Will Increased Wages Reduce Shortage of Nurses? A Panel Data Analysis of Nurses' Labor Supply.

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Abstract.

Shortage of nurses is a problem in several countries. It is an unsettled question whether increasing wages constitute a viable policy for extracting more labor supply from nurses. In this paper we use a unique matched panel data set of Norwegian nurses covering the period 1993-1997 to estimate wage elasticities. This data includes detailed information on 18,066 individuals over 5 years totaling 56,832 observations. The estimated elasticity when controlling for individual and time invariant fixed effects is significantly positive but not very high in magnitude. Individual and institutional features are significant and important for working hours. We have also access to information about contractual arrangements. It turns out that shift work is important for hours of work, and that omitting information about this common phenomenon will underestimate the wage effect.

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1. Introduction.

The health sector is labor intensive with a continuous and high demand for highly trained and specialized labor. Several countries suffer to a varying degree from a shortage of key health personnel. This is particularly relevant for nurses, and both UK and Scandinavian countries report scarcity of nurses within the hospital sector as well as in other parts of the public health sector. Remedies are not clear. In Norway, the nurses' unions claim that wages are too low, making the nurses unwilling to participate or work sufficiently long hours to meet stated demands for nursing. Thus, in Norway 40% of the nurses work part time. Several studies report low wage elasticities for nurses, see Antonazzo et al (2000) for a survey of US and UK studies. Anecdotal evidence often hints at an unwillingness of nurses to work longer hours, and that several decide to leave nursing altogether. A problem with existing studies is that they are often based on cross sections, and with missing information about variables of importance for the nurses' work decisions. In this paper we use a unique panel data set of Norwegian health care personnel to investigate the labor supply of nurses. We have access to information about individual characteristics, including the health care institution to which the nurse is affiliated, actual working hours, wages and type of contract for each nurse.

Wage policy may be of importance for the health sector if it can actually contribute to remedy the labor scarcity problem. For a work group like nurses there should be reasons to believe that increased wages may actually contribute to increasing nurses' labor supply. Surprisingly, the evidence to some degree seems to be to the contrary. On a general level, several labor market studies indicate positive labor supply elasticities for females, i.e., the positive substitution effect outweighs the negative income effect, see Killingsworth and Heckman (1986) for an overview. Since a large share of nurses is female, it might be expected that such results would carry over to nurses' labor supply. Furthermore, nurses do to a large degree work part time, which should make changes in individual labor supply easier than for groups of workers on ordinary full time contracts. Existing empirical studies, often based on cross sections, reveal quite small, and sometimes even negative, effects of wages on nurses' labor supply (see Link, 1992, Ault and Rutman, 1994, Phillips, 1995). Does this mean that female nurses behave differently from female workers in the general population? Or could it be that low wage elasticities are due o the omission of relevant features of the labour markets for health personnel? These omitted features may be job attributes or contractual arrangements. It could also be that the selection problem is at work in explaining why nurses, when deciding on hours of work, are not very sensitive to wage changes.

There are several econometric issues at hand. Firstly, wages cannot be considered as exogenous in a labor supply equation. In the UK and Scandinavian countries the market for health personnel to a large degree consists of one or a few large buyers. Thus, the labor market may resemble elements of a monopsonistic labor market, an issue well addressed in the literature (see e.g. Hirsch and Schumacher (1995, 1998)). In a monopsonistic labor market, the buyers, hospitals and other community health institutions, face an upward sloping supply curve. This implies that they consider the marginal incremental cost of increasing wages rather than the wage rate itself. This means that the buyer faces a marginal cost which is steeper than the wage curve. Thus, even though the hospitals claim that they would employ more workers at the going rate, it is not for certain that they would be willing to pay the additional cost from increasing the wage of all nurses. This may be of particular relevance in an institutional setting where the demand side of the labour market faces more or less a given budget. The later is the case in most public health care systems. We do not attempt to control for monopsony tendencies in the labor market as such. However, by controlling for institution and type of work performed, we may capture some effects from a non-competitive labor market since the availability and attractiveness of the different institutions matter for choice of employer. Furthermore, using instrumental variable estimation we take into consideration the simultaneous determination of wages and hours of work, thus singling out demand effects of importance for wage determination.

Secondly, several studies may be alleged to suffer from an omitted variable problem. Nurses work under quite different contractual arrangements. Notably, quite often they work shift hours, which affect contractual working hours as well as hourly pay. Shift hours are generally compensated with an hourly wage premium, and it is generally such that the mandated weekly working hours are shorter for shift workers. We believe that it is important to correct for shift work, and that the wage effect will be biased if a variable representing such contractual work arrangements is omitted. The reason is twofold. If shift hours are considered burdensome, a wage compensation is required (Moore and Viscusi, 1990). If this compensation is insufficient, lower labour supply is offered, and the estimated wage effect will be downwardly biased. It may also be the case that shift workers just consider it too demanding to work long hours, and that they respond less to wage changes than those working on ordinary day time contracts. In this case, the derived wage effect underestimates the true effect for some groups, and may give the wrong signals when considering an appropriate wage policy for nurses.

Thirdly, when investigating labor supply, care should be taken to control for selection and unobserved heterogeneity. There is likely to be a selection process driving the decision to work or not to work, as well as where to work. Since we only observe nurses holding a job in specific health care institutions, not controlling for selection will result in biased estimates. Similarly, labour market behaviour is also driven by individual characteristics only some of which are observed by the researcher. A panel data set will make it possible to correct for selection bias as well as unobserved heterogeneity.

We have access to a unique panel data set of Norwegian health personnel covering the period 1993-1997. The individualized data with information about wages, working hours and type of work are matched with other data sets including information about the individual and its household. We can also track trained nurses that are temporarily or permanently employed outside of the public sector. The matched data set is suitable for addressing the important question of nurses' labor supply in a consistent manner. For nurses employed by local and regional municipalities, information on wages and working hours are collected by the Norwegian Association of Local and Regional Authorities (NALRA) for one month (October) during each year. Statistics Norway provides information on background variables for all registered nurses during the relevant period. We have controlled for the type of position held by each individual, and for the fact that nurses on shift contracts have shorter mandated working hours. In particular, a variable representing the burden of shift work is highly significant, and contributes in itself to a negative effect on working hours. Thus, the inclusion of variables representing contractual arrangements is warranted, as is the inclusion of individual and institutional controls.

The rest of the paper is organized as follows. In the next section we provide some background information on the labor market for nurses. The data and sample properties are presented in Section 3. In Section 4 we derive the empirical specification and discuss some empirical modelling issues. Results are presented in Section 5, while Section 6 offers some concluding remarks.

2. Institutional features of the labor market for nurses.

According to OECD Health Data 2000, Norway is one of the countries with the highest density of nurses. In 1996 there were 14,9 registered nurses per 1000 inhabitants[1], outnumbering most other countries. Simultaneously, the Norwegian nurses' union claims there are more than 4000 full time vacancies. The number of nurses includes registered nurses only, i.e. auxiliary nurses are excluded. The difference between registered and auxiliary nurses is length and type of education. Registered nurses receive 3 (4) years of education at college, whereas auxiliary nurses are trained at the secondary school level. From the mid eighties a shift in the composition of nursing labor in favor of registered nurses has taken place especially at hospitals. In the rest of this paper we confine ourselves to registered nurses.

In Norway, most nurses are employed by publically owned institutions. Similar to other Scandinavian countries and the UK, the public sector is responsible for finance and most of the production of health care services[2]. Specialist services are the responsibility of counties. Somatic and psychiatric hospitals are owned and financed by 19 counties. Exceptions include two national and some private, specialized hospitals. Primary health care is the responsibility of municipalities but a considerable share of general practitioners run private practices. Nurses employed by these private practices are not in our data set, nor are nurses engaged by private specialists. Municipalities are also responsible for general public health services, and institutions for the elderly, including somatic and psychiatric nursing homes. Counties and municipalities are financed from risk adjusted grants from the government using local taxes,

[1] The comparable numbers for 1997 are 9.5 registered nurses per 1000 inhabitants for Norway and Germany, 4.5 for the UK and 5.9 for France.

[2] In 1997, according to OECD Health Data 2000, 82,7% of expenditures on health were public and only 0,1% of hospital beds were in private institutions.

and to a minor degree from user charges (co-payment). Owners of somatic hospitals (counties) also receive activity dependent DRG based payment. It is fair to say that the public health institutions are facing periodic (yearly) budget limits, but it is a matter of perception as to how strict these budget restrictions are. This is a fact of some importance when deriving wage effects. Given a fixed budget, institutions may not be willing to let nurses work longer hours following a wage increase. A phenomenon also hinted at in the monopsony theory approach to the nursing labor market.

Wages are bargained by the nurses' union on the one side, and NALRA, representing municipalities and counties, on the other side. Bargaining takes place every year. There may also be bargaining once a year at a local level, and each institution will have some discretion in bargaining individual wages by putting workers into specific wage categories. The bargained tariffs determine wage scales for every position and work category, including shift and overtime compensations. Individual contractual working hours are determined at the specific institution, at which level it is also determined who and how many to employ. Thus, the bargaining process resembles a 'right-to-manage' framework. Commonly, positions are offered as full time or as a given share of full time, and as shift work or ordinary day work. Overtime is only paid when weekly hours of work exceed full time working hours (37.5 hours for ordinary work and 35.5 hours for shift work per week). Nurses are not allowed to plan for overtime work but may of course work overtime in cases of particular demand.

3. Data.

The data used in this analysis consist of administrative data for the years 1993-1997 collected from different official data registers. Statistics Norway (SSB) provides detailed background information on all individuals who have completed their nursing education. The data from

SSB include information on whether the individual works or not, where the individual works and yearly income. However, this data set does not include information about wage rates or the number of hours worked. Information about the latter is obtained by merging the data from SSB with data from NALRA's personnel register[3]. The NALRA register includes information on all individuals working in the health sector in Norwegian counties and municipalities. An important advantage of this register is that it contains very detailed individual information on standard wages, overtime, compensation for work outside normal hours, and total number of hours worked. Furthermore, information about the workplace of the nurse (hospital, nursing home, etc), and kind of job, like staff nurse, ward nurse etc., is also included. Using register data should reduce the problems associated with measurement errors which usually plague survey type data[4].

Our sample covers the period 1993-1997. We include female nurses younger than 62 years of age who are registered with a completed nursing qualification and employed by municipalities or counties[5]. Nurses working in institutions which do not provide detailed information for all years were excluded. We will argue below that this limitation of the data set does not seriously affect the representativeness of our analysis. We have detailed wage and contractual information on 18,066 individuals over five years, totaling 56,832 observations. This sample constitutes about one half of the relevant population of Norwegian nurses. In Column 1 of Table 1 we report the number of observations each year for the total sample of female nurses. From Column 2 we see that the share of the nurses out of work is relatively constant over time, at approximately 8%. Almost 90 percent of the nurses are employed by

[3] Notice that the data in the NALRA register is collected only for the month of October each year. The data for this month is considered representative, since there are no public holidays and it is not a typical holiday month.
[4] Validation studies use administrative data to examine the presence and magnitude of measurement errors in survey data (see for e.g. Poterba and Summers (1986) and Bollinger (1998)).
[5] We have excluded male nurses (4613). Inclusion of male nurses will have a marginal effect on our results. Nurses older than 62 (1400) are excluded since they will have access to different pension schemes. Also nurses registered with more than one job in the health sector is excluded (2743).

institutions covered by the NALRA register, see Column 3. Lastly, Column 4 includes nurses working in institutions which have provided detailed and consistent wage information.

(Table 1 about here)

In Table 2 we report the frequency of the number of years worked by each nurse. Obviously, those who have not been at work in any of the five years cannot be found in the NALRA register, explaining the missing observations in the first row. Comparing the samples, we see that nurses are observed for fewer periods in the NALRA samples than in the total sample of female nurses. The reasons are threefold. Firstly, an individual may work for all years but may temporarily leave a specific institution covered by the NALRA registers. Secondly, a specific institution may not file adequate reports for all years. This will affect the number of observations in the most restricted sample. Thus, missing observations in the NALRA sub sample are not due to choices of individual nurses but lack of reports from an employer. Thirdly, an individual may leave the labor force for on or more years. As shown below, there seems to be little variation in the characteristics of nurses among the samples.

(Table 2 about here.)

The variables used in the analysis are defined in Table 3 and further explanation of some of these variables is given in the Appendix.

(Table 3 about here)

Sample statistics are reported in Table 4. If no figure is reported, it means that there are no observations for that variable in that sample. We immediately observe that the individual specific variables (age, experience, number of children, etc.) are very similar over the samples. The geographical variables, on the other hand, indicate an under-representation of nurses in central areas in the NALRA samples. In fact, most government owned institutions are situated in the capital and private health care tends to be over-represented in major cities. It is also the case that large hospitals and municipalities are less likely to report the necessary information for all years to the NALRA register. It total, barring a slight geographical misrepresentation, the data in the restricted sample seems representative for the total sample of female nurses.

(Table 4 about here)

4. Econometric model

We will consider the following model:

$$y_{it}^{*} = x_{it}\beta + \alpha_i + \varepsilon_{it}\,; \quad i = 1,...,N\,; \quad t = 1,...,T\,, \qquad (4.1)$$

$$d_{it}^{*} = z_{it}\gamma + \eta_i + u_{it} \qquad (4.2)$$

$$d_{it} = 1 \text{ if } d_{it}^{*} = 1\text{, 0 otherwise.} \qquad (4.3)$$

The unknown parameters we wish to estimate are β (and γ), while x_{it} and z_{it} are vectors of explanatory variables. All variables in z_{it} and x_{it} are assumed to be strictly exogenous[6] and z_{it} and x_{it} might contain common elements. The ε_{it} and u_{it} are unobserved disturbances.

[6] We consider the case where x_{it} is allowed to contain endogenous variables below.

The sample selection problem arises because the variable y_{it}^* is only observable for individuals with $d_{it} = 1$. If α_i and ε_{it} are dependent on d_{it}, the conditional expectation of (4.1) will differ from $x_{it}\beta$. Applying OLS on the observation for which y_{it}^* is observed will therefore lead to biased estimates of the β vector. If the sample selection process is constant over all periods a difference estimator eliminates the sample selection bias. In this case both the unobserved individual effect and the sample selection effect are differenced out.

To correct for sample selection we use the estimator proposed by Kyriazidou (1997). The individual effects, α_i and η_i, are fixed and are allowed to be correlated with the explanatory variables (x_{it} and z_{it}) and the error terms (ε_{it} and u_{it}). No distributional assumptions are made concerning the error terms. The estimator relies on time differencing (4.1) for those observations that have $d_{it} = d_{is} = 1,\ t \neq s$ [7]. This strategy will eliminate the individual-specific component but not the sample selection effect, unless the conditional expectation below is equal to zero:

$$\begin{aligned}
&\mathrm{E}(\varepsilon_{\mathrm{it}} - \varepsilon_{is} \mid d_{it} = d_{is} = 1, \zeta_i) = \\
&\mathrm{E}(\varepsilon_{it} \mid d_{it} = d_{is} = 1, \zeta_i) - \mathrm{E}(\varepsilon_{is} \mid d_{it} = d_{is} = 1, \zeta_i) \equiv \\
&\lambda_{it} - \lambda_{is}
\end{aligned} \tag{4.4}$$

Here $\zeta_i = (x_{it}, x_{is}, z_{it}, z_{is}, \alpha_i, \eta_i)$. To see that this may not necessarily equal zero, notice that the sample selection effect in period *t*, may be expressed as

$$\begin{aligned}
\lambda_{it} &= E(\varepsilon_{it} \mid u_{it} \le z_{it}\gamma + \eta_i, u_{is} \le z_{is}\gamma + \eta_i, \zeta_i) \\
&= \Lambda(z_{it}\gamma + \eta_i, z_{is}\gamma + \eta_i; F_{it}(\varepsilon_{it}, u_{it}, u_{is} \mid \zeta_i)).
\end{aligned}$$

[7] Our panel consists of five periods, thus the maximum number of differences is ten.

We see that the sample selection effect depends on the conditioning vector ζ_i and the joint conditional distribution of the error terms. Since this distribution may vary over individuals, as well as over time for the same individual, there is in general no reason to expect the unobserved conditional expectation in (4.4) to equal zero. To ensure the sample selection effect are the same in two periods, it is assumed that Λ is time invariant[8]. If this is the case, λ_{it} and λ_{is} will be equal only if $z_{it}\gamma = z_{is}\gamma$. Thus, applying first-differences in equation (4.1) eliminates both the fixed effect and the selection effect. Notice that since first-differences are taken on an individual basis, the functional form of Λ may vary across individuals.

In most cases $z_{it}\gamma$ and $z_{is}\gamma$ will not be exactly equal. However, differencing across observations when the values of $z_{it}\gamma$ and $z_{is}\gamma$ are close, will also approximately eliminate the unobserved expectation. Thus, to make the estimator operational, Kyriazidou (1997) suggests the following procedure. In the first step, get consistent estimates of the parameters in the selection equation. In this study, we estimate a conditional logit model using only the individuals who change status over time. In the second step, these estimates are used for constructing weights which are then included in a weighted least square regression. The estimator is

$$\hat{\beta}_n = \left[\sum_{i=1}^{n} \hat{\psi}_{in} (x_{it} - x_{is})' (x_{it} - x_{is}) d_{it} d_{is} \right]^{-1} \times \left[\sum_{i=1}^{n} \hat{\psi}_{in} (x_{it} - x_{is})' (y_{it} - y_{is}) d_{it} d_{is} \right], \tag{4.5}$$

where $\hat{\psi}_{in}$ are "kernel" weights, declining to zero as the difference $| z_{it}\hat{\gamma}_n - z_{it}\hat{\gamma}_n |$ increases:

[8] See Kyriazidou for a more detailed discussion on the assumptions needed.

$$\hat{\psi}_{in} = \frac{1}{h_n} K\left(\frac{(z_{it} - z_{is})\hat{\gamma}_n}{h_n} \right). \tag{4.6}$$

K is a "kernel density" function, and h_n is a sequence of "bandwidths" that tends to zero as $n \to \infty$.

So far all variables in x_{it} and z_{it} are assumed to be strictly exogenous. However, a straightforward generalization by Charlier, Melenberg and Van Soest (1997) allows for endogeneity in the Kyriazidou method using an IV estimator[9]. In particular, they propose the following estimator:

$$\hat{\beta}_{IV} = \left[\sum_{i=1}^{n} \hat{\psi}_{in} (\hat{x}_{it} - \hat{x}_{is})' (x_{it} - x_{is}) d_{it} d_{is} \right]^{-1} \tag{4.7}$$

$$\times \left[\sum_{i=1}^{n} \hat{\psi}_{in} (\hat{x}_{it} - \hat{x}_{is})' (y_{it} - y_{is}) d_{it} d_{is} \right],$$

where $(\hat{x}_{it} - \hat{x}_{is})$ are the instruments. This IV estimator will also eliminate a potential endogeneity problem due to measurement errors (see Dustmann and Barrachina, 2000).

5. Results.

Most of our discussion will concentrate on the estimated effect of wages on labour supply. The results are given in Table 5. The first column reports the OLS results, while the second column corrects for simultaneity in wage determination by applying a standard IV estimator (2SLS). Column three includes results from a fixed effects (FE) model, while column four has its IV counterpart (FE-IV). Similarly, the results in column five and six are based on

[9] Charlier, Melenberg and Van Soest (1997) prove the consistency of this estimator.

sample selection models using Kyriazidou's method (K) and its IV counterpart after instrumenting for wages (K-IV).

As instruments for wages of nurses we have used the mean wages of auxilliary nurses working in the same institution as the nurse, and the nurse's work experience. These instruments pass the Hausman test of overidentifying restrictions[10]. The corresponding results for the wage equations are reported in Table A1.

(Table 5 about here)

We note that apart from the wage elasticity and the variables representing the type of job, the coefficient estimates are reasonably stable over the different models. Age has a non-positive and concave effect, i.e. the nurses work shorter hours as they become older. The effect of family variables are as expected. Being married and having children have a negative impact on hours of work, as has spouse and non-labor income. Nurses working in psychiatric institutions work longer hours compared to the base category somatic hospitals, whereas labor supply is smaller in home nursing, and in nursing homes. Lastly, perhaps somewhat surprisingly, labor supply is highest in the least central areas but the relationship with centrality and labor supply is not monotonic.

Compared to a staff nurse, a senior nurse works longer hours according to the models that do not control for endogeneity in wage determination. Instrumenting for wages yield the opposite effect. Senior nurses work shorter hours. This highlights the importance of demand side effects for actual hours of work. This may be due to the type of contracts the nurses are offered. Also, that health institutions play an important role in setting working hours.

In the rest of the discussion we concentrate on the wage variable. From the OLS model in column 1 we find a highly significant *wage* elasticity of 0.253. Being on *shift work* has a negative effect on hours of work, -0.016, and so does the effect of being on a contract with less contracted working hours per week (*hour_35*, -0.046)). Thus, in addition to wages, the type of contract on which a nurse is engaged, is important for deriving labor supply effects. Omitting these variables will lead to biased estimates. The interpretation of the *shift work* variable is that it represents the degree of burden by working shift. In the OLS estimate the included second order effect, *shift work 2*, is positive, indicating that the burden is decreasing in share of overtime. This result is questionable, and its sign changes after controlling for endogeneity in wage determination.

The empirical labor market literature draws particular attention to three potential problems that may bias the simple OLS results. These are sample selection problems, unobserved heterogeneity and endogeneity of the wage variable. Another common problem is related to measurement errors. However, by using register data and not survey data, we should be much less exposed to the latter. However, we cannot rule out measurement problems because there still could be mistakes in reporting from health institutions. A priori, we have no reason to assume such mistakes to be systematic in any direction. Column 2 of Table 5 shows the results of a 2SLS estimator that instruments for wages. The effect on the wage elasticity is large, whereas the other variables are almost unaffected. The wage elasticity increases to 0.843, which is higher than what is found in several other studies cited earlier. The coefficient for the variable representing burden of *shift work* is higher than that of OLS, now at –0.02. However, the second order effect is negative, as we would expect, i.e., shift work will reduce hours of work, and the more time devoted to shift work, the stronger is this effect.

To control for individual heterogeneity, we apply the fixed effects (within) estimator. From column 3 of Table 5 we see that the estimated effect of the wage is smaller than that of OLS, with a wage elasticity of –0.024, though not significant at a 5% level. The variable

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[10] A test of overidentifying restrictions gave Chi2(1) = 1.26 (p-value = 0.26).

controlling for shift work has an effect similar to the OLS estimates, and is significant. Controlling for endogeneity in the wage variable by a fixed effect 2SLS estimator, column 4 (FE-IV), the wage elasticity increases much more dramatically than for OLS and results in a wage elasticity of 0.781, slightly lower than that for 2SLS in column 2. Note that the fixed effect 2SLS estimator gives reasonable results in the sense that more variables are significant and have the expected sign. In particular this is true for the wage variable as well as the second order effect of shift work.

So far, sample selection is controlled for only through the individual effects. However, this may be based on a too restrictive assumption. Verbeek and Nijman (1992) propose simple tests for sample selection in panel data models. One test is to include variables measuring whether the individual is observed in the previous period (V1), whether the individual is observed in all periods (V2) and the total number of periods the individual is observed (V3). The null hypothesis says that this kind of information should not give any information about the unobservables in the model. Another test, a Hausman type test, compares the fixed effects estimator from the balanced sample as opposed to an unbalanced sample. Since both tests reject the null hypothesis of no sample selection[11], we consider a model that explicitly takes sample selection into consideration.

To implement the estimator of Kyriazidou (1997) we estimate a conditional logit model in the first step. We only use the 7959 individuals who change status over time. The results are given in table A2. In the regression we use a number of variables characterising the municipality where the individual lives. Job-related variables are excluded since we do not observe this information for those who do not participate. These estimates are then used to construct "kernel weights". We have chosen a normal density function for the kernel, while the bandwidth is set to $h_n = h \cdot n^{-1/5}$. Kyriazidou proposed a plug-in procedure to obtain the optimal kernel bandwidth. However, Experimenting with different values of *h*, had very little effect on the estimates in the final regression. Finally, these weights were used in a weighted least square regression. To take account of the weights, we apply the Huber/White estimator for the variance. The results are given in column 5 of table 5. In column 6 in the same table, we present the results of the IV-counterpart proposed by Charlier, Melenberg and Van Soest (1997).

The results from the sample selection models indicate that the wage elasticities change only moderately from the FE model, now being only marginally smaller and equal to 0.78 for (K-IV). The variables representing shift work show similar results to what was found in the other specifications, i.e., a significantly negative effect as is expected with a negative second order effect for the K-IV estimatorl. However, before controlling for endogeneity, the wage elasticity is significantly negative, at –0.037. This is possible but not very likely. Thus, with tests showing that the instruments are valid, and given the signs and levels of significance for central variables, we conclude that the model in Column 6 gives the best representation of the nurses' labor supply. Taking into consideration that there is selection into work, and having controlled for type of contracts, and endogeneity in wage and hours-of-work decision, we find that wage elasticities are positive and significant.

6. Concluding remarks.

Based on studies of nurses' labor supply in the UK and USA, there are ample evidence indicating that nurses' wage elasticities are small. We have found that this is indeed the case in our panel data set of Norwegian nurses. This result obtained whenever we did not take into

[11] The estimates of V1, V2 and V3 was (standard deviations in parenthesis); V1: -0.026 (0.008), V2: 0.002 (0.003) and V3: -0.023 (0.002). The result of the Hausman type test was: chi2(21) = 63.37 (p-value: 0.00).

consideration the endogeneity of wage determination. It is interesting to note that this result came about in a fixed effect models, i.e., after controlling for nurses' heterogeneity, and it also occured after correcting for sample selection. However, we have shown that important effects may relate to the simultaneous determination of wages and hours of work. This may be due to the role played by the demand side in the labour market for nurses, which is represented by hospitals and other institutions that are publically owned (municipalities and counties), and which are likely to have some degree of market power in their local labor markets. Correcting for sample selection does not dramatically change the estimates of the wage elasticities.

Another important result form the analysis is that contractual information should be included in the analysis of health personnel' labor supply. Omitting information about shift work and which kind of job is performed, will bias the estimates of the wage elasticity. The reason is that the work contract specifies working conditions and payment, including standard hours of work and compensation for work outside of normal working hours.

The magnitude of the wage elasticity depends on the estimator chosen. A wage elasticity of 0.7 to 0.8 is higher than many previous studies have found, but it is still not very high. It may be sensitive to the instruments used, although tests here show that our instruments are valid. Interestingly, with a wage elasticity of the magnitude we have found, a considerable wage increase may actually help overcome some of the problems related to shortage of nurses.

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Data appendix.

The *hourly wage* is calculated by first adding the monthly basic income, overtime pay and all bonuses, and then dividing this total income by the number of hours worked. Bonuses include compensation for shift work on evenings, nights and weekends, and regular bonuses. Regular bonuses are typically compensation for meetings or other work outside normal working hours, mostly paid to ward nurses and leading nurses. Finally the wage is discounted by a price index.

Shift work is calculated as the share of total monthly income that a nurse receives as compensation for shift work. Another possibility would be the proportion of hours worked outside normal hours (shift hours divided by total hours of work). However, we do not have information about the actual number of shift hours, but believe that *shift work* is a close substitute for the exact magnitude of individual shift work. An advantage of calculating the importance of shift work this way, is that it implicitly takes into consideration that shift work of different types may be differently compensated due to variations in the burden of this particular type of work.

Hour_35.5 is a dummy variable taking value 1 if the nurse is on a shift contract implying 35.5 hours per week, 0 otherwise.

The nurses in our sample are divided into four categories: staff nurse, specialist nurse, ward nurse and leading nurse. *Staff nurses* have 3 (4) years of college education. *Specialist nurses* are nurses with at least one year of specialist training, in e.g. anaesthesia, surgery or intensive care. *Ward nurses* are nurses who are in charge of a ward, whereas *leading nurses* are in charge of a larger unit.

Centrality indicates the geographical position of the municipality in relation to larger urban settlement. The classification is performed by Statistics Norway and it is based on traveling time to a center where a higher order of central functions is found. “Centrality level 0” consists of the least central municipalities, whereas the most central municipalities are found in “Centrality level 3”.

Table 1. Number of observations each year.

	Total sample	Out of work	NALRA sample	NALRA sub sample
1993	28722 (18.1)	2344 (8.1)	19392 (18.0)	10378 (18.3)
1994	29984 (18.9)	2503 (8.4)	19861 (18.4)	10928 (19.2)
1995	31526 (19.8)	2599 (8.2)	21277 (19.7)	12442 (21.9)
1996	33403 (21.0)	2607 (7.8)	22954 (21.3)	11291 (19.9)
1997	35255 (22.2)	2879 (8.2)	24421 (22.6)	11793 (20.8)
Total	158890 (100)	12932 (8.1)	107905 (100)	56832 (100)

Table 2. Sample frequencies by number of work years.

No. of years	Total sample	NALRA sample	NALRA sub sample
0	1180 (3.1)	-	-
1	3561 (9.4)	4777 (14.6)	4144 (22.9)
2	3596 (9.5)	4864 (14.8)	2725 (15.1)
3	3552 (9.4)	4702 (14.3)	3089 (17.1)
4	4766 (12.6)	5423 (16.5)	2569 (14.2)
5	21097 (55.9)	13068 (39.8)	5539 (30.7)
Total	37752 (100)	32824 (100)	18066 (100)

Table 3. Variable definitions.

Variable name	Definition
Hours per year	Regular hours plus overtime.
Hourly wage	Hourly wage included all bonuses and overtime in NoK.
Shift work	Share of the monthly income that is bonus due to late, night and weekend duties.
Hour_35.5	1 if the individual is on a contract implying 35.5 hours per week, 0 otherwise.
Age	Respondent's age.
Age^2	Age squared.
Experience	Years with income above basic counting unit in pension system (NoK 37033 in 1993).
$Experience^2$	Experience squared.
Disable	1 if the individual is more than 50 percent disabled, 0 otherwise.
Non labour income	Spouse's income + capital income (respondent and spouse).
Number of children	Number of children younger than 18.
Children < 3	1 if the nurse have children aged 3 or younger, 0 otherwise.
Children 3-7	1 if the nurse have children between the ages of 3 and 7, 0 otherwise.
Children > 7	1 if the nurse have children older than 7, 0 otherwise.
Married	1 if the respondent is married or cohabitant with children, and 0 otherwise.
Position	Respondent working as:
	Staff nurse
	Nursing specialists
	Ward nurse
	Leading nurse
Working place	Nurse working in:
	Hospital
	Psychiatric
	Home nursing
	Health service
	Nursing home
	Other
Centrality:	Measures a municipality's geographical position related to the nearest centre with central functions.
	Centrality level 0 (least central)
	Centrality level 1
	Centrality level 2
	Centrality level 3 (most central)
County	Categorical variable for living in one of 19 Norwegian counties.

Table 4. Sample statistics, means and standard deviations (in parentheses).

	Total sample	NALRA sample	NALRA sub-sample
Hours per year	-	-	1375.6 (364.8)
Hourly wage	-	-	127.5 (16.7)
Shift work	-	-	11.9 (8.24)
Hour_35.5	-	0.80 (0.40)	0.84 (0.37)
Disable	0.02 (0.15)	0.01 (0.10)	0.01 (0.10)
Age	37.3 (8.14)	37.1 (8.04)	37.1 (7.94)
Age2	1457.3 (645.2)	1444.6 (634.3)	1439.6 (624.2)
Non labour income	197.9 (320.5)	198.9 (315.1)	201.3 (237.7)
Single	0.37 (0.48)	0.36 (0.48)	0.34 (0.47)
Number of children	1.20 (1.13)	1.17 (1.10)	1.19 (1.09)
Children < 3	0.22 (0.42)	0.22 (0.41)	0.22 (0.42)
Children 3 – 7	0.28 (0.45)	0.28 (0.45)	0.29 (0.45)
Children > 7	0.31 (0.46)	0.31 (0.46)	0 .32 (0.47)
Hospital	-	0.52 (0.50)	0 .60 (0.49)
Psychiatric	-	0.03 (0.18)	0.04 (0.20)
Home nursing	-	0.12 (0.33)	0.09 (0.29)
Health service	-	0.07 (0.25)	0.05 (0.21)
Nursing home	-	0.21 (0.41)	0.19 (0.39)
Other	-	0.04 (0.20)	0.03 (0.17)
Nurse	-	0.57 (0.49)	0.60 (0.49)
Nursing specialist	-	0.22 (0.41)	0.22 (.42)
Ward nurse	-	0.19 (0.39)	0.16 (0.37)
Senior nurse	-	0.02 (0.13)	0 .01 (0.12)
Experience	13.8 (6.87)	14.0 (6.73)	14.0 (6.63)
Centrality level 0	0.12 (0.33)	0.14 (0.35)	0.14 (0.35)
Centrality level 1	0.11 (0.32)	0.13 (0.34)	0.09 (0.30)
Centrality level 2	0.22 (0.41)	0.24 (0.43)	0.34 (0.47)
Centrality level 3	0.54 (0.50)	0.48 (0.50)	0.40 (0.49)
County 1	0.05 (0.21)	0.05 (0.23)	0.08 (0.27)
County 2	0.10 (0.30)	0.09 (0.28)	0.09 (0.29)
County 3	0.12 (0.33)	0.08 (0.26)	0.01 (0.08)
County 4	0.04 (0.20)	0.05 (0.21)	0.07 (0.26)
County 5	0.04 (0.20)	0.05 (0.21)	0.06 (0.24)
County 6	0.05 (0.20)	0.05 (0.22)	0.04 (0.20)
County 7	0.05 (0.20)	0.05 (0.22)	0.07 (0.26)
County 8	0.03 (0.18)	0.04 (0.19)	0.03 (0.17)
County 9	0.03 (0.16)	0.03 (0.16)	0.04 (0.20)
County 10	0.03 (0.18)	0.03 (0.18)	0.01 (0.13)
County 11	0.08 (0.27)	0.08 (0.27)	0.11 (0.32)
County 12	0.10 (0.29)	0.09 (0.29)	0.04 (0.21)
County 14	0.02 (0.14)	0.02 (0.15)	0.02 (0.16)
County 15	0.06 (0.24)	0.07 (0.26)	0.01 (0.12)
County 16	0.06 (0.24)	0.06 (0.25)	0.10 (0.30)
County 17	0.04 (0.19)	0.04 (0.19)	0.05 (0.22)
County 18	0.05 (0.22)	0.06 (0.24)	0.06 (0.25)
County 19	0.04 (0.20)	0.05 (0.21)	0.02 (0.17)
County 20	0.02 (0.13)	0.02 (0.14)	0.03 (0.17)
Sample size	37752	32824	18066

Table 5. Estimated effects on nurses labor supply.

	OLS	2SLS	FE	FE-2SLS	K	K-IV
Ln wage	0.25316**	0.84285**	-0.02419	0.78108**	-0.03732**	0.77528**
	(0.01256)	(0.04093)	(0.01345)	(0.09918)	(0.01008)	(0.07082)
Shift work	-0.01598**	-0.02024**	-0.00903**	-0.01512**	-0.00947**	-0.01544**
	(0.00042)	(0.00051)	(0.00042)	(0.00083)	(0.00038)	(0.00064)
Shift work 2	0.00003**	-0.00002	0.00001	-0.00005**	0.00004**	-0.00003**
	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)
Hour_35.5	-0.04581**	-0.07310**	-0.03740**	-0.07317**	-0.03553**	-0.07238**
	(0.00385)	(0.00430)	(0.00488)	(0.00703)	(0.00359)	(0.00498)
Disable	-0.36877**	-0.35784**	-0.21433**	-0.23847**	-0.22711**	-0.23272**
	(0.01066)	(0.01088)	(0.01927)	(0.02200)	(0.01994)	(0.02068)
Age	-0.00670**	-0.01767**	0.00324	-0.04133**	0.00177	-0.04064**
	(0.00118)	(0.00141)	(0.00360)	(0.00627)	(0.00278)	(0.00456)
Age2	0.00001	0.00013**	0.00012**	0.00048**	0.00018**	0.00050**
	(0.00002)	(0.00001)	(0.00004)	(0.00006)	(0.00003)	(0.00004)
Non labour income	-0.00008**	-0.00008**	-0.00002**	-0.00002**	-0.00003**	-0.00002**
	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.000006)	(0.00001)
Single	0.04803**	0.04189**	0.00878	0.00793	0.01094**	0.01144**
	(0.00258)	(0.00266)	(0.00544)	(0.00581)	(0.00420)	(0.00435)
Number of children	-0.04881**	-0.05351**	-0.10043**	-0.08643**	-0.09904**	-0.08601**
	(0.00197)	(0.00203)	(0.00479)	(0.00536)	(0.00377)	(0.00412)
Children < 3	-0.08628**	-0.07912**	-0.04748**	-0.04854**	-0.04486**	-0.04725**
	(0.00323)	(0.00332)	(0.00415)	(0.00444)	(0.00324)	(0.00341)
Children 3 - 7	-0.05503**	-0.05525**	-0.01666**	-0.01782**	-0.01593**	-0.01803**
	(0.00311)	(0.00317)	(0.00363)	(0.00392)	(0.00278)	(0.00292)
Children > 7	-0.04159**	-0.03585**	-0.03648**	-0.03384**	-0.03445**	-0.03274**
	(0.00339)	(0.00347)	(0.00338)	(0.00363)	(0.00249)	(0.00261)
Psychiatric	0.04834**	0.04743**	0.05031**	0.04874**	0.05362**	0.05610**
	(0.00504)	(0.00514)	(0.01324)	(0.01426)	(0.01217)	(0.01275)
Home nursing	-0.04698**	-0.04993**	-0.01450	-0.03996**	-0.01953*	-0.04019**
	(0.00363)	(0.00371)	(0.00822)	(0.00930)	(0.00781)	(0.00846)
Health service	-0.07316**	-0.07015**	-0.05345**	-0.00755	-0.05977**	-0.01015
	(0.01026)	(0.01045)	(0.01288)	(0.02236)	(0.01238)	(0.01666)
Nursing home	-0.04970**	-0.05273**	-0.01701*	-0.04396**	-0.01653*	-0.04028**
	(0.00278)	(0.00284)	(0.00706)	(0.00829)	(0.00677)	(0.00750)
Other	-0.03291**	-0.03273**	-0.00851	-0.02081	-0.00873	-0.01860
	(0.00660)	(0.00674)	(0.00989)	(0.01233)	(0.00948)	(0.01163)
Nursing specialist	0.06068**	0.01282**	0.01936**	-0.02786**	0.02010**	-0.02739**
	(0.00301)	(0.00441)	(0.00546)	(0.00864)	(0.00445)	(0.00652)
Ward nurse	0.05435**	-0.01046	0.02742**	-0.06167**	0.03329**	-0.05950**
	(0.00340)	(0.01157)	(0.00458)	(0.01841)	(0.00810)	(0.01171)
Senior nurse	0.09293**	0.00146	0.03419**	-0.03536**	0.02346**	-0.03687**
	(0.00918)	(0.00492)	(0.01306)	(0.00880)	(0.00374)	(0.00644)
Centrality level 1	-0.00754	-0.00296	-0.01837	-0.00204	-0.01809	0.00361
	(0.00425)	(0.00434)	(0.01414)	(0.01525)	(0.01431)	(0.01505)
Centrality level 2	-0.06895**	-0.05443**	-0.05710**	-0.04765**	-0.06340**	-0.03608**
	(0.00322)	(0.00342)	(0.00865)	(0.00933)	(0.01309)	(0.01392)
Centrality level 3	-0.05873**	-0.05092**	-0.02856**	-0.01967	-0.03358**	-0.01269
	(0.00313)	(0.00323)	(0.01054)	(0.01132)	(0.01177)	(0.01254)
Constant	6.55588**	4.04308**	7.31536**	4.68327**	0.00287	0.00228
	(0.05809)	(0.17609)	(0.08234)	(0.34172)	(0.00176)	(0.00186)
Number of observations	56832	56832	56832	56832	81503	81503

Standard errors in parentheses. ** and * is statistically different from zero at one and five percent significance level, respectively.

Table A1. Wage equations.

	OLS	FE	K
Shift work	0.00747**	0.00719**	0.00715**
	(0.00013)	(0.00015)	(0.00010)
Shift work 2	0.00009**	0.00009**	0.00009**
	(0.00001)	(0.00001)	(0.00001)
Hour_35.5	0.04777**	0.04707**	0.04726**
	(0.00121)	(0.00185)	(0.00126)
Disable	-0.01922	-0.00633	-0.00310
	(0.00338)	(0.00778)	(0.00779)
Age	0.01232**	0.03592**	0.03750**
	(0.00041)	(0.00275)	(0.00224)
Age2	-0.00015**	-0.00037**	-0.00037**
	(0.00001)	(0.00001)	(0.00001)
Non labour income	-0.00001	0.00001**	0.00001**
	(0.00000)	(0.00000)	(0.00000)
Single	0.00625	-0.00030	-0.00091
	(0.00082)	(0.00205)	(0.00144)
Number of children	0.00171**	-0.01684**	-0.01643**
	(0.00063)	(0.00179)	(0.00126)
Children < 3	-0.00903**	0.00357**	0.00407**
	(0.00103)	(0.00156)	(0.00107)
Children 3 - 7	0.00468**	0.00479**	0.00485**
	(0.00099)	(0.00137)	(0.00094)
Children > 7	-0.00248	-0.00118	-0.00109
	(0.00108)	(0.00128)	(0.00087)
Psychiatric	-0.00108	0.00850	0.00481
	(0.00160)	(0.00503)	(0.00368)
Home nursing	0.01374**	0.03294**	0.02964**
	(0.00116)	(0.00313)	(0.00220)
Health service	0.00004	0.02131**	0.01947**
	(0.00325)	(0.00789)	(0.00563)
Nursing home	0.01075**	0.03459**	0.03157**
	(0.00089)	(0.00269)	(0.00190)
Other	0.01166**	0.03883**	0.03671**
	(0.00210)	(0.00424)	(0.00305)
Nursing specialist	0.07772**	0.06405**	0.06464**
	(0.00091)	(0.00209)	(0.00144)
Ward nurse	0.08682**	0.07443**	0.07305**
	(0.00102)	(0.00169)	(0.00116)
Senior nurse	0.17070**	0.12258**	0.12038**
	(0.00284)	(0.00494)	(0.00335)
Centrality level 1	-0.01430**	-0.01148**	-0.01945**
	(0.00135)	(0.00538)	(0.00455)
Centrality level 2	-0.03096**	-0.01594**	-0.03853**
	(0.00102)	(0.00324)	(0.00404)
Centrality level 3	-0.01687**	-0.01372**	-0.02558**
	(0.00099)	(0.00397)	(0.00368)
Experience	0.00394*	0.00380	0.00261
	(0.00019)	(0.00246)	(0.00203)
Wage auxiliary nurses	0.43991**	0.37983**	0.36772**
	(0.00655)	(0.01335)	(0.00907)
Constant	2.39103**	2.12474**	-0.00005
	(0.03089)	(0.07626)	(0.00068)
Number of observations	56832	56832	81503

Standard errors in parentheses. ** and * is statistically different from zero at one and five percent significance level, respectively.

Table A2. Participation equation. Conditional logit.

Educated as nurse	-0.87142** (0.08793)
Age	0.20020** (0.04479)
Age2	-0.00469** (0.00058)
Non labour income	-0.00007 (0.00005)
Single	-0.16311** (0.06338)
Number of children	-0.25570** (0.05589)
Children < 3	-0.15501** (0.05148)
Children 3 - 7	0.13301** (0.04642)
Children > 7	-0.06290 (0.04561)
Disable	-1.02578** (0.25131)
County1	0.18511 (0.29488)
County2	-0.21152 (0.23476)
County3	-3.63525** (0.25663)
County4	-0.48826* (0.26730)
County5	-0.05825 (0.26821)
County6	-0.76912** (0.25962)
County7	-0.42708* (0.27485)
County8	-1.31308** (0.30353)
County9	-0.14414 (0.29677)
County10	-1.44914** (0.28018)
County11	0.15060 (0.25233)
County12	-2.15470** (0.24975)
County14	-0.02445 (0.31239)
County15	-3.41621** (0.30475)
County16	0.10602 (0.24019)
County17	-0.73016** (0.27044)
County18	-0.80635** (0.22142)
County19	-1.58192** (0.23024)
Hospital in municipality	0.37002** (0.07635)
Small city	0.79373** (0.13009)
Large city	0.33443** (0.12943)
Large municipality	-0.35300* (0.18107)
Medium municipality	-0.43313** (0.16614)
Number of observations	44568

Standard errors in parentheses. ** and * is statistically different from zero at one and five percent significance level, respectively.