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ABSTRACT

The Predictive Value of Subjective Labour Supply Data: A Dynamic Panel Data Model with Measurement Error*

This paper tests the predictive value of subjective labour supply data for adjustments in working hours over time. The idea is that if subjective labour supply data help to predict next year's working hours, such data must contain at least some information on individual labour supply preferences. This informational content can be crucial to identify models of labour supply. Furthermore, it can be crucial to investigate the need for, or, alternatively, the support for laws and collective agreements on working hours flexibility. In this paper I apply dynamic panel data models that allow for measurement error. I find evidence for the predictive power of subjective labour supply data concerning desired working hours in the German Socio-Economic Panel 1988-1996.

JEL Classification: C23, J22

Keywords: Labour supply, subjective data, measurement error, dynamic panel data models

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1. Introduction

This paper aims at testing the predictive value of subjective labour supply data for adjustments in working hours over time. The idea is that if subjective labour supply data help to predict next year's working hours, such data must contain at least some information on individual labour supply preferences. This informational content can be crucial to identify models of labour supply. Furthermore it can be crucial to investigate the need for, or, alternatively, the support for laws and collective agreements on working hours flexibility. To test the predictive value, I apply panel data models that account for measurement error.

In the mainstream economic literature empirical strategies are typically based on the idea that statistical inference should be based on 'revealed preferences', i.e. on 'realised behaviour'. This methodology is built on the general belief of (most) economists that it is only then that individuals have to reveal their true preferences. However, in several fields of economics it has become clear that only the informational content of realised behaviour can be limited to identify individual preferences. The use of subjective data is then an alternative methodology for applications with identification problems.[2] Subjective labour supply data can, for instance, be helpful to identify individual labour supply preferences. In an early example of this methodology, Ham (1982) uses subjective data on constraints on working hours in the Michigan Panel Study of Income Dynamics to identify a labour supply model with underemployment. His approach is followed and extended by many authors, including Ilmakunnas and Pudney (1990), Kahn and Lang (1991), Stewart and Swaffield (1997), and Euwals and Van Soest (1999). Another example for the use of subjective labour supply data (which is, however, less frequently published in the international literature) is the investigation of the need for and/or the support for laws and collective agreements on working hours flexibility. Examples, using the same data source as this study, are, for instance, Hunt (1998), Bell and Freeman (2000), and Pannenberg and Wagner (2001).

Whatever the reason is for subjective data being used – one should always investigate how credible the data really are. A way of testing their informational content is to test their predictive value.[3] In this paper I examine whether subjective data on desired working hours have predictive power for next year's working hours, conditional on this year's working hours. Since the data source for this

[2] For more extensive arguments favouring this idea, see, for instance, Manski (2000) and Kapteyn and Kooreman (1992).

[3] See Juster (1966) for an early and influential study using this idea. He finds no predictive power for subjective data on buying intentions in the US Survey on Consumer Finances.

study – the German Socio-Economic Panel (GSOEP) – provides subjective labour supply data over a long time period I will use panel data techniques. An advantage of these techniques is that they allow for the incorporation of measurement error in observed variables.[4]

The remainder of the paper is organised as follows: Section 2 discusses the labour supply data that are available in the GSOEP. Section 3 introduces the analytical framework for testing the predictive value of subjective labour supply data. Next, Section 4 presents descriptive statistics of the data, while Section 5 presents estimation results. Section 6 concludes.

[Insert Table 1 about here]

2. Survey Questions

The data source of this study is the German Socio-Economic Panel (GSOEP), which is a nationally representative annual panel on the household level. The first wave was conducted in 1984, and it is currently still running. Data on individual working time are collected on a yearly basis using the same questions in every year since 1988, which obviously facilitates a panel data analysis. The question concerning the subjective labour supply data was not conducted in the first year of the panel, 1984, nor was it conducted in 1996. Since the data of the year 1996 are useful for observing adjustments in actual working hours over time, this study uses the data from 1988 to 1996.

For the interpretation of the results a good understanding of the data on working time is crucial. This section presents the survey questions on actual and desired working time. Questions (1) to (3) of Table 1 concern the questions on actual working hours. The answers to these three questions by individual i at time t are denoted by contractual working hours hc_{it}, total working hours ht_{it}, and the overtime rule or_{it}. Due to the increasing popularity of working time accounts, compensation of over-time in a certain period with extra time off in another period is quite common in Germany. In the data used for this study the percentage of men and women that are compensated by extra time off (answer 'B') increased from 22% and 30%, respectively, in 1988 to 34% and 45% in 1996. Furthermore the percentage of men and women that are partly paid and partly compensated by extra time off (answer 'C') increased from 11% and 7%, respectively, in 1988 to 17% and 10% in 1996.

4 This is an improvement over Euwals *et al.* (1998), where the time-period covered by the data was too short for such an approach.

The answer to question (4) of Table 1 by individual *i* at time *t* is denoted by desired working hours hd_{it}. Comparing this question to questions (1) to (3) shows that a comparison of desired working hours hd_{it} to the outcomes on actual working hours is not straightforward: It is not clear for which outcome the desired working hours hd_{it} should have predictive value. One interpretation of question (4) is that due to the explicit reference to a budget constraint ("…considering analogous changes of your labour income…"), desired working hours hd_{it} refer to the paid part of working hours only. On the other hand, respondents might take into account that certain pecuniary rewards (like bonus payments and promotions) partly depend on unpaid overtime, which means desired working hours hd_{it} relate to total – paid and unpaid – actual working hours. The references of Section 1 that use the same data source all stick to the latter interpretation. But to facilitate this concern I will define two kinds of outcome variables on actual working hours: total actual hours ht_{it}, which are observed, and paid actual hours hp_{it}. The measurement of paid actual hours is somewhat problematic as choice 'C' of question (3) does not state how much of the overtime is paid. I use the following approximation:

$$(1) \qquad hp_{it} = hc_{it} + I(\, or_{it} = \text{'A'}) \, (ht_{it} - hc_{it}) + \tfrac{1}{2} \, I(\, or_{it} = \text{'C'}) \, (ht_{it} - hc_{it})$$

with $I(\, or_{it} = \text{'A'})$ an indicator function for individual *i* at time *t* giving answer 'A' to the question on the overtime rule. In case of answer 'C' I assume that half of the overtime is paid.

3. Panel Data Models with Measurement Error

In this section we formulate an empirical model that is able to test the predictive value of subjective labour supply data, and that explicitly allows for measurement error in observed variables. We develop an estimation procedure for the model by using the literature on dynamic panel data models where measurement error can be incorporated by exploiting the time-dimension of the panel data. The underlying idea, and crucial assumption, is that measurement error is uncorrelated over time so that variables of time periods other than the time period of interest can be used as instruments. See Griliches and Hausman (1986) for an early example exploiting this idea, and see Wansbeek (2001) for a recent example.

The next subsection formulates an empirical model that explains actual working hours from lagged actual and lagged desired working hours. For reasons discussed later, the second subsection formulates an empirical model that explains the adjustment in actual working hours over time from the lagged deviation between desired and actual working hours.

3.1 A Dynamic Panel Data Model with Measurement Error

We specify an empirical model to explain actual working hours by lagged actual and lagged desired working hours. Define ha_{it}^* as the true actual working hours (i.e. true total working hours ht_{it}^* or true paid working hours hp_{it}^*) of individual *i* at time *t*, and hd_{it}^* as the true desired working hours of individual *i* at time *t*. Define the following model:

$$(2) \qquad ha_{it}^* = \beta_0 + \beta_1\, ha_{it-1}^* + \beta_2\, hd_{it-1}^* + \varepsilon_i + \varepsilon_{it}$$

with ε_{it} an idiosyncratic error term, which we assume to be uncorrelated over time, and ε_i an individual specific error term.[5] Note that the error terms relate to true actual working hours, and have nothing to do with measurement error. For example, the individual specific error term might partly represent individual specific effects in labour supply preferences where certain individuals might prefer to work more hours than other individuals. For our test on the predictive value of the subjective labour supply data concerning desired working hours, the parameter of interest is β_2. The null hypothesis of the test is $\beta_2=0$, which means that there is no predictive value. The alternative hypothesis is $\beta_2>0$, which means there is predictive value in a way that is economically interpretable as individuals adjust their actual working hours into the preferred direction.

Note that the empirical model does not include individual labour supply characteristics, like family characteristics, observed at time *t-1*. The reason is that we expect these characteristics to have an impact on true actual working hours ha_{it}^* through lagged true desired working hours hd_{it-1}^* only. Therefore incorporation of these characteristics would need a structural simultaneous equations model in which these characteristics explain the true desired working hours hd_{it-1}^*. As it is not a goal to explain individual labour supply preferences, this is beyond the scope of this study.[6]

The idea behind the formulation of the model in terms of true actual and desired working hours is that observed actual and desired hours might be contaminated with measurement error. I define the relation between true actual and desired working hours (ha_{it}^*, hd_{it}^*) and observed actual and desired working hours (ha_{it}, hd_{it}) as follows:

$$(3) \qquad ha_{it} = ha_{it}^* + v_i^a + v_{it}^a$$

$$(4) \qquad hd_{it} = hd_{it}^* + v_i^d + v_{it}^d$$

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[5] We will allow the constant term to be time-specific, which is easy to incorporate. See, for instance, Arrelano and Bond (1991).

[6] See Euwals (2001) for a structural simultanous equations model that incorporates adjustments in actual working hours over time and labour supply, and that is estimated on the basis of the Dutch Socio-Economic Panel.

with (v_{it}^a, v_{it}^d) idiosyncratic error terms, which we assume to be uncorrelated over time, and (v_i^a, v_i^d) individual specific error terms. The interpretation of these error terms is purely measurement error, whereby the individual specific error terms allow for systematic (time-constant) over- or under-reporting of individual i. Substitution of equations *(3)* and *(4)* in equation *(2)* yields:

$$(5) \qquad ha_{it} = \beta_0 + \beta_1\, ha_{it-1} + \beta_2\, hd_{it-1} + (\varepsilon_i + (1-\beta_1)\, v_i^a - \beta_2\, v_i^d) + (\varepsilon_{it} + v_{it}^a) - (\beta_1\, v_{it-1}^a + \beta_2\, v_{it-1}^d)$$

The resulting model is a dynamic panel data model with some non-standard properties due to the error structure. Like in the standard dynamic panel data model the lagged dependent variable ha_{it-1} is endogenous. The solution offered by the literature is an instrumental variables approach within a Generalized Method of Moments (GMM) estimation procedure. A particular advantage of this method is that distributional assumptions are not needed.

As the observed actual and desired working hours of all time periods depend on individual specific error terms, the first task is to get rid of these individual specific error terms. The common solution is to take the first difference over time:

$$(6) \qquad ha_{it} - ha_{it-1} = \beta_1\, (ha_{it-1} - ha_{it-2}) + \beta_2\, (hd_{it-1} - hd_{it-2})$$
$$+ (\varepsilon_{it} - \varepsilon_{it-1}) + (v_{it}^a - v_{it-1}^a) - \beta_1\, (v_{it-1}^a - v_{it-2}^a) - \beta_2\, (v_{it-1}^d - v_{it-2}^d)$$

As we assume all error terms to be uncorrelated over time, serial correlation in the residuals of this model will only be due to lagged error terms. Now the literature proposes the two-times lagged dependent variable ha_{it-2} as an instrument for $(ha_{it-1} - ha_{it-2})$. And indeed is this variable uncorrelated with the error-term $(\varepsilon_{it} - \varepsilon_{it-1})$. But the measurement error causes an additional endogeneity problem: ha_{it-2} is correlated with v_{it-2}^a. Valid instruments are only obtained by using dependent variables that are at least three-times lagged, for instance ha_{it-3}. Notice that the observed desired working hours are endogenous as well, and that the three-times lagged variable hd_{it-3} is a valid instrument.

The goal is to get a consistent estimator for $\beta=[\beta_1, \beta_2]'$. Deriving an estimator that is efficient as possible by using all valid moment restrictions is beyond the scope of the paper.[7] Instead, we will follow the convenient and intuitively clear approach of Arellano and Bond (1991), which uses all valid lagged variables as instruments. First, define $\Delta ha=ha-ha_{-1}$ as a vector of first differences over time of the actual working hours stacked for individuals $i=1,\dots,N$ and time $t=1,\dots,T$. The size of the vector is $N(T-3)$ because for each individual the first three outcomes of the actual working hours cannot be used. Then define a matrix of instruments Z, which contains sufficiently lagged variables for (ha_{it-1}, hd_{it-1}) again stacked for individuals $i=1,\ldots,N$ and time $t=1,\ldots,T$. The size of this matrix is $N(T-3) \times (T-3)(T-2)$. The GMM estimator takes the following form:

$$(7) \qquad \beta_{GMM} = ([\Delta ha_{-1}, \Delta hd_{-1}]' Z\, W_N\, Z'[\Delta ha_{-1}, \Delta hd_{-1}])^{-1} ([\Delta ha_{-1}, \Delta hd_{-1}]' Z\, W_N\, Z' \Delta ha)$$

with W_N some weighting matrix. For details on the estimation procedure, and in particular on the relation to Arellano and Bond (1991), see Appendix A.

3.2 A Restricted Panel Data Model with Measurement Error

A disadvantage of the model of Subsection 3.1 is that it is very unrestrictive in the sense that even the predictive value of lagged actual working hours ha_{it-1}^* might be low. Especially in the case that the individual specific effects ε_i absorb a large part of the variation in actual working hours ha_{it}^*, this might very well happen.

Another interesting test on the predictive value of subjective labour supply data concerning desired working hours is based on the idea that the lagged deviation between desired and actual working hours $(hd_{it-1}^* - ha_{it-1}^*)$ might have predictive value for the adjustment of actual working hours over time $(ha_{it}^* - ha_{it-1}^*)$. So where the model of Subsection 3.1 considers the predictive value of desired working hours for the *level* of actual working hours, the model of this subsection considers the predictive value for *adjustments* in actual working hours over time. We define the model as follows:

$$(8) \qquad ha_{it}^* - ha_{it-1}^* = \beta_0 + \beta_2 (hd_{it-1}^* - ha_{it-1}^*) + \varepsilon_{it}$$

Note that the model does not include an individual specific effect at this level, as that would imply a constant rise or fall in the actual working hours of individual i. A way to achieve the model from the model of Subsection 3.1 is by imposing the restriction $\beta_1+\beta_2=1$, and by eliminating the individual specific effect ε_i. An interpretation of the restriction on the parameters is that it forces the model to 'distribute' the predictive value between the lagged actual and lagged desired working hours, as the actual working hours are weighted average of these two variables. The time-specific constant term allows for general upward and downward trends in actual working hours.

Now incorporation of measurement error (see equations *(3)* and *(4)*) leads to:

$$(9) \qquad ha_{it} - ha_{it-1} = \beta_0 + \beta_2 (hd_{it-1} - ha_{it-1}) - \beta_2 (v_i^d - v_i^a) + \varepsilon_{it} + (v_{it}^a - v_{it-1}^a) - \beta_2 (v_{it-1}^d - v_{it-1}^a)$$

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[7] See Baltagi (1995) for an overview of the literature on dynamic panel data models.

The model is not dynamic in the sense that it contains a lagged dependent variable. But due to the individual specific error terms that relate to measurement error, the model has an endogeneity problem that is similar to the one of the dynamic panel data model. Take first-differences over time, and define $\Delta ha_{it}=ha_{it}-ha_{it-1}$:

$$(10) \quad \Delta ha_{it} - \Delta ha_{it-1} = \beta_2 \left((hd_{it-1} - ha_{it-1}) - (hd_{it-2} - ha_{it-2}) \right) + (\varepsilon_{it} - \varepsilon_{it-1})$$
$$+ \left((v_{it}^{a} - v_{it-1}^{a}) - (v_{it-1}^{a} - v_{it-2}^{a}) \right) - \beta_2 \left((v_{it-1}^{d} - v_{it-1}^{a}) - (v_{it-2}^{d} - v_{it-2}^{a}) \right)$$

As we assume the error terms to be uncorrelated over time, serial correlation in the residuals of this model will be due to lagged error terms. In the case of no measurement error, two-times lagged variables (ha_{it-2}, hd_{it-2}) are valid instruments. An estimation procedure using all variables that are at least two-times lagged is similar to the one proposed by Arellano and Bond (1991). But the presence of measurement error makes two-times lagged variables invalid instruments. Instruments therefore have to be at least three-times lagged. The estimation procedure for this model is similar to the one described in Subsection 3.1, and we will not go into details here.

[Insert Table 2 and Figures 1.A and 1.B about here]

4. Data

From the GSOEP I select all employed individuals between ages 18 and 60 old that belong to a West-German household where the household head does not belong to a foreigner group[8] for all waves from 1988 to 1996. The selected sample includes employed individuals with valid data for at least 4 subsequent years.[9] Individuals that have invalid data on desired working hours in the fourth or a later year are maintained in the sample because they give an observed outcome on the actual working hours for that year.

Table 2 shows the sample statistics. For men there is a clear downward trend in paid working hours, which is consistent with the spreading of working time reductions and time accounts over the different sectors of the economy in these years. However, total working hours seem to be unaffected by this decline. For women, the developments are straightforward: There is a downward trend in

[8] Households with a household head belonging to a foreigner group are oversampled in the GSOEP, and we exclude them to avoid weighting.
[9] We ignore selection into and out-of employment, as incorporation would need a model with stronger assumptions.

total, paid and desired working hours. This is due in part to working time reductions and in part to the increasing incidence of part-time employment. Figures 1.A and 1.B show the distribution of actual and desired working hours. Clearly observable from these figures is the importance of working time reductions: the number of men working about 36 hours per week increased substantially between 1988 and 1995. Remarkably, the number of men that want long working hours (more than 40 hours per week) increased slightly between 1988 and 1995. For women the figures are much more diversified as a substantial fraction of women works part-time. Still, Figure 1.B expresses some lack of part-time jobs; especially the 'demand' for jobs of about 28 hours is substantially larger than the availability.

Table 3 gives a descriptive answer on whether for all years pooled the subjective data on desired working hours have predictive value for the next year's actual working hours. Individuals who have a wish to work fewer (more) hours have a relatively large probability to work fewer (more) hours the next year. However, it is hard to tell whether the total or the paid hours are better predicted by the desired hours. One measure for the success of prediction is the weighted percentage on the diagonal: With 41.9% of the observations on paid hours on the diagonal for men, the prediction is somewhat better than for total hours with 41.6%. For women, the prediction of total hours is better with 44.0% against 42.1%. However, drawing conclusions from Table 3 might be premature: Say that for individual *i* at time *t-1* the actual working hours are too low due to measurement error. Then we are likely to observe that the individual (1) wants to work more hours at time *t-1*, and (2) does work more at time *t*. This spurious correlation may contaminate Table 3 substantially, and that is exactly the reason why we need to apply a dynamic panel data model with instruments that are sufficiently lagged.

[Insert Table 3]

5. Estimation Results

Besides estimation results for the method described in Section 3, this section presents results for simpler methods like Ordinary Least Squares. The reason is that under a number of restrictive assumptions, simpler methods lead to consistent and efficient estimators. In the remainder, all reported estimation results of GMM-methods concern second step results.[10]

[10] The first step estimation results would lead to the same conclusions in a qualitative sense.

5.1 Results for the Dynamic Panel Data Model with Measurement Error

Table 4.A reports estimation results for men, while Table 4.B reports estimation results for women. The Tables first report Ordinary Least Squares (LEV-OLS) results for the model in levels (equation *(5)*). Note that in the case of absent individual effects and measurement error the method delivers a consistent and efficient estimator. Next, to account for measurement error in the levels-equation, the Tables report results of an instrumental variables approach that uses all at least two-times lagged variables as instruments (LEV-ME). Equation *(5)* shows that in the case of no individual specific effects these variables are valid instruments. Then to account for individual specific effects, the last three columns report results for the model in first differences over time (equation *(6)*). Besides the within group estimator for the fixed effect model (DIF-FE), results for the method proposed by Arellano and Bond (DIF-AB) are reported. Moreover, the Tables report results for the method that takes measurement error into account by using all variables that are at least three-times lagged as instruments (DIF-ME). This method is the only one that delivers a consistent estimator under the most general assumptions of this study.

Table 4.A shows that for men desired working hours have no predictive value for actual – total and paid – working hours. First, the LEV-OLS results show a significantly positive impact of desired working hours, see the parameter estimate for β_2 for both total and paid hours. That implies a predictive value of desired working hours. Now in the case of measurement error, but no individual specific effects, the model in levels (equation *(5)*) includes the error terms v_{it}^{a} and $-\beta_1 v_{it-1}^{a}$, so that the first-order serial correlation of the residual should be negative. The significantly negative test-statistic for first-order serial correlation for both total and paid hours is therefore in line with measurement error in actual working hours. This means that the LEV-OLS estimator is inconsistent. Next, the correction for measurement error (LEV-ME) leads to an insignificant impact of desired working hours, as the parameter estimate for β_2 is not significantly different from zero. The significantly negative test-statistic for first-order serial correlation is again in line with measurement error in actual working hours. As in the case of measurement error the model does not include an error term that relates to time-period *t-2*, there should be no second-order serial correlation present in the residuals of the model. This hypothesis gets accepted (in contrast to the LEV-OLS results), which implies that we accept the hypothesis that the measurement error is uncorrelated over time. So in the case that the assumption of no individual specific effect would be correct, the LEV-ME estimator is consistent and we find no evidence for a predictive value of the desired working hours.

[Insert Tables 4.A and 4.B about here]

For the model in first differences over time, the fixed effect results (DIF-FE) show a significantly positive impact of desired working hours for both total and paid hours. Next, accounting for the endogeneity of lagged actual working hours (DIF-AB) leads to an insignificant impact of desired working hours. The lack of second-order serial correlation in the residuals of the model in first-differences, see the insignificant test-statistic for second-order serial correlation, implies that two-times lagged variables are valid instruments (see Arellano and Bond (1991) for the interpretation of this test). But incorporation of measurement error into the model implies that the first-difference equation (equation *(6)*) includes measurement error terms v_{it}^{a} and $\beta_1\, v_{it-2}^{a}$. And that should lead to a positive second-order serial correlation in the residuals of the first-difference equation. Thus the insignificant test-statistic for second-order serial correlation for total and paid hours surprisingly implies an absence of measurement error in actual working hours. As the Sargan test accepts the hypothesis that the model is not over-identified, the results according to DIF-AB are satisfactory! We nevertheless consider the results correcting for measurement error (DIF-ME). For total hours, this method leads to a significantly *negative* impact of desired working hours, see the parameter estimate for β_2. As the test-statistic for second-order serial correlation is insignificant, there is no evidence for measurement error in actual working hours. Overall, the results for the different estimation methods are contradictory, and we have to conclude that for men there is no evidence for a predictive value of subjective labour supply data (unless one believes the results of LEV-OLS).

Table 4.B shows that the estimation results are also contradictory for women. The LEV-OLS results give a significantly positive impact of desired working hours, see the parameter estimate for β_2 for both total and paid hours. The significantly negative test-statistic for first-order serial correlation and the insignificant test-statistic for second-order serial correlation are in line with measurement error in actual working hours that is uncorrelated over time (see equation *(5)* and paragraph 2 of this Subsection). Taking measurement error into account (LEV-ME) leads to nice results for both total and paid working hours: the desired working hours have a significantly positive impact, the test-statistic for first-order serial correlation is significantly negative, the test-statistic for second-order serial correlation is insignificant, and the Sargan test does not reject the model specification. From these results one would conclude that there is measurement error in actual working hours, and that after accounting for it there is still evidence for a predictive value of the desired working hours.

For the model in first differences, fixed effects results (DIF-FE) give a significantly positive impact of desired working hours for total hours, but not for paid hours. Correcting for the endogeneity of the lagged dependent variable (DIF-AB) leads to disappointing results: The impact of the desired working hours is insignificant, as the parameter estimate for β_2 is not significantly different from zero for both total and paid hours. The test-statistic on second-order serial correlation is not significantly different from zero, which implies that we find no evidence for measurement error in actual working hours (see equation *(6)* and paragraph 3 of this Subsection). So also for women the results according to the method DIF-AB are satisfactory, leading to the conclusion that there is no predictive value of the desired working hours. We nevertheless consider the results correcting for measurement error (DIF-ME), but that does not alter the conclusions: again the impact of the desired working hours is insignificant, and again the test-statistics on serial correlation hint at an absence of measurement error in actual working hours.

In the case of no individual specific effects, and depending on the presence of measurement error, one of the estimators according to the methods for the model in levels is consistent and efficient. Despite the contradictory results for women we might therefore still be able to conclude that desired working hours have a predictive value due to the significant results for the model in levels (see equation *(5)*). The question is whether individual specific effects are indeed absent. In that case, assuming that there is measurement error, the method DIF-ME delivers a consistent but inefficient estimator. Thus it is possible to apply a Hausman test. Unfortunately, a simple look at the parameter estimates and standard errors for LEV-ME and DIF-ME already shows that they are very different. The Hausman test confirms this for both total and paid hours by rejecting the null hypothesis of equality (realizations are 24.0 for total hours and 75.6 for paid hours with both a χ^2-distribution with 2 DF). The results according to LEV-ME are therefore invalid. For women, we have to conclude there is no evidence for a predictive value of subjective labour supply data either.

[Insert Tables 5.A and 5.B about here]

5.2 Results for the Restricted Panel Data Model with Measurement Error

For the model that explains the *level* of actual working hours, we find no evidence for a predictive value of the subjective labour supply data. But a remarkable result is that the parameter estimates for β_1 are low for the models that correct for individual specific effects. As we expect lagged actual working hours to be a strong predictor for current actual working hours, a parameter estimate close to one would seem more reasonable. The individual specific effects, however, explain away a major part of the variation in actual working hours. This leaves a minor role for the lagged actual working hours. Subsection 3.2 discusses this problem and proposes an empirical model that explains the *adjustments* of actual working hours over time. Subsection 5.2 reports and discusses the estimation results for the model in levels (see equation *(9)*) and for the model in first-differences over time (see equation *(10)*). Table 5.A and 5.B report the estimation results for men and women, respectively.

The level-equation results of Table 5.A lead to the conclusion that desired working hours have a predictive value. The method that accounts for measurement error (LEV-ME) gives a significantly positive parameter of interest (β_2) for both total and paid hours, which means that the subjective data have predictive value for adjustments in actual working hours over time. In the case of measurement error, but no individual specific effects, the model in levels (equation *(9)*) includes the error terms v_{it}^a and $-(1-\beta_2)v_{it-1}^a$, so that the first-order serial correlation of the residual should be negative. The significantly negative test-statistic for first-order serial correlation is therefore in line with measurement error in actual working hours. As the model does not include an error term that relates to time-period *t-2*, and as we assume that the measurement error is uncorrelated over time, there should be no second-order serial correlation present in the residuals of the model. The second-order serial correlation test accepts this hypothesis for both total and paid hours. So in the case that the assumption of no individual specific effect would be correct, we find evidence for a predictive value of the subjective labour supply data.

The first-difference equation results of Table 5.A are, however, less clear. For the method that accounts for measurement error (DIF-ME) the parameter of interest (β_2) is insignificantly different from zero for both total and paid hours. But a presence of measurement error would imply that the model in first-differences (equation *(10)*) includes measurement error terms v_{it}^a and $(1-\beta_1)v_{it-2}^a$. That should lead to a positive second-order serial correlation in the residuals of the first-difference equation. The significantly negative test-statistic for second-order serial correlation for both total and paid hours thus gives clear evidence for measurement error in actual working hours. The contradictory results for the model in levels and the model in first-differences over time lead to the question whether individual specific effects are present. Assuming the presence of measurement error, Hausman tests for the absence of individual specific effects on the basis of the parameter estimates and standard errors for LEV-ME and DIF-ME accept the null hypothesis (realizations are

0.09 for total hours and 0.04 for paid hours with both a χ^2-distribution with 1 DF). The estimators according to LEV-ME are therefore consistent and efficient, and we do find evidence that the subjective data concerning desired working hours have predictive value.

Table 5.B shows that the estimation results for women are even better than for men. For the level-equation results (LEV-OLS, LEV-ME) the parameter of interest *(β_2)* is significantly positive for both total and paid hours. The outcomes of the test-statistics on first-order and second-order serial correlation are in line with measurement error in actual working hours that is uncorrelated over time (see equation *(9)* and paragraph 2 of this Subsection). Next, on the basis of the first-difference equation results (DIF-BA, DIF-ME) we can draw the same conclusion: The parameter of interest *(β_2)* is significantly positive parameter for both total and paid hours, and the outcomes of the test-statistics on serial correlation are in line with measurement error in actual working hours. So on the basis of these results we can conclude that we find evidence for measurement error in actual working hours, and that after accounting for this measurement error there is evidence for a predictive power of the subjective labour supply data concerning desired working hours. Next, note that individual specific effects in this model for adjustments in actual working hours over time purely have an interpretation of measurement error (equation *(8)* does not include an individual specific effect). Now Hausman tests on the basis of the parameter estimates and standard errors for LEV-ME and DIF-ME lead to an interesting result: For total working hours there is no evidence for individual specific effects, while for paid working hours we do find evidence for individual specific effects (realizations are 2.32 for total hours and 9.28 for paid hours with both a χ^2-distribution with 1 DF). This is in line with the measurement problem that we have for paid working, as this clearly allows for systematic measurement error on the individual level (see equation *(1)* of Section 2).

Given the nice estimation results for the model for the adjustment of actual working hours over time, a remaining question is whether the predictive value is better for total or for paid hours. One way to evaluate this is by looking at the size of the parameter of interest *(β_2),* whereby for the interpretation we should not forget that the degree of adjustment also depends on existing restrictions on working hours. For men, we find that the parameter estimates for total and paid hours according to LEV-ME of Table 5.A are not significantly different. As these were the most credible results, for men we clearly find no evidence on this issue. For women, we find that the parameter estimates for total and paid hours according to DIF-ME of Table 5.B are also not significantly different. As for total hours we found no evidence for individual specific effects, the estimation result according to LEV-ME might also be used. In that case we do find that the parameter estimate for paid hours according to DIF-ME is significantly larger than the parameter estimate for total hours according to LEV-ME. So we find some evidence that for women the predictive value of desired working hours is better for paid hours than for total working hours.

6. Conclusions

This paper tests the predictive value of subjective labour supply data for adjustments in working hours over time. The idea is that if subjective labour supply data help to predict next year's working hours, such data must contain at least some information on individual labour supply preferences. This informational content is crucial to identify models of labour supply. Furthermore it is crucial to investigate the need for, or, alternatively, the support for laws and collective agreements on working hours flexibility.

The paper uses two panel data models that both account for measurement error. The first model is a dynamic panel data model explaining the *level* of actual working hours from lagged actual and lagged desired working hours. The second model explains the *adjustments* in actual working hours over time from the lagged difference between desired and actual working hours. The paper applies the GMM estimator proposed by Arellano and Bond (1991), whereby measurement error in observed variables is taken into account by using sufficiently lagged variables as instruments.

The German Socio-Economic Panel 1988-1996 yields the following results: Conditional on lagged actual working hours, *lagged desired working hours* have *no predictive value* for the *level of the actual working hours*. The explanation is that individual specific effects explain a major part of the variation in actual working hours, leaving little explanatory power for both lagged actual and lagged desired working hours. However, according to the results of the second model, *lagged desired working hours* have *predictive value* for *adjustments in actual working hours over time*. We find evidence that for women the predictive value is somewhat better for paid hours than for total hours.

The conclusion of this study is that subjective labour supply data concerning desired working hours have no added (or predictive) value in a panel data context that allows for individual specific effects. However, the subjective labour supply data on desired working hours can be used to analyse preferred adjustments in working hours over time.

Appendix A: GMM for a Dynamic Panel Data Model with Measurement Error

The error structure of the model of Subsection 3.1 is more complicated than the one of a standard dynamic panel data model. A more extensive discussion of the estimation procedure is therefore necessary. For convenience we first reformulate equation *(6)*:

(A.1) $ha_{it} - ha_{it-1} = \beta_1 (ha_{it-1} - ha_{it-2}) + \beta_2 (hd_{it-1} - hd_{it-2}) + (\eta_{it} - \eta_{it-1})$

with:

(A.2) $\eta_{it} = \varepsilon_{it} + v_{it}^{a} - \beta_1 v_{it-1}^{a} - \beta_2 v_{it-1}^{d}$

Due to the incorporation of measurement error, the two times lagged variables ha_{it-2} and hd_{it-2} are endogenous. Thus, the instruments have to be at least three-times lagged. Define a vector of first-differences error-terms for a general number of time-periods T, using an individual level notation: $\Delta\eta_i = [\eta_{i4} - \eta_{i3}, \ldots, \eta_{iT} - \eta_{iT-1}]'$. This vector is of size *(T-3)*. Then define a matrix of instruments Z_i being a block diagonal matrix whose *s*-th block is given by $[ha_{i1}, hd_{i1},\ldots, hd_{is}, hd_{is}]$. This matrix is of size $(T-3) \times (T-3)(T-2)$. Each row of the matrix Z_i contains the instruments that are valid for the given period. Consequently, the set of all moment conditions can be written as:

(A.3) $E\{ Z_i' \Delta\eta_i \} = 0$

or alternatively:

(A.4) $E\{ Z_i' (\Delta ha_i - \beta_1 \Delta ha_{i,-1} - \beta_2 \Delta hd_{i,-1}) \} = 0$

Pre-multiplying the differenced equation *(A.1)* in the vector form by Z_i' results in:

(A.5) $Z_i'(\Delta ha_i) = \beta_1 Z_i'(\Delta ha_{i,-1}) + \beta_2 Z_i'(\Delta hd_{i,-1}) + Z_i'(\Delta\eta_i)$

Define the vector of parameters $\beta = [\beta_1,\beta_2]'$ and drop the individual level notation by defining the matrix of instruments $Z = [Z_1',\ldots, Z_N']'$. This matrix is then of size $N(T-3) \times (T-3)(T-2)$. Define $\Delta ha=ha-ha_{-1}$ as a vector of size *N(T-3)* of first differences over time of actual hours stacked for individuals $i=1,\ldots,N$ and time $t=1,\ldots,T$. Then we get the model:

(A.8) $Z'(\Delta ha) = Z'[\Delta ha_{-1},\Delta hd_{-1}]\, \beta + Z'(\Delta\eta)$

The GMM-estimator is then given by:

(A.9) $\beta_{GMM} = ([\Delta ha_{-1},\Delta hd_{-1}]'Z\, W_N\, Z'[\Delta ha_{-1},\Delta hd_{-1}])^{-1} ([\Delta ha_{-1},\Delta hd_{-1}]'Z\, W_N\, Z'\Delta ha)$

where W_N is a positive definite weighting matrix. The properties of the estimator depend upon the choice for W_N, although it is consistent as long as this matrix is positive definite. The optimal weighting matrix, in the sense that it gives the smallest asymptotic covariance matrix for the GMM estimator, should satisfy:

$$(A.10)\quad plim_{N\to\infty} W_N = V\{ Z_i'(\Delta\eta_i) \}^{-1} = E\{ Z_i'(\Delta\eta_i)(\Delta\eta_i)' Z_i \}^{-1}$$

In the case where no restrictions are imposed upon the covariance matrix of η, this can be estimated using a first-step consistent estimator of β and replacing the expectation operator by a sample average. This gives:

$$(A.11)\quad W_N^{opt} = \{ (1/N) \textstyle\sum_{I=1,\ldots,N} Z_i'(\Delta\eta_i^r)(\Delta\eta_i^r)' Z_i \}^{-1}$$

where $\Delta\eta_i^r$ is the residual vector from a consistent first-step estimator. Notice that as no restrictions are imposed upon the covariance matrix of η, which allows for any covariance structure between the three error-terms (ε, v^a, v^d).

Define the variances $V(\varepsilon_{it})=\sigma^2_\varepsilon$, $V(v_{it}^a)=\sigma^2_a$, and $V(v_{it}^d)=\sigma^2_d$, and define H as a square matrix that has twos in the main diagonal, minus ones in the first sub-diagonals and zeros otherwise. Then in the case of no measurement error, the covariance matrix of the errors would be equal to $\sigma^2_\varepsilon H$, and a good choice for the first-round estimator would be $W_N=H$. Here we get another slight deviation from Arellano and Bond (1991): In the case of measurement error, the covariance matrix of the errors of equation (A.1) becomes $(\sigma^2_\varepsilon+(1+\beta_1^2\,\sigma^2_a)+\beta_2^2\sigma^2_d)H+\beta_1\sigma^2_aF$, with square matrix F with ones in the main diagonal, minus twos in the first sub-diagonals, ones in the second sub-diagonals, and zeros otherwise. As this covariance matrix depends on the parameters of interest, no optimal first-round estimator exists. As any full-rank weighting matrix gives a consistent first-round estimator, we will use matrix H for the first round.

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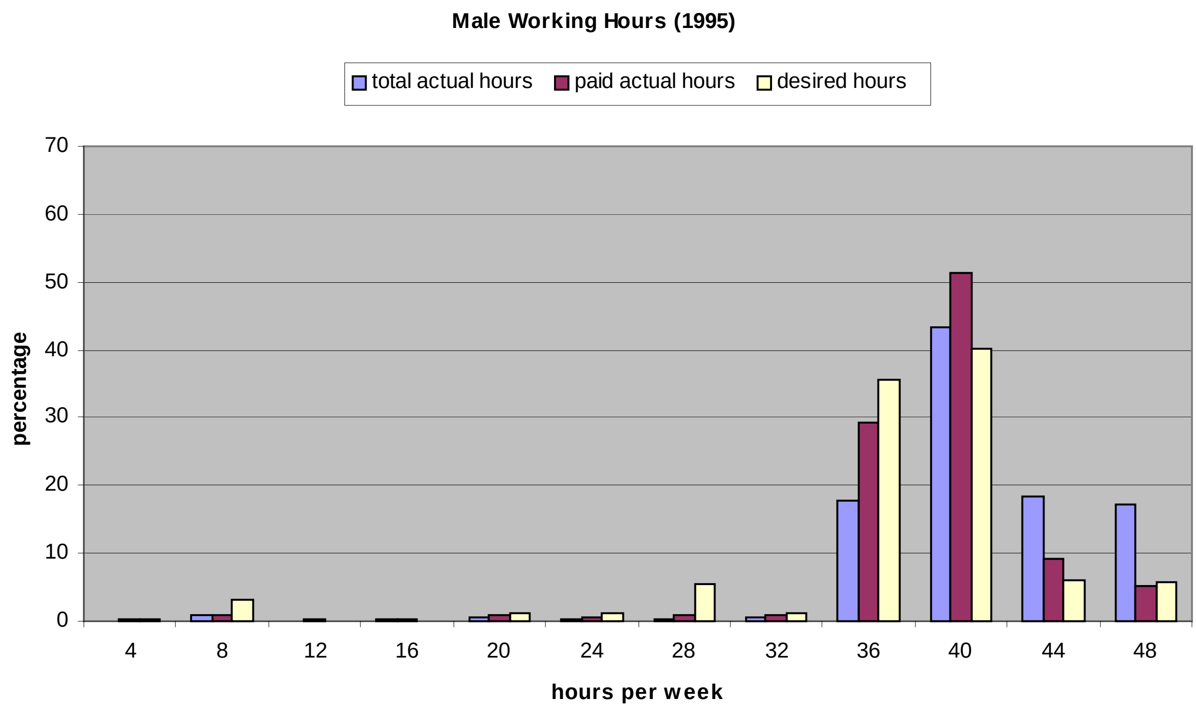
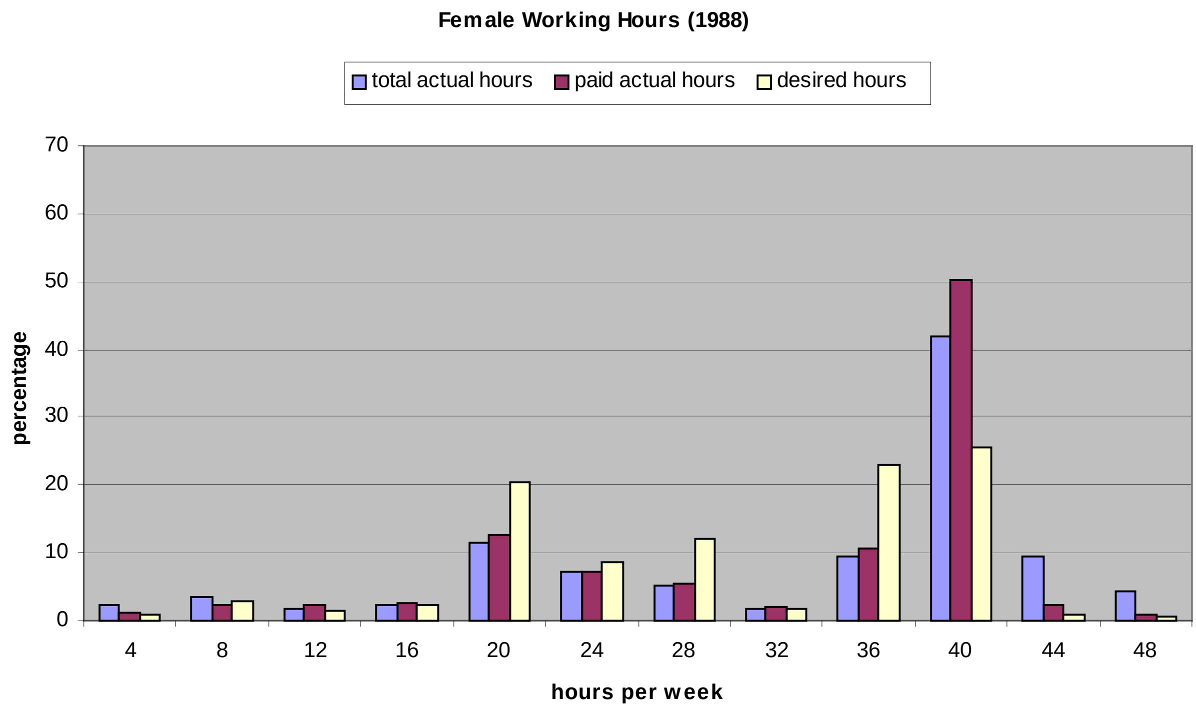
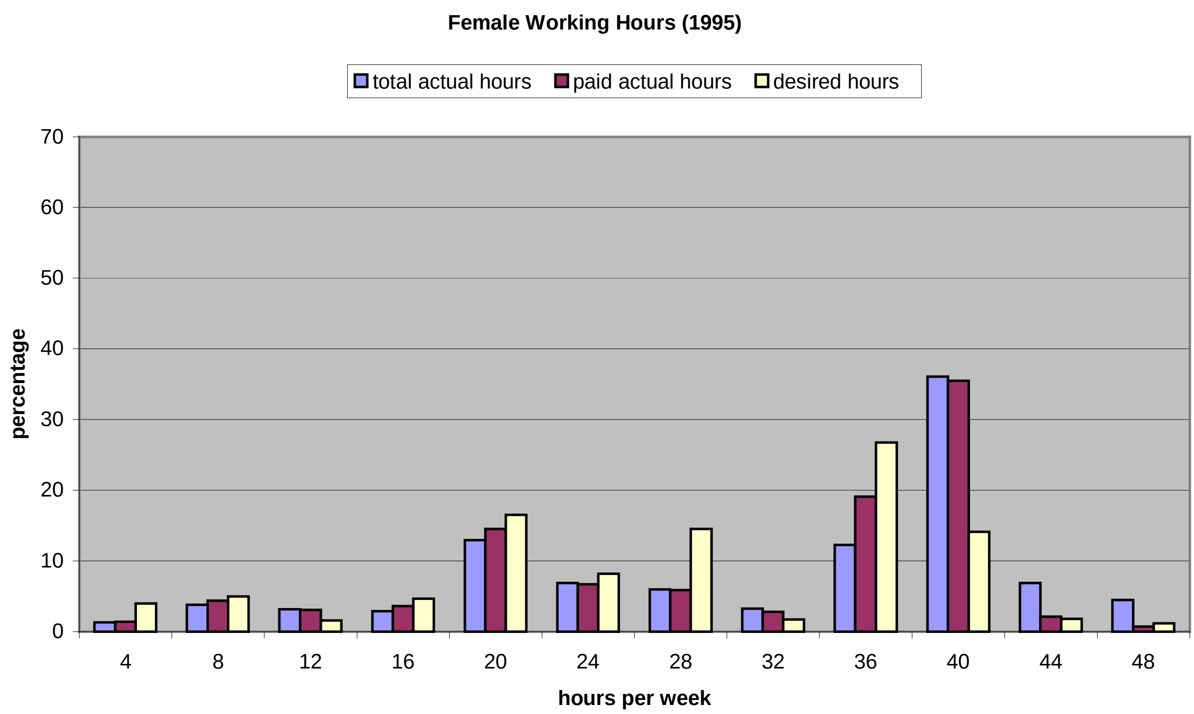
Figure 1.A: Male Working Hours



Note: Employed men, ages 18 to 60, with valid data on both actual and desired hours. Classification h: (h-1,h+2) except 4:(1,6) and 48:(47,80).

Figure 1.B: Female Working Hours





Note: Employed women, ages 18 to 60, with valid data on both actual and desired hours. Classification h: (h-1,h+2) except 4:(1,6) and 48:(47,80).

Table 1: Questions in the German Socio-Economic Panel

No.	Question	Variable
(1)	What is the average amount of your contracted working hours (excluding overtime)?	
	Answer in hours per week	→ hc_{it}
(2)	What is the average amount of your total working hours including possible overtime?	
	Answer in hours per week	→ ht_{it}
(3)	In case you do work overtime: Do you get paid, do you get compensated by extra time off at another time, or do you not get compensated at all?	
	Possible answers: (A) Paid; (B) Compensated by extra time off; (C) Partly paid, partly compensated by extra time off; (D) Not compensated at all.	→ or_{it}
(4)	If you could choose the extent of your working hours by yourself, considering analogous changes of your labour income: What is the amount of your desired working hours?	
	Answer in hours per week	→ hd_{it}

Table 2: Sample Statistics

	Men				Women			
year	#obs.	Total hours	Paid hours	Desired hours	#obs.	Total hours	Paid hours	Desired hours
1988	1967	41.72	40.28	38.41	1336	33.78	33.04	30.32
		(8.43)	(4.41)	(5.96)		(11.55)	(10.10)	(9.56)
1989	1900	42.51	40.19	38.17	1283	34.34	33.23	30.51
		(7.47)	(5.11)	(5.87)		(11.35)	(10.20)	(9.55)
1990	1827	41.75	39.68	37.80	1303	33.70	32.65	29.96
		(7.75)	(5.17)	(5.83)		(11.23)	(10.07)	(9.55)
1991	1856	42.25	39.70	37.79	1371	33.37	31.71	29.35
		(7.14)	(5.49)	(6.07)		(11.31)	(10.35)	(9.67)
1992	1759	42.07	39.57	37.88	1349	33.03	31.59	29.11
		(6.80)	(5.38)	(5.38)		(11.27)	(10.46)	(9.81)
1993	1711	41.82	39.14	37.98	1294	32.87	31.36	29.13
		(6.43)	(4.40)	(5.70)		(11.20)	(10.34)	(9.65)
1994	1615	41.72	39.04	38.15	1262	32.59	31.07	29.58
		(6.68)	(4.93)	(5.36)		(11.19)	(10.35)	(9.46)
1995	1679	41.92	38.81	37.45	1292	32.68	30.87	28.61
		(7.66)	(5.84)	(7.99)		(11.29)	(10.45)	(10.82)
1996	1623	41.65	38.70		1285	32.02	30.37	
		(7.36)	(5.48)			(11.39)	(10.49)	

Note: Standard deviations between parentheses. For a given year, only individuals with valid data on all three (two for 1996) variables are included.

Table 3: Cross-Tabulation of Sign of Desired and Realised Changes in Working Hours

Total hours	Men			Women		
	$hd_{it}-ha_{it}<0$	$hd_{it}-ha_{it}=0$	$hd_{it}-ha_{it}>0$	$hd_{it}-ha_{it}<0$	$hd_{it}-ha_{it}=0$	$hd_{it}-ha_{it}>0$
$ha_{it}-ha_{it-1}<0$	41.9%	29.4%	24.4%	42.6%	23.0%	20.2%
$ha_{it}-ha_{it-1}=0$	28.3%	38.5%	30.8%	28.4%	43.4%	27.9%
$ha_{it}-ha_{it-1}>0$	29.8%	32.1%	44.9%	29.1%	33.5%	51.8%
	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
#observations	7675	2387	1605	5016	2052	1053

Paid hours	Men			Women		
	$hd_{it}-ha_{it}<0$	$hd_{it}-ha_{it}=0$	$hd_{it}-ha_{it}>0$	$hd_{it}-ha_{it}<0$	$hd_{it}-ha_{it}=0$	$hd_{it}-ha_{it}>0$
$ha_{it}-ha_{it-1}<0$	44.7%	31.4%	27.9%	39.8%	25.0%	21.2%
$ha_{it}-ha_{it-1}=0$	30.6%	44.7%	37.9%	39.2%	49.3%	41.4%
$ha_{it}-ha_{it-1}>0$	24.7%	24.0%	34.2%	21.0%	25.7%	37.5%
	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
#observations	6153	2385	2139	4276	2370	1475

Note: Data of the years 1988 to 1996 are pooled.

Table 4.A: Estimation Results of the Dynamic Panel Data Model for Men

	Equation in levels		Equation in first differences		
Total hours	LEV-OLS	LEV-ME	DIF-FE	DIF-AB	DIF-ME
β_1	**0.546**	**0.942**	0.028	**0.108**	**0.359**
	(0.020)	(0.018)	(0.020)	(0.029)	(0.130)
β_2	**0.092**	-0.006	**0.050**	0.025	**-0.265**
	(0.016)	(0.017)	(0.018)	(0.023)	(0.128)
First-order	**-5.435**	**-11.575**	**-11.797**	**-9.635**	**-4.633**
serial correlation	[1711]	[1711]	[1711]	[1376]	[1376]
	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}
Second-order	**7.686**	-0.638	0.162	1.447	1.753
serial correlation	[1711]	[1711]	[1376]	[1140]	[1140]
	{0.000}	{0.523}	{0.871}	{0.148}	{0.080}
Sargan test		64.014		61.848	31.192
		[54]		[52]	[40]
		{0.165}		{0.165}	{0.839}

	Equation in levels		Equation in first differences		
Paid hours	LEV-OLS	LEV-ME	DIF-FE	DIF-AB	DIF-ME
β_1	**0.608**	**0.911**	**0.065**	**0.170**	**0.312**
	(0.022)	(0.023)	(0.032)	(0.043)	(0.110)
β_2	**0.056**	0.019	**0.031**	0.014	-0.100
	(0.010)	(0.010)	(0.012)	(0.014)	(0.080)
First-order	**-7.745**	**-9.697**	**-9.110**	**-7.834**	**-4.453**
serial correlation	[1711]	[1711]	[1711]	[1376]	[1376]
	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}
Second-order	**3.733**	-1.475	0.263	1.414	1.203
serial correlation	[1711]	[1711]	[1376]	[1140]	[1140]
	{0.000}	{0.140}	{0.792}	{0.157}	{0.229}
Sargan test		67.746		48.728	32.465
		[54]		[52]	[40]
		{0.099}		{0.603}	{0.796}

Note: All models include year-dummies (which are not reported). LEV-ME takes measurement error into account by using at least two-times lagged as instruments. DIF-FE concerns the within-group estimator for the fixed effects model, while DIF-AB concerns the method of Arellano and Bond (1991). DIF-ME takes measurement error into account by using at least three-times lagged variables as instruments. The test statistics on first- and second-order serial correlation are standard normal, while the Sargan test statistic is χ^2. Between ( ) are standard errors, between [ ] are numbers of observations for the tests on serial correlation and degrees of freedom for the Sargan test. Between { } are p-values of the corresponding tests.

Table 4.B: Estimation Results of the Dynamic Panel Data Model for Women

	Equation in levels		Equation in first differences		
Total hours	LEV-OLS	LEV-ME	DIF-FE	DIF-AB	DIF-ME
β_1	**0.717**	**0.912**	**0.106**	**0.215**	**0.406**
	(0.017)	(0.017)	(0.028)	(0.040)	(0.103)
β_2	**0.177**	**0.044**	**0.053**	-0.009	-0.079
	(0.016)	(0.020)	(0.028)	(0.023)	(0.090)
First-order	**-8.314**	**-8.665**	**-9.762**	**-7.453**	**-4.729**
serial correlation	[1236]	[1236]	[1236]	[938]	[938]
	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}
Second-order	1.094	-1.685	-0.696	1.216	1.568
serial correlation	[1236]	[1236]	[939]	[721]	[721]
	{0.274}	{0.092}	{0.487}	{0.224}	{0.117}
Sargan test		62.046		58.217	41.957
		[54]		[52]	[40]
		{0.211}		{0.257}	{0.386}

	Equation in levels		Equation in first differences		
Paid hours	LEV-OLS	LEV-ME	DIF-FE	DIF-AB	DIF-ME
β_1	**0.796**	**0.901**	**0.179**	**0.210**	**0.318**
	(0.014)	(0.017)	(0.031)	(0.039)	(0.069)
β_2	**0.101**	**0.059**	0.016	-0.026	0.015
	(0.011)	(0.020)	(0.015)	(0.016)	(0.071)
First-order	**-6.931**	**-7.254**	**-8.363**	**-6.841**	**-5.961**
serial correlation	[1236]	[1236]	[1236]	[938]	[938]
	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}
Second-order	1.536	-0.731	0.969	1.376	1.797
serial correlation	[1236]	[1236]	[938]	[721]	[721]
	{0.125}	{0.465}	{0.332}	{0.169}	{0.072}
Sargan test		57.803		66.212	50.851
		[54]		[52]	[40]
		{0.337}		{0.089}	{0.117}

Note: All models include year-dummies (which are not reported). LEV-ME takes measurement error into account by using at least two-times lagged as instruments. DIF-FE concerns the within-group estimator for the fixed effects model, while DIF-AB concerns the method of Arellano and Bond (1991). DIF-ME takes measurement error into account by using at least three-times lagged variables as instruments. The test statistics on first- and second-order serial correlation are standard normal, while the Sargan test statistic is χ^2. Between ( ) are standard errors, between [ ] are numbers of observations for the tests on serial correlation and degrees of freedom for the Sargan test. Between { } are p-values of the corresponding tests.

Table 5.A: Estimation Results of the Restricted Panel Data Model for Men

	Equation in levels		Equation in first differences		
Total hours	LEV-OLS	LEV-ME	DIF-FE	DIF-AB	DIF-ME
β_2	**0.307**	**0.053**	**0.518**	**0.466**	0.099
	(0.017)	(0.014)	(0.028)	(0.033)	(0.151)
First-order	**-10.921**	**-12.078**	**-12.846**	**-12.603**	**-7.161**
serial correlation	[1711]	[1711]	[1376]	[1376]	[1376]
	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}
Second-order	**3.476**	-0.651	**4.030**	**4.098**	**3.774**
serial correlation	[1711]	[1711]	[1140]	[1140]	[1140]
	{0.000}	{0.515}	{0.000}	{0.000}	{0.000}
Sargan test		26.734		35.861	18.480
		[27]		[26]	[20]
		{0.478}		{0.094}	{0.556}

	Equation in levels		Equation in first differences		
Paid hours	LEV-OLS	LEV-ME	DIF-FE	DIF-AB	DIF-ME
β_2	**0.161**	**0.039**	**0.298**	**0.220**	0.058
	(0.012)	(0.011)	(0.024)	(0.025)	(0.093)
First-order	**-10.357**	**-10.445**	**-10.481**	**-10.311**	**-8.833**
serial correlation	[1711]	[1711]	[1376]	[1376]	[1376]
	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}
Second-order	-0.508	-1.609	**3.895**	**3.891**	**3.494**
serial correlation	[1711]	[1711]	[1140]	[1140]	[1140]
	{0.611}	{0.108}	{0.000}	{0.000}	{0.000}
Sargan test		36.519		35.894	27.198
		[27]		[26]	[20]
		{0.104}		{0.094}	{0.130}

Note: All models include year-dummies (which are not reported). LEV-ME takes measurement error into account by using at least two-times lagged as instruments. DIF-FE concerns the within-group estimator for the fixed effects model, while DIF-AB concerns the method of Arellano and Bond (1991). DIF-ME takes measurement error into account by using at least three-times lagged variables as instruments. The test statistics on first- and second-order serial correlation are standard normal, while the Sargan test statistic is χ^2. Between ( ) are standard errors, between [ ] are numbers of observations for the tests on serial correlation and degrees of freedom for the Sargan test. Between { } are p-values of the corresponding tests.

Table 5.B: Estimation Results of the Restricted Panel Data Model for Women

	Equation in levels		Equation in first differences		
Total hours	LEV-OLS	LEV-ME	DIF-FE	DIF-AB	DIF-ME
β_2	**0.250**	**0.101**	**0.389**	**0.295**	**0.273**
	(0.017)	(0.017)	(0.027)	(0.032)	(0.112)
First-order	**-9.146**	**-8.733**	**-8.861**	**-9.163**	**-7.337**
serial correlation	[1236]	[1236]	[938]	[938]	[938]
	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}
Second-order	-0.428	-1.752	1.948	**2.145**	**1.966**
serial correlation	[1236]	[1236]	[721]	[721]	[721]
	{0.669}	{0.080}	{0.051}	{0.032}	{0.049}
Sargan test		25.490		27.219	16.650
		[27]		[26]	[20]
		{0.547}		{0.398}	{0.676}

	Equation in levels		Equation in first differences		
Paid hours	LEV-OLS	LEV-ME	DIF-FE	DIF-AB	DIF-ME
β_2	**0.158**	**0.115**	**0.230**	**0.169**	**0.437**
	(0.013)	(0.019)	(0.022)	(0.024)	(0.104)
First-order	**-7.377**	**-7.264**	**-7.877**	**-7.714**	**-8.429**
serial correlation	[1236]	[1236]	[938]	[938]	[938]
	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}
Second-order	-0.413	-0.790	**2.366**	**2.395**	**2.101**
serial correlation	[1236]	[1236]	[721]	[721]	[721]
	{0.680}	{0.429}	{0.018}	{0.017}	{0.036}
Sargan test		27.034		22.442	13.444
		[27]		[26]	[20]
		{0.462}		{0.664}	{0.858}

Note: All models include year-dummies (which are not reported). LEV-ME takes measurement error into account by using at least two-times lagged as instruments. DIF-FE concerns the within-group estimator for the fixed effects model, while DIF-AB concerns the method of Arellano and Bond (1991). DIF-ME takes measurement error into account by using at least three-times lagged variables as instruments. The test statistics on first- and second-order serial correlation are standard normal, while the Sargan test statistic is χ^2. Between ( ) are standard errors, between [ ] are numbers of observations for the tests on serial correlation and degrees of freedom for the Sargan test. Between { } are p-values of the corresponding tests.

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