0.0116	0.0738	0.00755	0.00931
	(0.00755)	(0.334)	(0.339)	(0.00756)	(0.00778)
Constant	-0.610***	-32.06***	-25.22***	3.009***	3.222***
	(0.0765)	(3.395)	(3.928)	(0.0807)	(0.0897)
Observations	54164	53011	52348	40239	39789
Number of individuals	10395	10357	10322	8735	8700
R-squared	0.026	0.051		0.128	
Hausman test[+]			0.001		0.000

Standard errors in parentheses, * significant at 10%; ** significant at 5%; *** significant at 1%. [+] Reports p-value of the Hausman test of endogeneity. In IV regression (log) hourly wage is instrumented using two dummies for education, interactions between education dummies and quartic in age and country-year dummies.

Table 13: Effects of windfall gains and interactions – men.

Dependent variable:	Employment dummy	Working hours per week		Log working hours per week	
	(1)	(2)	(3)	(4)	(5)
	FE	FE	FE IV	FE	FE IV
windfall gains dummy	-0.292***	-12.85***	-12.35***	-0.00101	-0.0175
	(0.0719)	(3.857)	(3.929)	(0.0688)	(0.0718)
hourly wage		-0.933***	-0.510		
		(0.0446)	(0.334)		
interaction of windfall gains with wage		0.0820**	-0.212		
		(0.0393)	(0.144)		
log hourly wage				-0.366***	-0.185***
				(0.00810)	(0.0465)
interaction of windfall gains with log wage				-0.00325	-0.0191
				(0.00685)	(0.0201)
Age	0.0862***	4.614***	4.361***	0.0560***	0.0388***
	(0.00470)	(0.252)	(0.288)	(0.00448)	(0.00612)
interaction of windfall gains with age	0.0154***	0.687***	0.750***	0.00231	0.00469
	(0.00360)	(0.193)	(0.200)	(0.00347)	(0.00373)
age^2	-0.00104***	-0.0531***	-0.0516***	-0.000498***	-0.000386***
	(5.60e-05)	(0.00300)	(0.00307)	(5.39e-05)	(6.03e-05)
interaction of windfall gains with age^2	-0.000180***	-0.00862***	-0.00898***	-3.98e-05	-6.76e-05
	(4.26e-05)	(0.00228)	(0.00233)	(4.14e-05)	(4.38e-05)
married dummy	0.0353***	2.579***	2.514***	0.0387***	0.0344***
	(0.00992)	(0.529)	(0.542)	(0.00884)	(0.00924)
interaction of windfall gains with married dummy	-0.0251***	-0.735	-0.758	-0.00908	-0.0100
	(0.00904)	(0.485)	(0.494)	(0.00824)	(0.00850)
children 0-6 in hhold dummy	-0.0152*	-0.328	-0.726	0.0130*	0.00975
	(0.00897)	(0.479)	(0.488)	(0.00790)	(0.00817)
interaction of windfall gains with children 0-6 dummy	-0.0214**	-1.235**	-0.893*	-0.0224***	-0.0210**
	(0.00955)	(0.510)	(0.519)	(0.00845)	(0.00881)
children 7-15 in hhold dummy	-0.0321***	-1.285***	-1.408***	0.00313	0.00272
	(0.00839)	(0.448)	(0.455)	(0.00749)	(0.00770)
interaction of windfall gains with children 7-15 dummy	-0.000463	-0.112	0.0145	-0.0125	-0.0105
	(0.00939)	(0.502)	(0.507)	(0.00834)	(0.00855)
Constant	-0.807***	-49.14***	-44.71***	3.053***	3.198***
	(0.0951)	(5.093)	(5.583)	(0.0887)	(0.0976)
Observations	26176	25626	25327	22503	22278
Number of individuals	5087	5073	5061	4691	4679
R-squared	0.045	0.072		0.141	
Hausman test[+]			0.001		0.048

Standard errors in parentheses, * significant at 10%; ** significant at 5%; *** significant at 1%. [+] Reports p-value of the Hausman test of endogeneity. In IV regression (log) hourly wage is instrumented using two dummies for education, interactions between education dummies and quartic in age and country-year dummies.

Table 14: Effects of windfall gains and interactions – women.

Dependent variable:	Employment dummy	Working hours per week		Log working hours per week	
	(1)	(2)	(3)	(4)	(5)
	FE	FE	FE IV	FE	FE IV
windfall gains dummy	-0.387***	-7.540**	-8.464**	0.213*	0.0951
	(0.0909)	(3.465)	(3.528)	(0.115)	(0.125)
hourly wage		-0.919***	-0.224		
		(0.0512)	(0.425)		
interaction of windfall gains with wage		0.210***	0.115		
		(0.0442)	(0.177)		
log hourly wage				-0.438***	-0.170**
				(0.0124)	(0.0786)
interaction of windfall gains with log wage				-0.00632	0.0393
				(0.0113)	(0.0383)
age	0.0558***	2.361***	1.944***	0.0511***	0.0246***
	(0.00586)	(0.224)	(0.283)	(0.00741)	(0.00950)
interaction of windfall gains with age	0.0204***	0.401**	0.482***	-0.00848	-0.00642
	(0.00453)	(0.173)	(0.182)	(0.00581)	(0.00626)
age^2	-0.000670***	-0.0278***	-0.0251***	-0.000394***	-0.000246**
	(7.03e-05)	(0.00268)	(0.00284)	(9.10e-05)	(9.82e-05)
interaction of windfall gains with age^2	-0.000236***	-0.00500**	-0.00596***	9.49e-05	6.62e-05
	(5.41e-05)	(0.00206)	(0.00214)	(7.04e-05)	(7.51e-05)
married dummy	0.0403***	1.212***	1.279***	0.00334	-0.00508
	(0.0121)	(0.464)	(0.482)	(0.0135)	(0.0145)
interaction of windfall gains with married dummy	-0.0549***	-1.788***	-1.803***	-0.0315***	-0.0288**
	(0.0103)	(0.396)	(0.414)	(0.0117)	(0.0125)
children 0-6 in hhold dummy	-0.0739***	-4.075***	-4.127***	-0.100***	-0.107***
	(0.0117)	(0.448)	(0.460)	(0.0134)	(0.0141)
interaction of windfall gains with children 0-6 dummy	0.00775	-1.070**	-1.017**	-0.0330**	-0.0340**
	(0.0124)	(0.475)	(0.492)	(0.0144)	(0.0154)
children 7-15 in hhold dummy	-0.0564***	-3.356***	-3.230***	-0.0778***	-0.0807***
	(0.0105)	(0.400)	(0.406)	(0.0121)	(0.0127)
interaction of windfall gains with children 7-15 dummy	0.0176	0.406	0.353	0.0333**	0.0353**
	(0.0117)	(0.447)	(0.454)	(0.0135)	(0.0141)
Constant	-0.440***	-18.02***	-10.49**	2.912***	3.231***
	(0.118)	(4.520)	(5.328)	(0.145)	(0.159)
Observations	27988	27385	27021	17736	17511
Number of individuals	5308	5284	5261	4044	4021
R-squared	0.017	0.039		0.130	
Hausman test[+]			0.007		0.007

Standard errors in parentheses, * significant at 10%; ** significant at 5%; *** significant at 1%. [+] Reports p-value of the Hausman test of endogeneity. In IV regression (log) hourly wage is instrumented using two dummies for education, interactions between education dummies and quartic in age and country-year dummies.

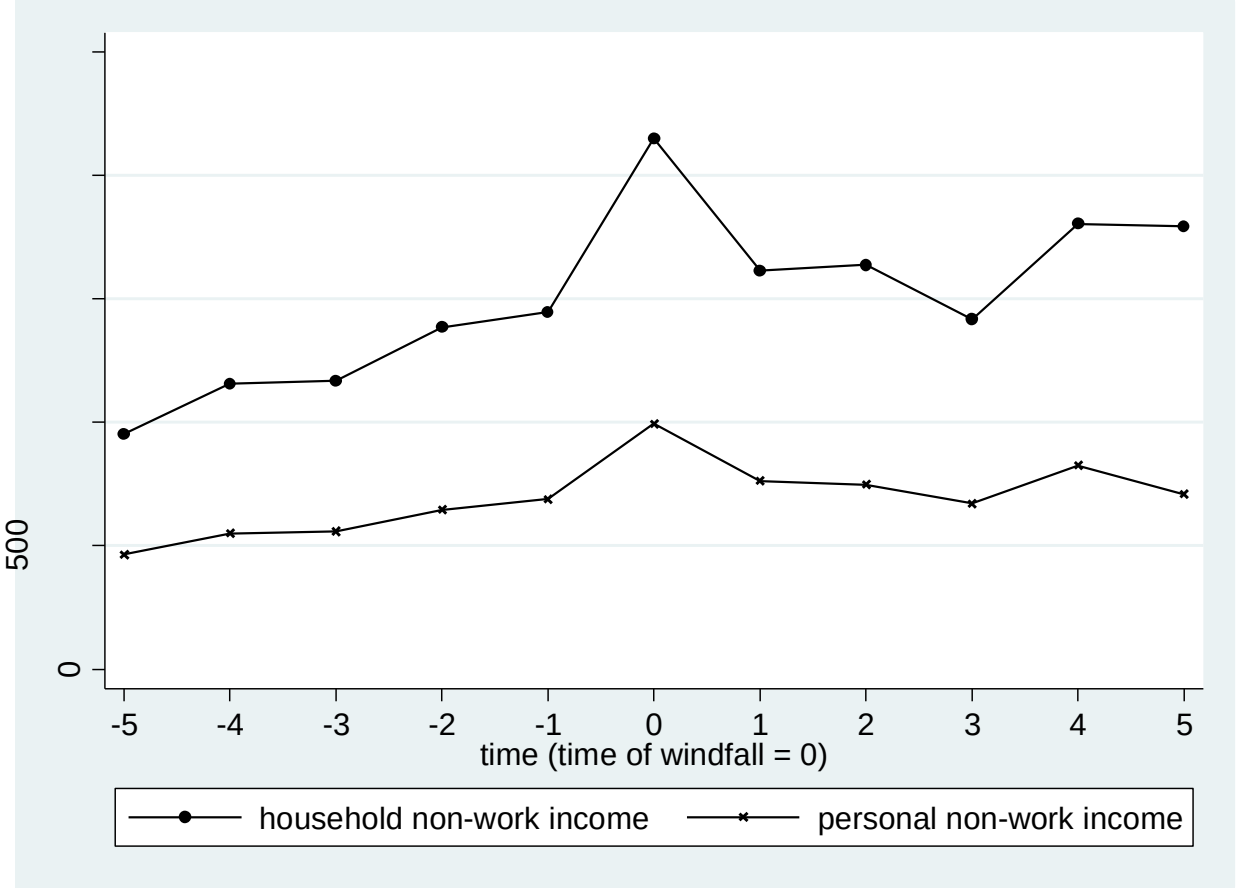
Table 15: Effects of windfall gains on labour supply by types of individuals.

	Full sample			Men			Women		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
25 yrs, single, no children	-0.021**	-0.259	0.033***	-0.020*	-1.002	0.019	-0.025	0.682	0.049**
	(0.034)	(0.609)	(0.005)	(0.091)	(0.182)	(0.173)	(0.119)	(0.311)	(0.016)
30 yrs, single, no children	0.012*	0.979***	0.033***	0.007	0.279	0.024**	0.012	1.455***	0.035**
	(0.093)	(0.006)	(0.000)	(0.411)	(0.597)	(0.011)	(0.318)	(0.002)	(0.011)
30 yrs, married, with one child	-0.039***	-1.587***	-0.016**	-0.040***	-1.372***	-0.007	-0.035***	-1.365***	-0.028*
	(0.000)	(0.000)	(0.041)	(0.000)	(0.010)	(0.410)	(0.002)	(0.003)	(0.054)
40 yrs, single, no children	0.046***	2.152***	0.028***	0.034***	1.494***	0.023***	0.050***	2.107***	0.017
	(0.000)	(0.000)	(0.000)	(0.000)	(0.003)	(0.007)	(0.000)	(0.000)	(0.202)
40 yrs, married, no children	0.003	0.533*	0.003	0.009	0.736	0.013*	-0.005	0.305	-0.011
	(0.701)	(0.083)	(0.650)	(0.275)	(0.110)	(0.090)	(0.666)	(0.455)	(0.371)
40 yrs, married with children	0.003	-0.340	-0.012	-0.013	-0.143	-0.018*	0.021	-0.358	-0.010
	(0.764)	(0.427)	(0.225)	(0.275)	(0.819)	(0.087)	(0.165)	(0.540)	(0.589)
55 yrs, single, no children	0.016*	0.652	0.006	0.008	-0.051	-0.002	0.020	0.853	0.015
	(0.069)	(0.109)	(0.535)	(0.471)	(0.934)	(0.826)	(0.142)	(0.108)	(0.394)
55 yrs, married, no children	-0.028***	-0.966***	-0.018**	-0.017**	-0.809*	-0.013	-0.035***	-0.950**	-0.013
	(0.000)	(0.002)	(0.032)	(0.042)	(0.093)	(0.167)	(0.001)	(0.020)	(0.384)

p-values in parentheses; testing the null whether linear combination of coefficients equal to zero. * significant at 10%; ** significant at 5%; *** significant at 1%. (1) Employment dummy as dependent variable, FE; (2) Working hours per week as dependent variable, FE IV; (3) Log working hours per week as dependent variable, FE IV. In (2) and (3) wages are also included in the regression; in these cases effects are calculated at the value of the average wage in the sample (all, men or women).

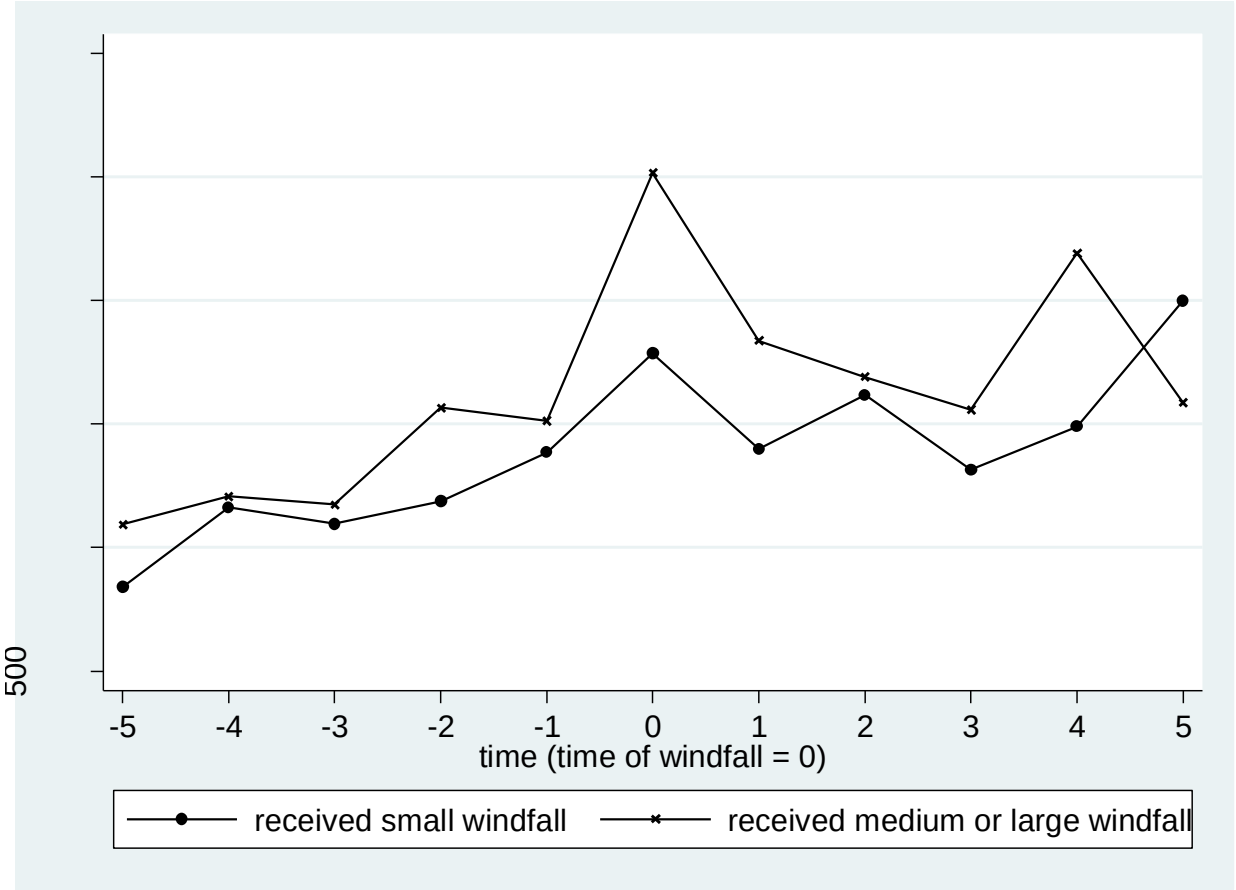
List of Figures

Figure 1: Non-work income over time for those who received windfall gains.



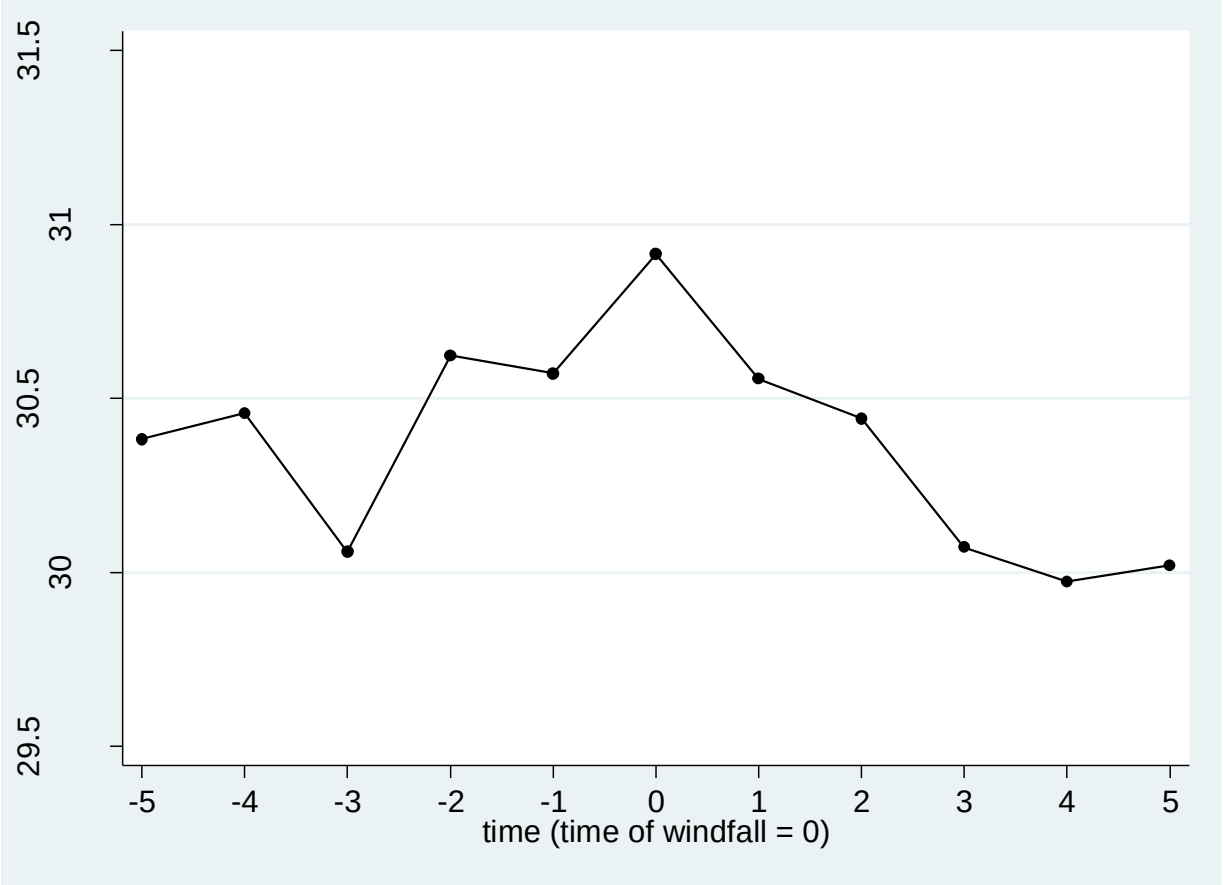
Source: European Community Household Panel Longitudinal Users' Database. Individuals who received windfall gains of age 25-60. Time period 0 is period when windfall gains were received.

Figure 2: Non-work household income over time by size of windfall gains.



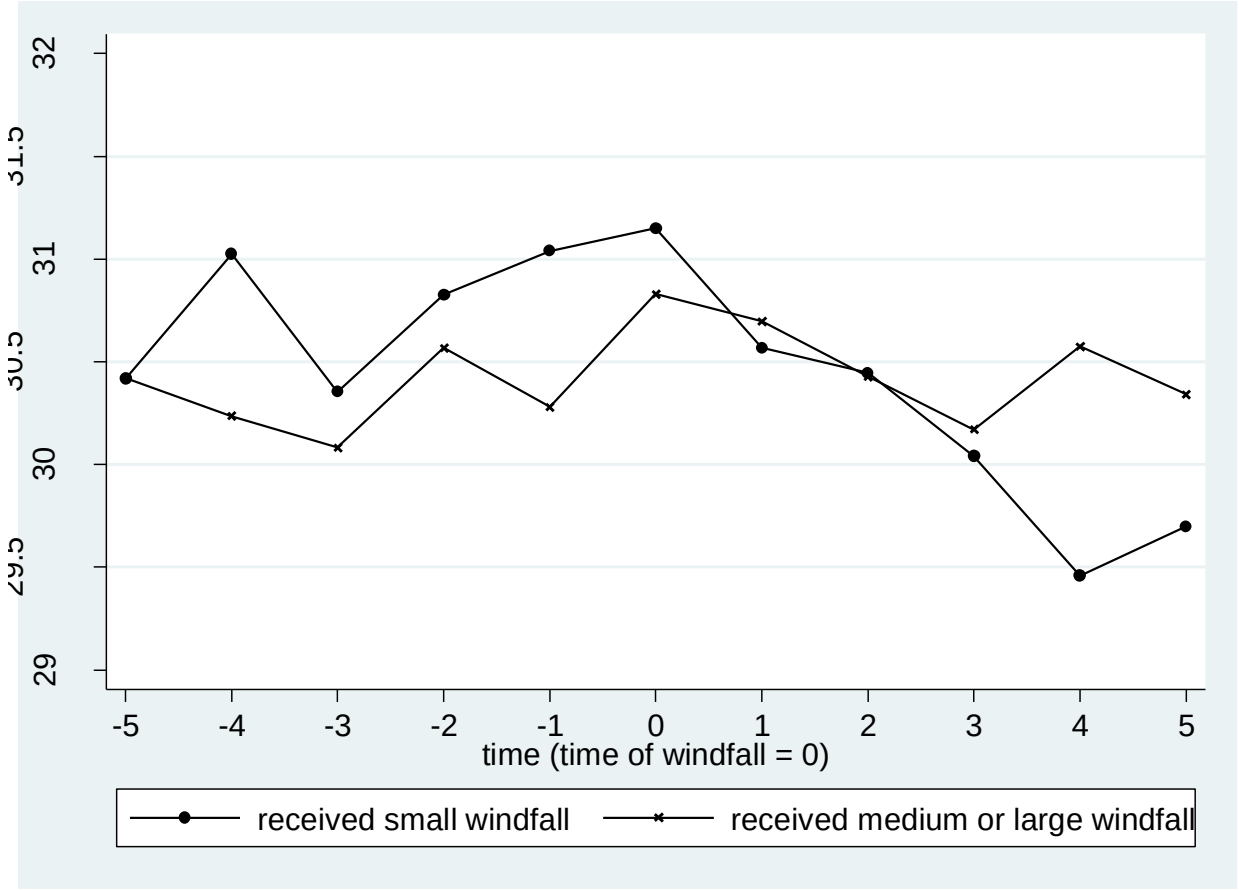
Source: European Community Household Panel Longitudinal Users' Database. Individuals who received windfall gains of age 25-60. Time period 0 is period when windfall gains were received. Small windfall gains (2000-10,000 EUR), medium windfall gains (10,000-50,000 EUR), large windfall gains (more than 50,000 EUR)

Figure 3: Working hours per week over time.



Source: European Community Household Panel Longitudinal Users' Database. Individuals who received windfall gains of age 25-60. Time period 0 is period when windfall gains were received.

Figure 4: Working hours per week over time by size of windfall gains.



Source: European Community Household Panel Longitudinal Users' Database. Individuals who received windfall gains of age 25-60. Time period 0 is period when windfall gains were received. Small windfall gains (2000-10,000 EUR), medium windfall gains (10,000-50,000 EUR), large windfall gains (more than 50,000 EUR)

Appendix

Table A.1: Effects of windfall gains on probability of becoming self-employed.

Dependent variable: Self-employed dummy						
	all	men	women	all	men	women
	(1)	(2)	(3)	(4)	(5)	(6)
windfall gains dummy	0.00807***	0.0122***	0.00399			
	(0.00231)	(0.00358)	(0.00297)			
small windfall gains dummy				0.00198	0.00599	-0.00195
				(0.00294)	(0.00454)	(0.00378)
medium windfall gains dummy				0.00900***	0.0147***	0.00345
				(0.00317)	(0.00492)	(0.00406)
large windfall gains dummy				0.0144***	0.0175**	0.0120*
				(0.00535)	(0.00832)	(0.00685)
Age	0.0208***	0.0312***	0.0114***	0.0212***	0.0316***	0.0117***
	(0.00175)	(0.00272)	(0.00222)	(0.00174)	(0.00272)	(0.00222)
age^2	-0.000243***	-0.000359***	-0.000139***	-0.000245***	-0.000361***	-0.000140***
	(1.99e-05)	(3.09e-05)	(2.53e-05)	(1.99e-05)	(3.09e-05)	(2.53e-05)
married dummy	0.0219***	0.0335***	0.00945*	0.0219***	0.0334***	0.00944*
	(0.00437)	(0.00680)	(0.00560)	(0.00437)	(0.00680)	(0.00560)
children 0-6 in household dummy	-0.000748	-0.00464	0.00135	-0.000758	-0.00475	0.00147
	(0.00367)	(0.00552)	(0.00486)	(0.00367)	(0.00552)	(0.00487)
children 7-15 in household dummy	-0.00284	-0.00471	-0.00221	-0.00280	-0.00469	-0.00214
	(0.00333)	(0.00516)	(0.00429)	(0.00333)	(0.00516)	(0.00429)
Constant	-0.316***	-0.490***	-0.156***	-0.328***	-0.502***	-0.169***
	(0.0378)	(0.0591)	(0.0482)	(0.0377)	(0.0589)	(0.0481)
Observations	54210	26177	28033	54210	26177	28033
Number of individuals	10397	5088	5309	10397	5088	5309
R-squared	0.005	0.011	0.002	0.006	0.011	0.002

Standard errors in parentheses, * significant at 10%; ** significant at 5%; *** significant at 1%. All regressions include individual fixed effects.

Table A.2: Effects of windfall gains on probability of becoming self-employed (with interactions).

Dependent variable: Self-employed dummy			
	all	men	women
	(1)	(2)	(3)
windfall dummy	-0.0731*	-0.0709	-0.0698
	(0.0374)	(0.0580)	(0.0483)
age	0.0159***	0.0283***	0.00510
	(0.00243)	(0.00379)	(0.00311)
interaction of windfall gains with age	0.00465**	0.00449	0.00435*
	(0.00187)	(0.00290)	(0.00241)
age^2	-0.000182***	-0.000322***	-6.07e-05
	(2.91e-05)	(4.52e-05)	(3.73e-05)
interaction of windfall gains with age^2	-6.13e-05***	-5.84e-05*	-5.82e-05**
	(2.22e-05)	(3.44e-05)	(2.87e-05)
married dummy	0.0201***	0.0257***	0.0114*
	(0.00508)	(0.00801)	(0.00645)
interaction of windfall gains with married dummy	0.00361	0.0139*	-0.00218
	(0.00447)	(0.00730)	(0.00549)
children 0-6 in hhold dummy	0.00358	0.00496	0.000725
	(0.00476)	(0.00724)	(0.00625)
interaction of windfall gains with children 0-6 dummy	-0.00653	-0.0161**	0.00311
	(0.00503)	(0.00770)	(0.00661)
children 7-15 in hhold dummy	0.00251	0.00485	-0.00122
	(0.00435)	(0.00678)	(0.00558)
interaction of windfall gains with children 7-15 dummy	-0.00808*	-0.0149**	-0.000610
	(0.00486)	(0.00758)	(0.00625)
Constant	-0.225***	-0.436***	-0.0395
	(0.0492)	(0.0768)	(0.0629)
Observations	54210	26177	28033
Number of individuals	10397	5088	5309
R-squared	0.006	0.011	0.002

Standard errors in parentheses, * significant at 10%; ** significant at 5%; *** significant at 1%. All regressions include individual fixed effects.

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