



OLDER COUPLES' LABOUR MARKET REACTIONS TO FAMILY DISRUPTIONS

David Haardt

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Institute for Social and Economic Research, University of Essex, Wivenhoe Park,
Colchester. Essex CO4 3SQ UK
Telephone: +44 (0) 1206 872957 Fax: +44 (0) 1206 873151 E-mail: iser@essex.ac.uk
Website: <http://www.iser.essex.ac.uk>

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ABSTRACT

In this paper, I analyse how spouses in older couples react to 'shocks' or 'surprises' in their partner's labour income using data from the British Household Panel Survey, 1991–2004. Wives' labour supply proves to be much more sensitive to shocks than husbands'. After a divorce or separation, wives reduce their labour supply while the effect on husbands' labour supply is positive or not statistically significant. If a wife becomes unemployed, it does not affect her husband's labour supply while wives whose husband becomes unemployed reduce their labour supply, too. A decline in husband's health causes the wife to reduce her working hours while husbands tend to increase their labour supply when facing a decline in wife's health. Partner's death does not have statistically significant labour supply effects. Negative income shocks due to other reasons (such as choice) tend to reduce partner's labour supply and vice versa, but only slightly.

NON-TECHNICAL SUMMARY

In this paper, I analyse how spouses in older couples change their working hours when experiencing 'shocks' or 'surprises' in their partner's labour income. I define 'older' as between ages 40 and 70. My analysis is limited to couples in which both partners were initially working. The data I analyse are from the British Household Panel Survey, 1991–2004.

Previous research only analysed women's labour supply reactions to husbands' income shocks; my research is the first to examine also the other direction. While I find that husbands' labour supply is much less sensitive to wives' income shocks than vice versa, there are some instances where I do find such reactions, small though they may be.

In line with earlier research by others on the United States, I distinguish between five different income shocks: the income shock associated with a divorce or separation, the income shock associated with partner's unemployment, the income shock associated with partner's health decline, the income shock associated with partner's death, and the income shock associated with neither of these events.

Average weekly working hours of women in my sample, including usual overtime, are 29. All predicted changes mentioned in the following paragraph should therefore be interpreted starting from an initial value of 29.

The average income shock associated with divorce or separation leads to a decrease of wife's working hours by 5–6 hours a week. (This reaction is opposite to earlier research by others on the United States which showed that US wives of working age increase their working hours substantially upon husband's unemployment.) The average income shock associated with husband's unemployment leads to a decrease of wife's working hours by 2.5–3 hours a week. The average income shock associated with husband's health decline leads to a decrease of wife's working hours by 0.5–2 hours a week.

Husbands, on the other hand, do not react to wife's unemployment, and their reactions to a divorce or separation, or to wife's health decline, appear to be opposite: men tend to increase their labour supply when facing these events. However, these effects are not very well determined statistically.

Partner's death does not have any statistically significant effects on working hours of men or women. Negative (positive) shocks to partner's income associated with neither of the four aforementioned events lead to very small reductions (increases) in labour supply.

The exact size of the change in working hours of course depends on how important partner's income was for a given person, and on other circumstances which may or may not be controlled for in my analysis.

My research does not explicitly analyse the causal mechanisms at work. However, previous research by others suggests that the dominance of benefits which are means-tested with respect to family income may be at least partly responsible for the fact that wives in the UK tend to magnify income shocks experienced by their partner through their own labour supply decisions.

1 Introduction

The labour supply of older couples is attracting more and more interest as policy-makers attempt to increase the labour market participation of older people and delay the average retirement age.

Of particular interest are the interactions within couples' labour supply, that is, how one spouse's labour supply affects partner's labour supply. Understanding these interactions is important in order to assess the consequences of phenomena such as increases in women's state pension age, lower career stability, or higher demographic risks.

In the United Kingdom, the state pension age for women is 60 while for men it is 65. The state pension age for women is planned to rise to 65 between 2010 and 2020. How will older men in 10 or 20 years' time respond to the larger labour supply of their wives? On a related issue, Campbell (1999) shows that older men's employment has been declining substantially in Britain, while that of older women increased. Even though there has recently been a reversal in older men's employment, as demonstrated by Disney and Hawkes (2003: 21–22), it is not yet clear whether earlier levels will be reached again. Overall, work income as a share of older people's total income has been falling in the UK (OECD 2000: 44). The labour supply consequences of these changes on the individual concerned as well as on his or her partner are not immediately clear. As far as demographic risks are concerned, it is important to point out that the divorce rate among the 40 to 60 year olds is rising, which is different from the overall trend (cf. table 1). This implies an increasing number of older men and women losing partner's income and perhaps having to respond to this loss.

	Husbands	Wives
All ages	0.97	0.97
Age 40–44	1.16	1.15
Age 45–49	1.15	1.16
Age 50–59	1.25	1.23
Age 60 and over	0.94	0.86

Table 1: 1998 divorce rate (divorces per 1,000 married in the corresponding age group) divided by 1985 divorce rate.

Calculated from National Statistics PV9841B, Internet: <http://www.statistics.gov.uk/STATBASE/Product.asp?vlnk=4491>.

I consider the following research questions in this paper: what are the effects of unexpected changes in partner's income (which could also have been caused by a demographic changes, such as a divorce) on the labour supply of older married or cohabiting men and women in the United Kingdom? Does the cause of the income shock make a difference? Are these effects symmetric or not, in the sense that husbands react to changes

in wife's income in the same way as vice versa? If not, what may be the reason for the asymmetries?

In order to address these questions, I build upon the methodological framework of Haurin (1989). While a lot of work has been done on explicit modelling of joint retirement, either in structural models which estimate the parameters of a particular couple utility function (cf. for instance Gustman and Steinmeier 2004) or in reduced-form hazard regression models which model the discrete choice of the couple over all possible combinations of employment statuses (cf. for instance Blau 1998) and, while these authors find strong interdependencies in older couples' labour market decisions, these models cannot directly address how unexpected changes affecting only one spouse are transmitted to the partner.¹ Furthermore, these models cannot incorporate demographic instability since they have to focus on stable couples; when looking at older people, this means not only ignoring separation/divorce but also widowhood.

Haurin (1989), contrary to this other work, explicitly focused on the effects of labour market shocks to one member in a couple on the labour supply of his or her partner. Generally speaking, 'shocks' (or, as Weiss and Willis, 1997, call them, 'surprises') are differences between actual and predicted values. To Haurin (1989), these are deviations of husband's actual income from its predicted value caused by an hours shock to the husband. A positive shock is defined to occur if the husband earns more than predicted due to working more than predicted; a negative shock occurs if he earns less due to working less. These have the advantage that fixed person- and couple-specific effects cancel out since Haurin only analyses *changes*. Moreover, it allows one to look directly at the transmission mechanism of a shock to one individual on the partner.

Haurin (1989) estimates the impact of such shocks on changes in the wife's non-labour hours ('leisure') between 1981 and 1982 while also controlling for (changes in) city size, the number of children in the household, the number of other household members, assets, respondent's health status, and respondent's and husband's wage (treated as endogenous). He finds that women tend to increase their labour supply substantially after a separation/divorce. He does not find statistically significant effects on wife's labour supply when looking at events other than separation/divorce.

This paper builds upon Haurin's research to analyse how labour market shocks and demographic shocks affect the labour supply of older couples in the United Kingdom. There are several important differences between Haurin's work and this paper:

First, while Haurin only analyses the effects of men's shocks on women's labour supply, I analyse shocks in both directions to be able to see whether the effects are symmetric or

¹Gustman and Steinmeier (2004) also emphasise that the husband is more strongly influenced by the wife's retirement decision than the other way around. This may be because of gender roles, perhaps indicating that the husband wants to retire not before the wife.

not. It has been common to focus exclusively on women's labour supply, assuming that husbands will usually be employed full-time and that the reasons for husbands' hours changes are exogenous and involuntary (i.e., labour demand side related). One of my aims is to see whether such a view is appropriate for contemporary UK or not. (The following section of this paper will cover the theoretical arguments in more detail.)

Second, I analyse the effects of labour income shocks as a whole rather than only labour income shocks due to hours changes. The rationale for this specification will be given in the next section. Decomposing the labour income shock into hours shock and wage rate shock is left as a topic for future work.

Third, while Haurin analyses all working women, I focus on older people, specifically on couples where both partners are aged 40 to 70. Starting from age 40 is useful since there are first increases in labour market exit rates and decreases in return rates to the labour market between ages 40 and 50 (cf. Haardt 2006: figures 2 and 3, pp. 19 and 20).

Fourth, I emphasise the importance of dynamics in the econometric model. To this end, I employ the Arellano-Bond (1991) GMM dynamic panel estimator which was not yet available at the time of Haurin's paper.

Fifth and last, I analyse the United Kingdom between 1991 and 2004 (using data from the British Household Panel Survey, BHPS) while Haurin analysed the United States between 1981 and 1982. To my knowledge, a similar analysis has not yet been carried out for the UK. My data are more recent and cover a longer time span which, together with the Arellano-Bond framework, allows better specification of the dynamics.

Section 2 of this paper gives an overview of the theoretical background on within-couple shocks. Section 3 describes the methodology in more detail and Section 4 the data. Section 5 presents and discusses the regression results. Section 6 draws some conclusions.

2 Theoretical Background

The effects of husband's unemployment on wife's labour supply have been subject of much research (research on the effects in the opposite direction has been rather limited, for reasons discussed in the introduction). Most of this research has focused on the question whether a so-called 'added worker effect' (AWE) or an opposite 'discouraged worker effect' (DWE) can be observed in the data.

The AWE suggests that the wife should want to compensate for the income loss associated with husband's unemployment by increasing her labour supply. The DWE, on the other hand, suggests that husband's unemployment may in fact have the opposite

effect by conveying a signal of difficult labour market conditions to the wife.²

Another aspect which should not be forgot, and which may have implications for the symmetry or asymmetry of the effects of shocks, are gender roles. Sociologists suggest that men who have become unemployed may put pressure on their wives to reduce, or at least not increase, their labour supply, since having the wife take over the breadwinner role may be detrimental to the husband's self-esteem. Also wives themselves may be opposed to becoming the breadwinner.³

In the United Kingdom, the effects of the benefit system have attracted a lot of attention in this topic area. A substantial and growing part of benefits in the UK are means-tested, constituting a considerable disincentive to work once one spouse has become unemployed. Bingley and Walker (2001: 159) point out 'that the labour supply disincentives from the welfare system facing women married to men who remain unemployed are made significantly worse by the reform [of the Job Seeker's Allowance]'.

The empirical evidence for the US is mixed, with some authors finding evidence for an AWE and others not. For the UK, there is a consensus that the benefit system increases the risk of women married to men who became unemployed to leave the labour market too. There is not too much research using panel data, and even less cross-national comparative research. McGinnity (2002: 473) compared the UK and Germany using panel data, finding 'some evidence of an added-worker effect in Germany' but 'a disincentive effect of means-tested benefit on partners' employment in Britain'.

Haurin (1989: 59), cited in the introduction, found, for the USA, no statistically significant effect whatsoever of husband's unemployment or bad health on wife's labour supply. However, he does find evidence for what we may call an AWE after separation/divorce: 'If the woman worked 960 hours in 1981, the increase in work time for those women recently divorced or separated is 540 hours, while the estimate for widows indicates a slight decline in work time' (but the latter estimate is not statistically significant at any reasonable level).

The analysis of the effects of an individual's labour-market shocks on the partner, of AWE versus DWE, could be done in several ways. Haurin (1989) looked at the effects of partner's income shocks due to partner's hours changes on own hours. One could also look at the effects of partner's income shocks on own income. In any case, a dynamic model which analyses changes or first differences seems to be appropriate.

I analyse the effects of partner's income shocks on own hours, rather than the two other options just mentioned. I am mainly interested in the effects which income shocks

²Cf. Bingley and Walker (2001: 157–158) for a brief introduction to the AWE and DWE literature.

³As McGinnity (2002: 474) writes: 'According to McKee and Bell (1985), in interviews with couples in which the husband was unemployed, both husbands and wives mentioned how negatively they viewed the prospect of the woman becoming the breadwinner; many became emotional at the prospect.'

have due to the income change as such, not due to the underlying hours change (moreover, a shock may also come about due to a change in the wage rate). This is the reason why I analyse income shocks. On the other hands, income is not a response variable which people can easily choose—in many cases, the response will be working more hours, even though there may also be changes to higher wage jobs. This is why I analyse the effects on hours rather than on income.

The following section presents the model I used to analyse the effects of these income shocks for one member of a couple on his or her partner’s work hours.

3 Econometric Model

A simple econometric model based on the theoretical background just introduced may take the form

$$h_{i,t} = \mathbf{e}_{i,t}\beta + \sigma_{P,t}\gamma + \eta_i + v_{i,t}, \quad (1)$$

where the dependent variable h is hours, \mathbf{e} the vector of explanatory variables excluding the shock variable, β the corresponding coefficient vector, σ partner’s income shock, and γ the coefficient of the shock variable. Finally, η and v are error terms (as the subscripts indicate, η is time-constant for each individual while v is the standard ‘white noise’ error term).

Equation 1 raises a number of questions. Which variables are important to be included in \mathbf{e} ? Are all elements of \mathbf{e} exogenous? What if some are not? Which sign does γ have, that is, are income shocks to one individual magnified or offset by his or her partner? Does γ have the same size for the effect of husband’s shock on wife’s hours as vice versa? Do σ and γ vary depending on the cause of the income shock? Are typical hours reactions large enough to matter? Do only contemporaneous right-hand side variables matter or also lagged values? What about lagged values of the dependent variable?

A highly flexible framework which allows taking these issues into consideration is the dynamic panel data model by Arellano and Bond (1991). It starts from a generalised version of equation 1, viz.

$$h_{i,t} = \sum_{j=1}^n h_{i,t-j}\alpha_j + \sum_{k=0}^o \mathbf{x}_{i,t-k}\beta_{1k} + \sum_{l=0}^p \mathbf{w}_{i,t-l}\beta_{2l} + \sum_{m=0}^q \mathbf{z}_{i,t-m}\beta_{3m} + \eta_i + v_{i,t}, \quad (2)$$

where we now have three vectors of explanatory variables and three corresponding coefficient vectors rather than just \mathbf{e} and β . First, \mathbf{x} , the vector of strictly exogenous variables

(incorporating, among others, σ), second, \mathbf{w} , the vector of non-endogenous predetermined variables, and third, \mathbf{z} , the vector of endogenous predetermined variables. The difference between these three vectors will be discussed shortly.

The three vectors of explanatory variables, as well as the dependent variable, may appear with different numbers of lags: n is the number of lags of the dependent variable while o , p , and q are the numbers of lags of the three vectors of explanatory variables. The model requires n to be larger than or equal to one while o , p , and q may also be zero.

Differencing yields

$$\Delta h_{i,t} = \sum_{j=1}^n \Delta h_{i,t-j} \alpha_j + \sum_{k=0}^o \Delta \mathbf{x}_{i,t-k} \beta_{1k} + \sum_{l=0}^p \Delta \mathbf{w}_{i,t-l} \beta_{2l} + \sum_{m=0}^q \Delta \mathbf{z}_{i,t-m} \beta_{3m} + v_{i,t}, \quad (3)$$

which removes the η term. Technically, the difference between strictly exogenous variables, non-endogenous predetermined variables, and endogenous predetermined variables is that while $\Delta \mathbf{x}$ are their own instruments, \mathbf{w}_{t-1} to \mathbf{w}_T are used as instruments for $\Delta \mathbf{w}$ and \mathbf{z}_{t-2} to \mathbf{z}_T as instruments for $\Delta \mathbf{z}$. In other words, ‘the less exogenous’ a variable, the further we go back in time to get our instruments.

The decision which variables belong to which group is entirely up to the researcher. Apart from theoretical considerations, the Sargan test (cf. Arellano and Bond, 1991) can be used to test for exogeneity of \mathbf{x} . Also the explanatory variables themselves as well as the numbers of lags are of course to be chosen by the researcher. I will discuss my decisions in that respect in the following section of this paper, which presents the data and variables used, including a detailed presentation of the shock variables.

4 Data, Sample Selection Criteria, and Variables

4.1 The Data

The data which I use are from the British Household Panel Survey (BHPS), a longitudinal survey of households with detailed socio-demographic and economic information. The individuals of a representative sample of 5,500 British households were first interviewed in 1991 and have been followed since then, with data from 13 waves (annual interviews) currently available (cf. Taylor 2005). The BHPS provides me with a large and reliable sample of older couples, interviewed between autumn 1991 and spring 2004 (since 6.4% of the interviews of wave 13 were carried out in spring 2004).

The analysis sample which I use for my regressions contains 974 couples and a total of 7,543 person-years (3,788 person-years for the influence of husbands on their wife, 3,755

	partner present	no partner
respondent working	8,888	3,609
respondent not working	5,881	3,950

Table 2: Partnership and work patterns (in person-years) in $t - 1$ for subsequent wave pairs of female respondents (pooled person-wave data using BHPS waves 1–13).

	partner present	no partner
respondent working	10,121	1,732
respondent not working	4,982	1,560

Table 3: Partnership and work patterns (in person-years) in $t - 1$ for subsequent wave pairs of male respondents (pooled person-wave data using BHPS waves 1–13).

for the opposite direction).⁴ Haurin (1989: 57) had a sample of 800 women (or 1,600 person-years).

4.2 Sample Selection Criteria

First, I only analyse couples where both partners are aged 40 to 70 since the focus of this paper is on older people. As mentioned before, I use age 40 as the lower bound since there one can see a first increase in the exit rate out of employment between age 40 and 50, and age 70 as the upper bound since there is only very little labour market activity beyond this age.

Tables 2 and 3 summarise the partnership and work patterns in $t - 1$ in pairs of subsequent BHPS waves. This shows that most people in the age group 40–70 do have a partner.

Table 4 shows work patterns among older couples (without requiring the presence of two subsequent waves) and confirms that the probability of working is much smaller if

⁴The difference in the number of person-years stems from different numbers of missing values in the health variable and the education variables across sexes, as well as from differential follow-up in the subsequent wave.

	wife working	wife not working
husband working	10,936	3,981
husband not working	2,352	5,276

Table 4: Work patterns of older couples (pooled person-wave data using BHPS waves 1–13).

the partner does not work. Moreover, we can also see from this table that most couples in this age group are couples where both spouses work. This is why I will focus on this group of the population in my analysis.

Second, there is a small number of observations where the person whose person ID the respondent mentioned as the partner mentions a different person as their partner than the respondent. Closer investigation showed that these cases are due to different interview dates of the two spouses in question, with a partner change in between. I drop these observations since they are only very few and since it would not be clear how to handle them properly.

Third, I can of course only use those observations where all the variables of my analysis have non-missing values. To this end, I made sure to use only variables which are observed most of the time. One important variable which has an above average proportion of missing observations is health status. I interpolate and extrapolate gaps of one year's duration in health status. Longer gaps are not filled.

One important consideration affecting sample size is the number of lags of the dependent and explanatory variables chosen for the econometric model. Due to these lags, a single missing is sufficient to remove several observations from the analysis sample. This is particularly critical for some of the shock variables. For example when employing what turns out to be my preferred lag structure ($n = o = p = 2; q = 1$), there are only 20 separation events among women and 12 among men.⁵ Therefore, in addition to the just mentioned preferred lag structure, I also use a 'minimal lag structure' (i.e., $n = 1; o = p = q = 0$) to maximise the effective sample size. This increases the occurrence of marital separations by 50% for women (to 30) and by 83% for men (to 22).

Self-employed people are treated in the same way as employees.

Summing up, I look at all shocks occurring between autumn 1992/1993 (due to the one/two lags of the dependent variable) and spring 2004 to couples where both partners are aged 40 to 70, where both partners were working in $t - 1$, and where all the required data are properly observed.

4.3 Variables

4.3.1 Dependent Variable

The dependent variable is the natural logarithm of the sum of actual current working hours (including overtime) and one (adding one is done to deal with zero hours). I decided

⁵The disparity is again for several reasons: a different prevalence of missing values for the health and education variables, differential follow-up in the subsequent wave, repartnering of one of the two former partners which means that he or she will not be treated as separated in my data.

to use this specification rather than just hours in levels to reduce possible heteroskedasticity. Using $\ln(h + 1)$ rather than any other $\ln(h + x)$ (where $x > 0$) is arbitrary, but assuming $x = 1$ should not generate systematic biases. Taking logs also reduces second-order autocorrelation of the residuals significantly which is important since a violation of this assumption would render the estimator inconsistent (cf. Arellano and Bond 1991: 278).

4.3.2 Explanatory Variables

The most important explanatory variable is the shock variable which is constructed similarly to Haurin's (1989). The shock variable measures how different partner's actual labour income is from partner's predicted labour income, scaled by own labour income and household non-labour income to reflect the importance of partner's labour income for the household as a whole.

More precisely, my shock variable σ is constructed as follows:

$$\sigma_{P,t} = \frac{y_{P,t} - \hat{y}_{P,t-1}(1 - \pi_R)}{10000(y_{R,t} + w_t)}, \quad (4)$$

where R and P subscripts are used to refer to respondent and partner, respectively. Labour income is represented by y ; π denotes the sex-specific overall separation/divorce probability within my sample, and w household non-labour income.

The numerator consists of actual labour income of the partner minus predicted labour income of the partner, where expected labour income takes the separation/divorce probability into account (even though there will be an endogeneity issue).

The denominator scales this deviation by dividing by the sum of respondent's labour income and household non-labour income. The denominator also contains a scaling factor, 10,000, since this gives a reasonable range of coefficient sizes. The smaller the denominator is, the larger will the relative effect of the shock be.

If the respondent does not have a partner in t , $y_{P,t}$ is set equal to zero, rendering $\sigma_{P,t}$ strictly negative.

Partner's predicted labour income $\hat{y}_{P,t-1}$ is constructed based on a similar idea as the surprises to partner's earning capacity in Weiss and Willis (1997: S306). They 'construct a set of predictions of this variable for each partner conditional on available information about the person at each year'. What I do to incorporate this idea is to run labour income predictions of the following type:

$$y_{R,t} = \beta \mathbf{s}_{R,t} + \epsilon_{R,t} \quad (5)$$

where $\beta \mathbf{s}_{R,t}$ is a vector of explanatory variables composed of a set of seven education

dummies, the regional unemployment rate for the respondent’s sex, the number of children under the age of 18 in the household, household size, respondent’s health status, and partner’s health status. The results of these regressions are reported in Table 9 in Appendix A.

I then add to the predicted values the average residual of the corresponding person *up to the corresponding wave*, i.e., $\sum_{k=1}^t \epsilon_{R,k}/t$ to yield the final prediction $\hat{y}_{R,t}$ which is used in the construction of the shock variable. I interpret this average residual as the overall influence of unobservables on R’s expected income which has been revealed up to point t .

Coming back to my main shock regressions, I run each of these twice, once with the overall $\sigma_{P,t}$ and once with several disaggregated σ variables, each of which corresponds to a certain type of ‘event’. To this end, I define five events:

1. R separated or divorced between $t - 1$ and t *and* no P present at t (I will from now on, for simplicity, always use the word ‘separation’, even though I refer to both separation and divorce)
2. R widowed between $t - 1$ and t *and* no P present at t
3. R remains partnered; P experienced health decline between $t - 1$ and t
4. R remains partnered; P become unemployed between $t - 1$ and t
5. none of the above four events (i.e., still with a partner—who may be somebody else compared to $t - 1$ —who remains with unchanged health and in employment between $t - 1$ and t)

These five events are mutually exclusive with the exception of 3 and 4 which may occur simultaneously. This brings about the question of how to code cases where both of these events occur at the same time. Essentially, there are four possible ways:

- use *three* mutually exclusive events generated from the two not mutually exclusive events: health decline only; unemployment only; health decline *and* unemployment
- code all simultaneous events as health decline only (artificially made mutually exclusive)
- code all simultaneous events as unemployment only (artificially made mutually exclusive)
- code all simultaneous events as both a health decline event *and* also as an unemployment event (not mutually exclusive)

Fortunately, there are surprisingly few overlaps between health events and unemployment events. This means that the choice between the four ways how to treat simultaneous events is not that important: the key results were always the same when repeating my regression analysis with all four choices. I settled with the last choice since the first suffers from the problem of few overlaps while the second and the third are somewhat artificial.

The five event dummy variables are then interacted with $\sigma_{P,t}$ as defined above. The resulting five types of disaggregated shocks are called ‘separation shock’ $\sigma_{P,t}^{sep}$, ‘widowhood shock’ $\sigma_{P,t}^{wid}$, ‘health shock’ $\sigma_{P,t}^{hl}$, ‘unemployment shock’ $\sigma_{P,t}^{unem}$, and ‘no event shock’ $\sigma_{P,t}^{noev}$. From the last paragraphs it follows that only $\sigma_{P,t}^{hl}$ and $\sigma_{P,t}^{unem}$ can *both* be non-zero for a given observation.

The econometric model which I use implies that the explanatory variable used is in fact the *difference* between this year’s shock variable and last year’s shock variable. This may lead to complications in the interpretation of the effects of the shocks. However, it is important to keep in mind that separation/divorce, death of the partner, partner’s health decline, and partner’s unemployment cannot occur twice after each other, implying that the difference of each of these four shock variables will always be equal to the shock variable itself. Only the ‘no event’ shock can occur twice (or indeed more often) after each other.

In what follows, I will now go on to present the other explanatory variables used in my regression analysis.

- Age of respondent (in years)
- Age squared of respondent (in years)
- State pension age dummy for respondent (1 if respondent is of state pension age or older, 0 otherwise)
- Health dummy for respondent (1 if respondent has a health problem which limits the type or amount of work, 0 otherwise)
- Household size
- Number of children under the age of 18 in the household
- Home ownership (one dummy for outright ownership and one for mortgage-based ownership; base category are non-owners)
- Household non-labour income
- Shock variable(s) σ_P (as detailed above)

In terms of the classification into strictly exogenous variables, non-endogenous predetermined variables, and endogenous predetermined variables mentioned earlier on, all of the above-mentioned variables are assumed to be strictly exogenous, except for household size and number of children (both non-endogenous predetermined) as well as the two home ownership dummy variables and household non-labour income (all endogenous predetermined).

There are some theoretical arguments for this classification. The three age variables are clearly exogenous. The health variable could be subject to some ex post rationalisation, but since strictly objective measures are not available in the BHPS and are subject to criticism, too, I assume my health variable to be exogenous as well.⁶ The shock variable(s) is (are) subject to the same assumption. Household size and the number of children are clearly not exogenous since they are subject to choice within the household, but can be taken as given at the beginning of any time period which is why I assume these variables to be non-endogenous predetermined. Household non-labour income, on the other hand, is certainly endogenous since its formation is a result of past labour supply and income. This classification is also supported by the results of the Sargan test.

I use the squared value of age, divided by 1000. Furthermore, I also use a state pension age dummy variable which equals 1 if age is larger than or equal to 60 (for women) or 65 (for men). This is due to the fact that the UK state pension can be drawn starting from this age and there is no employment protection or redundancy pay beyond that age, forming a strong incentive to withdraw from the labour market. The state pension dummy therefore enables a shift of the age-profile of the dependent variable at age 65 (for husbands) or 60 (for wives).

I also experimented with the plain age variable in levels, and with the logarithm of age. The former has the problem that since the Arellano-Bond model is a difference model, $age_t - age_{t-1} = 1$ for approx. 88% of observations, and is only identified through observation pairs where the two interview dates (usually September to May) and the birthday interact in unusual ways. If, for instance, somebody who has his or her birthday in October is interviewed in September in wave $t-1$ and in May in wave t , we will observe $age_t - age_{t-1} = 2$. Since age may therefore capture mere seasonality rather than a genuine age effect, I ran all the regressions twice, once with age in levels and once without age in levels. The key results, in particular the coefficients of the shock variables, were not too different but in general the model fared better without the age variable which is why I will, later on, only report those results. Experiments with $\ln(\text{age})$ were not very successful either.

⁶Bound (1991) discusses and analyses the advantages and disadvantages of subjective and objective health measures.

The health dummy variable comes from the following question in the BHPS interview: *Does your health limit the type of work or the amount of work you can do?* I recode this variable so that 1 corresponds to yes and 0 to no. This variable has virtually no missing cases but, unfortunately, was not asked in wave 9 of the BHPS. Therefore, I use linear imputation to fill gaps which are one wave long (which affects virtually only wave 9): if the same answer was given before and after the gap, this answer is imputed for the gap. If different answers were given, a value of 0.5 is imputed.

Household size and number of children under the age of 18 in the household are derived variables included in the BHPS release.⁷ The probability that a couple in this age group has children present in the household is only about one fifth but I still include the variable.

The home ownership dummy variables, one for outright ownership and one for mortgage-based ownership, are used as proxies for wealth. The base category are non-owners. My dummy variables are generated from a categorical variable on housing tenure which the BHPS provides.⁸

Household non-labour income is the same variable as used in the denominator of the shock variable(s). It is the sum of last month's household transfer income and household investment income, two derived variables present in the BHPS.⁹ These variables include approx. 15-35% imputed data. I divide it by 10000 to rescale the variable.

Finally, the regional claimant count rate of the respondent's sex is used as an additional instrument since it is reasonable to assume that the regional unemployment rate affects some of the explanatory variables but not working hours directly. These data come from National Statistics for the 12 standard UK regions: East, East Midlands, London, North East, Northern Ireland, Northwest and Merseyside, Scotland, Southeast, Southwest, Wales, West Midlands, and Yorkshire and Humberside. Since information on the region of residence is available in the BHPS in the same manner, I am able to merge these unemployment data into the BHPS. I use the sex-dependent time series without seasonal adjustment.

I also wanted to include other variables but was not able to do so for various reasons. First, I would have liked to include information about individuals' employment history (for instance the percentage of years working when the respondent was 15 to 40 years old), but since I am using difference regressions the effects of time-constant variables are not identified. Second, I would have liked to include information on job tenure as Haurin

⁷Variables wHHSIZE and wNKIDS on wHHRESP.

⁸Variable wTENURE on wHHRESP.

⁹Variables wFIHHMT and wFIHHMI on wHHRESP. My variable is therefore *not* equivalent to the BHPS variable household non-labour income, wFIHHMNL, which also includes pension and benefit income.

Variable	H→W PLS	H→W MLS	W→H PLS	W→H MLS
R hours	29.2099	29.3651	42.8213	42.8879
Household size	2.9393	2.9984	2.9465	2.9958
Number of children	0.2212	0.2824	0.2224	0.2797
Home owner (outright)	0.2711	0.2528	0.2754	0.2541
Home owner (mortgage)	0.6333	0.6500	0.6338	0.6493
HH non-labour income (£/month)	131.4280	126.0680	132.1790	125.7400
R of state pension age (SPA)	0.0684	0.0626	0.0290	0.0283
R health problem	0.1147	0.1140	0.0929	0.0940
R's age (in years)	53.5448	50.7148	53.3153	52.6569
Person-years	3,788	5,032	3,755	4,987
Persons	974	1,257	985	1,248

Table 5: Means of the explanatory variables, excluding the shock variables, in the four regression samples (PLS: preferred lag structure; MLS: minimal lag structure).

did, but information on when the current job started is often missing. It would have been highly interesting to use information on the reasons for quitting a job to distinguish between voluntary and involuntary exits from or changes of employment, but these data are missing for approx. 35-40% of applicable cases which made estimation infeasible. Lastly, I also experimented with information on hours preferences (for similar reasons), but was not able to get reasonable results (the dummy variables for preferring more or less working hours were either insignificant or had the same sign).

In Table 5, I present the means of the dependent and explanatory variables for my four regression samples, first the two samples where the wife is the respondent (R) and the husband the partner (P) and then the two opposite samples. In both cases there is one column for the (smaller) sample with the preferred lag structure (PLS) and one for the (larger) sample with the minimal lag structure.

From Table 5 we learn that the women in our sample are on average working 29 hours per week and the men 43 (keep in mind that my analysis is restricted to couples in which both spouses were working in $t-1$, and that these figures are actual total hours, including overtime). We can also see that people with less regular response patterns are more likely to have children in the household, to have a lower level of household non-labour income, and to be younger (since the PLS samples involve stronger conditioning on response in several subsequent years of the survey than the MLS samples).

Table 6 shows the means and medians of the shock variables. When looking at the means (in the upper panel), some surprising results can be seen (for instance the large absolute value of the financial impact caused by wife's death). However, the medians (in the lower panel) show much more regular patterns than their means reported in Table 5. More than 50% (in fact, many more) of separations/divorces, of unemployment events,

Variable	H→W PLS	H→W MLS	W→H PLS	W→H MLS
Means				
P's overall shock	-0.2831	-0.0578	0.0212	0.2136
P's separation or divorce shock	-1.8664	-1.3693	-0.0451	-0.0661
P's no event shock	-0.2709	-0.0375	0.8120	0.8202
P's health shock	-0.1377	-0.1519	0.0017	0.0129
P's unemployment shock	-0.7309	-0.5677	-29.8877	-24.2884
P's death (widowhood) shock	-0.1281	-0.1555	-274.6688	-235.4402
Medians				
P's overall shock	0.0208	0.0192	0.0061	0.0058
P's separation or divorce shock	-0.1740	-0.1557	-0.0415	-0.0451
P's no event shock	0.0218	0.0203	0.0064	0.0061
P's health shock	0.0043	0.0029	0.0032	0.0023
P's unemployment shock	-0.1561	-0.1422	-0.0478	-0.0385
P's death (widowhood) shock	-0.0689	-0.0895	-0.0521	-0.0690
Person-years	3,788	5,032	3,755	4,987
Persons	974	1,257	985	1,248

Table 6: Means (upper panel) and medians (lower panel) of the shock variables in the four regression samples; all values x1,000 (PLS: preferred lag structure; MLS: minimal lag structure).

and of deaths are associated with negative income shocks. On the other hand, more than 50% of the 'no event' shocks and of the health shocks are associated with positive income shocks. This is also true for the aggregate shock measures. The fact that partner's income is higher than expected when the partner experiences a health shock is however not necessarily surprising given that health is one of the predictors in the labour income regressions. This means that directly after experiencing a health shock the income shock has not yet reached its final level.

How does my specification compare to that of Haurin? Apart from the fact that Haurin analyses hours shocks while I analyse income shocks, he also uses city size dummy variables (which are not available in the BHPS) and assets. I use information on home ownership and household non-labour income instead of assets which should be closely related. I include the state pension age dummy variable in the hours regressions (the 'second stage', so to say) while Haurin uses it in the wage regressions. As a side remark, I use household size rather than the number of others in the household (the latter is equal to the former minus two minus the number of children).

As far as the auxiliary regressions are concerned (labour income regressions in my case, wage regressions in the case of Haurin), there are several differences which can be studied in more detail by comparing Table 9 in my Appendix A to Table 2 in Haurin (1989: 58). Two differences worth mentioning are that I use education dummies rather

than years of schooling (since the latter is not that meaningful in a UK context) and that I do not include race since there is only a rather small proportion of ethnic minorities in the BHPS and since there is a larger heterogeneity among ethnic minorities in the UK than in the US. Finally, since correcting for selection gave a slightly worse fit while complicating the model, my labour income regressions are not selection corrected. In my work as well as in his, the education variables serve to identify the auxiliary regressions as they are excluded from the hours regressions.

5 Results

5.1 Introductory Comments

In this section, I present and discuss the results of my regression analysis. Table 7 shows the estimated effects of husbands' shocks on wives, Table 8 the other way around.

5.2 Results for the Shock Variables

The aggregate shock variables, not distinguishing by the cause of the shock, are not very precisely estimated. If anything, we can say that there is a slight tendency towards synchronisation of labour supply (meaning a positive sign of the coefficient). This tendency towards synchronisation is linked to Table 4 earlier on, which showed that there are more couples in which either both spouses work or no spouse works than couples in which only one spouse works.

The results become more pronounced and more interesting when disaggregating the aggregate shock variables into the five separate shock variables each.

The coefficient of husband's separation shock variable is positive and highly statistically significant using both lag structures. This means that women who experience a negative income shock due to a separation or divorce decrease their labour supply. If a woman was working 29 hours per week (the rounded sample mean, as mentioned earlier on), then the hours decrease caused by the average separation shock size will be 6 hours (to 23) when using the preferred lag structure or 5 hours (to 24) when using the minimal lag structure.¹⁰ Looking in the other direction, the coefficients are always negative and, in the case of the minimal lag structure, also statistically significant at the 5% level, implying that husbands upon divorce tend to increase their labour supply. If we use the minimal lag structure, in which this coefficient is statistically significant, and consider

¹⁰To obtain these and the following figures throughout this section, consider the following equations: $\exp[\ln(29 + 1) + (-0.0018664 \cdot 121.9100)] - 1 = 22.89$ and $\exp[\ln(29 + 1) + (-0.0013693 \cdot 129.2994)] - 1 = 24.13$. The addition of 1 when forming the logarithm as well as the subtraction of 1 at the end come from the fact that I define my dependent variable in terms of $\ln(\text{hours}+1)$ to deal with zero hours.

H's shock(s) → ΔW's ln(hours)	Preferred lag structure		Minimal lag structure	
	Overall	Disaggr.	Overall	Disaggr.
LD(Dep. Var.)	-0.1565***	-0.1542***	-0.1091***	-0.1088***
L2D(Dep. Var.)	-0.0213	-0.0204		
D1(HH Size)	-0.0243	-0.0303	0.0112	0.0084
LD(HH Size)	-0.0109	-0.0113		
L2D(HH Size)	-0.1088*	-0.1059*		
D1(No. of children)	-0.0507	-0.0484	-0.3942***	-0.3913***
LD(No. of children)	-0.4953***	-0.5044***		
L2D(No. of children)	0.0311	0.0431		
D1(OR home owner)	0.2862	0.3650	0.8921***	0.9181***
LD(OR home owner)	1.2023***	1.0552***		
D1(MG home owner)	0.0502	0.0180	0.7809***	0.7414***
LD(MG home owner)	1.5375***	1.4358***		
D1(HH NL income)	3.0783***	2.8418**	0.7670	0.6425
LD(HH NL income)	0.0236	-0.0389		
D1(W of SPA (60+))	-0.7145***	-0.7179***	-0.7754***	-0.7783***
D1(W health prob)	-0.0180	-0.0282	-0.0069	-0.0107
LD(W health prob)	-0.1281**	-0.1544***		
L2D(W health prob)	-0.0562	-0.0683		
D1(W's squared age)	-0.6574	-0.6055	-0.8765**	-0.8427**
D1(σ_H)	2.6013**		0.0950	
LD(σ_H)	-3.8076			
L2D(σ_H)	-0.4305			
D1(σ_H^{sep})		121.9100***		129.2994***
D1(σ_H^{noev})		2.1123*		0.0687
LD(σ_H^{noev})		-3.9597		
L2D(σ_H^{noev})		-0.5096		
D1(σ_H^{hl})		157.9105***		99.8133**
LD(σ_H^{hl})		187.0018*		
L2D(σ_H^{hl})		177.5330*		
D1(σ_H^{unem})		156.1461***		155.6443***
LD(σ_H^{unem})		-44.6745		
L2D(σ_H^{unem})		4.8481		
D1(σ_H^{wid})		27.9154		-534.5843
Constant	-0.1391***	-0.1434***	-0.0905**	-0.0938**
Sargan test	0.5625	0.5040	0.6587	0.6770
AB test (order 1)	0.0344	0.0281	0.0000	0.0000
AB test (order 2)	0.3738	0.2386	0.4409	0.3932

Table 7: Regression coefficients for Husband's shock(s) → ΔWife's ln(hours).

Preferred LS: $n = o = p = 2; q = 1$. Minimal LS: $n = 1; o = p = q = 0$.

D1 = first difference; LD = lagged difference; L2D = second lag of the difference.

***: Stat. significant at 1% level; **: 5% level; *: 10% level; +: 15% level.

W's shock(s) → ΔH's ln(hours)	Preferred lag structure		Minimal lag structure	
	Overall	Disaggr.	Overall	Disaggr.
LD(Dep. Var.)	-0.2523***	-0.2557***	-0.1702***	-0.1714***
L2D(Dep. Var.)	-0.0820***	-0.0828***		
D1(HH Size)	-0.0779	-0.0375	-0.1559***	-0.1471***
LD(HH Size)	0.0484	0.0315		
L2D(HH Size)	-0.1006*	-0.1067*		
D1(No. of children)	0.0084	0.0086	-0.0354	-0.0382
LD(No. of children)	0.3468**	0.3177**		
L2D(No. of children)	-0.3787***	-0.3659***		
D1(OR home owner)	0.0925	0.1889	0.5297**	0.5511**
LD(OR home owner)	0.5838+	0.5204		
D1(MG home owner)	0.2041	0.3198	0.7053***	0.7353***
LD(MG home owner)	0.6498*	0.5687*		
D1(HH NL income)	1.8712+	1.7501	0.9917	0.9239
LD(HH NL income)	-0.9317	-0.9457		
D1(H of SPA (60+))	-1.4991***	-1.5051***	-1.6290***	-1.6312***
D1(H health prob)	-0.1196*	-0.1207**	-0.0977*	-0.0963*
LD(H health prob)	-0.1640***	-0.1665***		
L2D(H health prob)	-0.0378	-0.0371		
D1(H's squared age)	-1.1472**	-1.1266**	-1.4173***	-1.3896***
D1(σ_W)	0.1883		0.0955	
LD(σ_W)	0.5939			
L2D(σ_W)	-1.0416			
D1(σ_W^{sep})		-5199.3450		-4971.6520**
D1(σ_W^{noev})		0.5940		0.2383
LD(σ_W^{noev})		0.9373		
L2D(σ_W^{noev})		-0.7040		
D1(σ_W^{hl})		-69.1389		-208.3941+
LD(σ_W^{hl})		576.6800		
L2D(σ_W^{hl})		476.1624		
D1(σ_W^{unem})		-0.1215		-0.1938
LD(σ_W^{unem})		83.7226		
L2D(σ_W^{unem})		26.8775		
D1(σ_W^{wid})		-0.0134		0.0513
Constant	-0.0516	-0.0539	-0.0224	-0.0254
Sargan test	0.5248	0.5278	0.5016	0.4768
AB test (order 1)	0.0000	0.0000	0.0000	0.0000
AB test (order 2)	0.8743	0.7777	0.3260	0.3074

Table 8: Regression coefficients for Wife's shock(s) → ΔHusband's ln(hours).

Preferred LS: $n = o = p = 2; q = 1$. Minimal LS: $n = 1; o = p = q = 0$.

D1 = first difference; LD = lagged difference; L2D = second lag of the difference.

***: Stat. significant at 1% level; **: 5% level; *: 10% level; +: 15% level.

a man who initially worked 43 hours per week (again, the rounded sample mean), then the hours increase caused by the average separation shock size equals 17 (to 60 hours per week).

The health shock variable is consistently positive for the effect of men on women, implying that wives reduce their working hours when experiencing a negative income shock due to husband's health decline. When looking again at a woman who initially worked 29 hours, the contemporaneous effect predicts an hours decrease caused by the average health shock size of approx. two thirds of an hour when using the preferred lag structure, and of just below half an hour when using the minimal lag structure. However, even though these effects look small, one should not forget that the effect seems to be long-lasting since the coefficients of both the first and second lags of the difference are also statistically significant. In that sense, the total effect may be an hours reduction of two hours or perhaps even more. Looking in the other direction, at the effects of wife's health shock on husband's hours, the effect is again rather blurred but, at least in the first instance, there seems to be an opposite tendency for husbands to increase rather than reduce their working hours when the wife experiences an income loss due to bad health. This can be seen from the statistically significant coefficient when using the minimal lag structure. However, the average size of this shock is in fact actually positive, as discussed earlier on. The size of the effect is very small: using the average (positive) shock size, there is virtually no change in husband's labour supply. The asymmetry in the health shock effect, i.e., that the coefficients are of opposite sign, could for instance be explained by different patterns of caregiving (i.e., wives providing caregiving for husbands with health problems, but not vice versa).

The unemployment shock appears to affect women similarly as the separation and health shocks: positive sign (possibly indicating, as discussed in the literature review in the introduction, a disincentive effect of the benefit system and/or a DWE) and similar size. Applying the average unemployment shock on a woman working 29 hours leads to a predicted reduction of 3 hours in wife's hours when using the preferred lag structure and of 2.5 hours when using the minimal lag structure. In the other direction, there are no statistically significant effects, and the coefficient size is also very small.

The effects of widowhood or widowerhood are never statistically significant and do not show any clear pattern. The coefficient size is much larger for women than for men, implying that women's labour market reaction to widowhood is noticeable (but not well determined) while men's is virtually nonexistent. Of course we also suffer from low case numbers here since death of a partner is by far the most infrequent of the events used.

The effect of a 'no event' shock, that is an unexpected income change brought about without separation/divorce, death, unemployment, or health change of the partner (this

means that such a ‘no event’ shock could be for instance due to choice) is hardly statistically significant but generally speaking positive (the only statistically significant ‘no event’ shock is the contemporaneous effect of the husband’s shock on wife’s hours in the preferred lag structure model). It is fair to say that the results for the no event shock are not too different from those for the overall shock variable discussed a couple of paragraphs ago. This can, as already mentioned, point in several directions: it could be that this phenomenon is due to choice and the complementarity of leisure, but it could also be that we are actually observing the disincentive effects of the benefit system and/or a discouraged worker effect. In any case the results for the no event shock are not very well determined, and small in size.

I also tested for equality of the coefficients of the disaggregated shock variables. In particular, the effects of the separation, health, and unemployment shocks on women’s hours appear to be rather similar. However, statistical tests indicate that only the effects of husband’s health and unemployment shocks on wife’s hours in the preferred lag specification are found to be equal to each other at a reasonable error margin (2% in this case). No other two shock variable coefficients are found to equal each other at a 20% or lower level. Therefore, the rather detailed disaggregation used is worthwhile.

Finally, I would also like to compare my findings about the effects of the shocks to those of Haurin (1989). The only statistically significant shock effect which Haurin found was an increase in wife’s labour supply after a divorce or separation. Recall that the size of this increase in Haurin’s paper, starting from an annual hours mean of 960, was 540 hours. Assuming two weeks off (since he uses US data), this translates into an increase by 10.8 hours per week from 19.2 to 30 hours per week. Looking at my results for the UK, the corresponding figures, as mentioned earlier on, are a *decrease* by 5–6 hours per week from 29 to 23–24 hours per week. This contrast in the direction of the effect can be seen as consistent with the differences between Britain and the US with respect to AWE versus DWE found in the more general literature on couples in which the husband becomes unemployed, as outlined in the introduction of this paper.

5.3 Results of the Control Variables

The number of children in the household shows surprisingly clear results: there is, over time, no well-determined effect in either direction on husband’s working hours, but a clear negative effect on wife’s working hours. In other words, other things being equal, women raise their labour supply after a child leaves the household (and reduce it after a child is born into the household, which is of course less important in this age group). The size of this effect is large: considering again a wife who worked 29 hours per week, the predicted hours increase after a child leaves the household is approx. 19.5 (to 48.5) when using the

preferred lag structure and 14.5 (to 43.5) when using the minimal lag structure.

The coefficients of the home ownership variables reveal that one year after buying a house, both partners increase their working hours, other things being equal. The effect is stronger for mortgage-based ownership than for outright ownership (as one might have expected), and more pronounced for wives than for husbands. However, even though there are quite a lot of changes in ownership status (i.e., there is no problem of small case numbers), the effect sizes are unplausibly large, especially for the effect on the wife. When becoming mortgage-based homeowners, a husband previously working 43 hours per week is predicted to increase his weekly working hours by 34 to 48 (to 77–91). When becoming outright homeowners, the predicted increase in husband’s working hours is 31 to 35 hours (to 74–78). Looking at the wife, the predicted hours increase caused by moving towards mortgage-based home ownership is 33 to 110 hours per week (to 62–139). When becoming outright homeowners, the effect on the wife is 43 to 70 hours (to 72–99).

If household non-labour income increases, wives increase their labour supply. The source of this effect is not immediately clear, but the effect is small (starting from its mean value, a 50% increase in household non-labour income will cause a woman who previously worked 29 hours per week to work approx. half an hour more).

Not very surprisingly, reaching state pension age is associated with a substantial downward shift in the age-hours relation. For men who worked 43 hours per week the effect of this variable alone predicts a decrease by 34 hours to 9 hours per week when turning 65 using the preferred lag structure, and by 35.5 hours to just 7.5 hours when using the minimal lag structure. For wives working 29 hours, the predicted hours reduction explained by turning 60 is 15.5 (to 13.5) when using the preferred lag structure or 16 (to 13) when using the minimal lag structure. These huge effects are in accord with research on the labour market transitions of older men and women in the UK (cf. Haardt 2006: figures 2, 18, and 20).

An own health decline reduces working hours, but not by as much as one would have expected. The husband’s own health effect is very well determined. Considering again a husband who worked 43 hours per week, the predicted hours reduction equals 5 (to 38 hours per week) when using the preferred lag structure or 4 (to 39 hours per week) when using the minimal lag structure. The wife’s own health effect is only statistically significant when using the preferred lag structure and comes with a one-lag delay. If a wife working 29 hours per week experiences a health decline, she will reduce her working hours by 3.5 hours (to 25.5) when using only one shock variable or by 4 hours (to 25) when disaggregating the shock variable.

6 Conclusions

In this paper, I analysed how spouses in older couples react to ‘shocks’ or ‘surprises’ in their partner’s labour income using data from the British Household Panel Survey, 1991–2004. To this end, I build upon the work of Haurin (1989) who used US data from 1981 and 1982 to analyse the effects of husband’s income shocks caused by underlying hours shocks on the labour supply of wives of all ages. Apart from the different shock measure, the fact that I use more recent British data, and the fact that I focus on people aged 40 to 70, I also look at the influence of wife’s shocks on husband’s hours. Furthermore, I am able to model dynamics in a more comprehensive way by using the Arellano-Bond (1991) GMM methodology which was not yet available when Haurin wrote his article.

As expected, I find that wives’ labour supply is much more sensitive to partner’s shocks than husbands’. In fact, husband’s labour supply seems to be affected by only two of the types of shocks considered, by a divorce or separation shock, and by a health shock of the partner. Other unexpected changes in wife’s income are not found to be statistically significant.

After a divorce or separation, wives reduce their labour supply while the effect on husbands’ labour supply is less well-determined (not statistically significant or positive). A woman whose initial labour supply equalled the regression sample mean (29 hours per week) is predicted to reduce her labour supply by 5–6 hours to 23–24 hours per week. This is opposite to Haurin’s results who found that for the US in the early 80s, separation or divorce lead to an increase in women’s labour supply. My results also predict that husbands who initially worked 43 hours per week (again the regression sample mean) will increase their labour supply by 17 hours to 60 hours per week upon divorce or separation. However, this effect is only statistically significant in one of two lag structures used.

Wife’s unemployment does not have a statistically significant effect on husband’s labour supply while wives whose husband becomes unemployed reduce their labour supply, too. Here, the predicted reduction is 2.5–3 hours to 26–26.5 hours per week.

Partner’s health decline causes wives to reduce their working hours while husbands tend to increase theirs when facing the opposite situation. The contemporaneous effect on a woman who used to work 29 hours per week is a reduction by just half an hour to two thirds of an hour, but the effect appears to be long-lasting which is why the cumulative effect over time may well be a reduction by 2 or more hours (to 27 or less hours per week). If anything, negative income shocks due to wife’s bad health appear to *increase* husband’s labour supply.

The effects of widowhood and widowerhood are not very well determined and in the latter case also negligibly small. None of the coefficients is statistically significant at any

reasonable level.

Negative (positive) income shocks of the partner due to other reasons (such as choice) tend to reduce (increase) labour supply, but only slightly. The coefficient size is very small.

Even though the separation or divorce shock was the only statistically significant shock type in Haurin's analysis, one can draw out broader implications of the comparison between the US and the UK: in the US, there seems to be a clear tendency towards income replacement when looking at the effect on wife's hours, whatever the cause of the negative income shock of the husband (i.e., an offsetting reaction), while in the UK, only the husband seems to respond according to this pattern (if at all) while the wife always 'follows' the direction of the husband's income shock regardless of its cause (i.e., a magnifying reaction).¹¹ This suggests that the household-level consequences of husband's income shocks are larger in the UK than in the US.

As far as the other explanatory variables are considered, a couple of results are worth reiterating. First, the presence of children reduces wives' labour supply considerably. Second, home ownership, especially if owned with a mortgage, increases the labour supply of both spouses substantially. Third, there is an enormous impact of reaching state pension age which is in line with research on older people's labour market transitions. Fourth and last, the presence of a health problem reduces one's own labour supply, but not by as much as one may have expected.

Naturally, a lot of work remains to be done. One particularly interesting aspect, as mentioned in the introduction of this paper, would be a decomposition of my income shock variable into the income shock caused by an hours change (as in Haurin) and the income shock caused by a wage change. When analysing the effects of divorce and separation, and, even more so, of widowhood and widowerhood, one cannot emphasise enough the importance of (even) larger panels. Even specialised data sets such as the English Longitudinal Study of Ageing (ELSA) would not be able to provide a larger sample size than I was able to use in this paper. Finally, it will remain important to investigate further the exact causal mechanisms behind the spousal interactions found in this paper.

¹¹This is shown by the fact that all the statistically significant shock coefficients in my analysis are positive when looking at the effects on wives and negative when looking at the effects on husbands; when comparing my results to Haurin (1989), keep in mind that his dependent variable is defined in terms of leisure rather than in terms of work.

Appendix A

	Husbands	Wives
R has degree	1029.8730***	889.9460***
R has teaching qual	200.3199***	548.0318***
R has other higher qual	459.3972***	392.3119***
R has nursing qual	112.4810	329.0929***
R has A levels	267.0934***	223.2863***
R has O levels	210.8050***	155.5519***
R has other voc qual	155.7274***	96.0080***
R's age	143.7684***	48.0894***
R's squared age/1000	-1779.8480***	-716.6486***
Regional unemp rate for men	-39.6510***	-46.6171***
R has health prob	-583.7513***	-250.6256***
P has health prob	-131.9625***	-54.1034***
Number of children in HH	11.6350	-106.3363***
HH size	45.3694***	-23.3564***
Constant	-1253.0860***	105.5838
Number of observations	20,928	21,597
Adjusted R-squared	22.54%	28.83%

Table 9: Last month's labour income regressions, pooled BHPS data (base qualification: no qualification).

***: Statistically significant at the 1% level; **: 5% level; *: 10% level.

References

- [1] Arellano, M. and Bond, S. (1991). ‘Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations’, *Review of Economic Studies*, vol. 58(2), pp. 277–297.
- [2] Bingley, P. and Walker, I. (2001). ‘Household Unemployment and the Labour Supply of Married Women’, *Economica*, vol. 68(270), pp. 157–185.
- [3] Blau, D. M. (1998). ‘Labor Force Dynamics of Older Married Couples’, *Journal of Labor Economics*, vol. 16(3), pp. 595–629.
- [4] Bound, J. (1991). ‘Self-Reported Versus Objective Measures of Health in Retirement Models’, *Journal of Human Resources*, vol. 26(1), pp. 106–138.
- [5] Campbell, N. (1999). ‘The Decline of Employment Among Older People in Britain’, CASEpaper CASE/19, London: Centre for Analysis of Social Exclusion, London School of Economics and Political Science.
- [6] Disney, R. and Hawkes, D. (2003). ‘Declining employment of older workers: has Britain turned the corner?’, mimeo, London: Institute for Fiscal Studies.
- [7] Gustman, A. L. and Steinmeier, T. L. (2004). ‘Social security, pensions and retirement behaviour within the family’, *Journal of Applied Econometrics*, vol. 19(6), pp. 723–737.
- [8] Haardt, D. (2006). ‘Transitions out of and back to employment among older men and women in the UK’, ISER Working Paper 2006-20, Colchester: University of Essex.
- [9] Haurin, D. R. (1989). ‘Women’s Labor Market Reactions to Family Disruptions’, *Review of Economics and Statistics*, vol. 71(1), pp. 54–61.
- [10] McGinnity, F. (2002). ‘The labour-force participation of the wives of unemployed men: Comparing Britain and West Germany using longitudinal data’, *European Sociological Review*, vol. 18(4), pp. 473–488.
- [11] OECD (2000). *Reforms for an Ageing Society*, Paris: Organisation for Economic Co-operation and Development.
- [12] Taylor, M. F. (ed.) with Brice, J., Buck, N., and Prentice-Lane, E. (2005). *British Household Panel Survey User Manual Volume A: Introduction, Technical Report and Appendices*, Colchester: University of Essex. Internet: <http://www.iser.essex.ac.uk/ulsc/bhps/doc/vola/>

- [13] Weiss, Y. and Willis, R. J. (1997). ‘Match Quality, New Information, and Marital Dissolution’, *Journal of Labor Economics*, vol. 15(1), pt. 2, pp. S293–S329.