COMPENSATING WAGE DIFFERENTIALS AND SHIFT WORK PREFERENCES*
Evidence from France

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Abstract

Workers with difficult working conditions can be expected to be compensated by higher wages. They may, for example, choose shift work because of compensating wages but it is also possible that they prefer shift work. The previous empirical evidence is mixed. We study if there are compensating wages for shift work by estimating a switching regression model with endogenous switching using French matched employer–employee data for male full time blue collar workers. It is crucial to adjust for selectivity and not to pool data for shift and day workers. A main result is that there is a significant shift premium, the wage rate for shift workers is 16 percent higher than for day workers. A second main result is that the shift premium is significant for shift work choice. This premium compensates workers who do not self–select into shift work. A 1 percentage point increase in the premium increases the shift work probability by 0.87 percentage points.

Keywords: shift work premium, compensating wage differentials, switching regression model with endogenous switching
JEL classifications: J28, J31, J33

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1 Introduction

The theory of equalizing differences predicts that people who have difficult working conditions are compensated by higher wages. These ideas go back to the writings of Adam Smith. Rosen (1986) surveys the theory and the empirical evidence which, however, is mixed. Non–normal working hours is an example of a work characteristic that could generate compensating wage differentials. Many people in industrialized countries work nonstandard hours. According to the Current Population Survey almost 17 percent of all full time wage and salary workers in the U.S. were working shift in 1997. In France, 12 percent of the workforce worked in rotating teams in 1994. Kostiuk (1990) is a seminal empirical work on compensating wage differentials for shift work. He notes that most previous studies of shift work find little or no wage differential.

Why have the empirical studies had problems finding compensating wage differentials? The theory may be wrong.[1] Another reason may be that the workers preferences are heterogenous. Some may choose shift because of compensating wage differentials while others prefer shift work. But the more workers who prefer shift work, the lower shift premia are necessary. In addition, self–selection into shift work may make it more difficult to identify wage differentials that actually exist. Finally, wages for day workers may be determined in a different way than wages for shift workers. Then that data for these two groups cannot be pooled.[2] An additional potential problem arises when data should be pooled. The resulting empirical model may then be logically inconsistent. Estimating shift premia and shift choice fit well in the framework of switching regression models with endogenous switching.[3] It provides a unified framework for testing selectivity, pooling, and logical consistency.

Our sample of 1,998 male full time blue collar private sector workers comes from a matched employer–employee French data set for 1992.[4] At that time, women were only legally allowed to work at night in medical and social institutions.[5] It was not possible, for example, for women to work

[1] The segmented markets hypothesis instead predicts a positive relationship between working conditions and wages, see Doeringer and Piore (1971), Cain (1976), and Taubman and Wachter (1986). Daniel and Sofer (1998) present a bargaining model in which there can be a positive relationship on one segment of the labor market while there is a negative on another segment. Using French data, they find that wages compensate for bad working conditions in firms with weak unions while this is not the case in firms with strong unions. They, however, assume that the choice to join a union is exogenous.

[2] The quality of the data could, of course, also be an important problem.

[3] Lee (1978), Willis and Rosen (1979), Hartog and Oosterbeek (1993), and Oosterbeek and van Praag (1995) are examples where union, education, sector, and firm size differentials are estimated using this model structure.

[4] The Labor Cost and Wage Structure Survey (ECMOSS) is collected by INSEE, the French National Statistics Institute. Appendix A reports more about the data.

[5] In the research department of the French Ministry of Labor reports that only 5 percent

on rotating teams. We, therefore, only study men. The reason why we restrict the sample to full time workers is that hourly wages can only be calculated as annual gross remuneration divided by annual number of paid for hours. We cannot, however, take the possibility that firms compensate for shift work by reducing the actual number of work hours into account. Our measures of shift compensation may, therefore, be downward biased. Restricting the sample to full time workers, however, reduces the risk that we do not capture shift compensation accurately. Most white collar workers have a free choice of when to work. It is, therefore, difficult to compare them with blue collar workers

We distinguish between workers who work ordinary time schedules—day workers—and those who do not—shift workers. Our definition of shift workers is the same as Kostiuk's. Anyone who has scheduled working time outside normal working hours during the week is considered as a shift worker.[6] The shift workers include those working in rotating teams, but also night workers and those who work uncommon hours, an uncommon work week, and an extended work day.

There are several advantages with these data compared to the data that previously have been used to estimate shift premia. The shift work measure is good. We have information about both workers and firms, and we have many potential determinants of shift choice.[7]

Our two main results are:

1. There is a significant shift premium, the wage rate for shift workers is 16 percent higher than for day workers. This premium is higher than previously reported in the literature. Kostiuk, for example, finds an 8 percent shift premium for male full time manufacturing workers using U.S. data.[8]

2. Shift choice is the result of wage differentials, not shift preferences. The shift premium is significant for the choice to work shift. A 1 percentage point increase in the shift premium increases the probability of shift work by 0.87 percentage points.

In our case, it turns out that it is crucial to adjust for selectivity and that it is not possible to pool data for shift and day workers. As data should not be pooled in our case, the problem of logical inconsistency does not arise.

of women work night. The corresponding share of men was 18 percent, see DARES (1993). In December 2000 the French Parliament approved a law also giving women the right to work night.

[6] We try to exclude people who can decide their own working time, for example people with flexible hours, from the sample.

[7] The quality of our data is at least as good as that of the data used by Kostiuk (1990).

[8] Schumacher and Hirsch (1997) find shift premia in the range 4 – 11 percent, depending on shift type, for a sample of registered nurses in the U.S. Using Swedish data for male employees, Agnarsson (1998) estimates a 5 percent shift premium.

Model selection is crucial. Suppose that we erroneously pool the data and do not correct for selectivity, the shift premium is then underestimated to 4 percent. If instead we correct for selectivity but still erroneously pool the data, the shift premium is overestimated to 21 percent.

The paper is organized as follows: In section 2, we discuss the model specification and how the model should by estimated. The estimations of shift choice models and wage equations can be found in section 3. Section 4 concludes.

2 Models and estimation strategy

There are several potential problems related to the empirical estimations. A first problem is misspecification. Is it possible to pool data for shift workers and day workers? Suppose that the wage equations are:

$$\text{shift work wages:} \quad w_s = \beta_s X + u_s, \tag{1a}$$

$$\text{day work wages:} \quad w_d = \beta_d X + u_d, \tag{1b}$$

where w_s and w_d are log hourly wage rates, the vector X includes the standard explanatory variables in wage equations, while u_s and u_d are error terms. The subindices s and d refer to shift work and day work.[9] Suppose that the returns to each worker characteristic is the same for all workers ($\beta_s = \beta_d$ for all X). We can then pool the data and estimate a single wage equation. But if the returns differ we must allow shift worker and day workers to have different wage equations (different βs).

The second problem is selectivity. This may arise as long as the shift choice is not completely random. Suppose that choice is determined according to:

$$\text{shift choice:} \quad S^* = \gamma Z + \delta(w_s - w_d) + \upsilon, \tag{2}$$

where S^* is a latent variable for shift work with the corresponding binary variable S, Z is a vector of variables that influence shift choice, and υ is an error term. The term $w_s - w_d$ captures the shift premium. Some, but not all, of the variables in X also appear in Z.

The error terms may be correlated giving rise to selectivity bias. Let $\sigma_{u_s\upsilon}$ and $\sigma_{u_d\upsilon}$ represent the covariances between the error term in the choice equation, υ, and the error terms in the wage equations, u_s, u_d. The covariance $\sigma_{u_s\upsilon}$ can be expected to be positive while $\sigma_{u_d\upsilon}$ can be expected to be negative. Suppose that we study a worker with abilities not captured by the exogenous variables in the shift work wage equation. These abilities are reflected in a higher wage. This, in turn, will give rise to a positive error term u_s. In addition, suppose that because of this higher wage, the person

[9] All explanatory variables may not have an influence in both equations. For some elements of X the β_s– or β_d–coefficient may be zero.

becomes more likely to choose shift work than captured by the explanatory variables in the shift choice equation. We will then have a positive error term υ. Moreover, the covariance $\sigma_{u_s\upsilon}$ will be positive. There will, in other word, be a positive selection into shift work. On the other hand, a positive selection into day work would imply that $\sigma_{u_d\upsilon}$ is negative.

We will have use for the reduced form of the choice equation. It is:

$$S^* = \gamma Z + \delta(\beta_s - \beta_d)X + \delta(u_s - u_d) + \upsilon, \tag{3}$$

which can be given new parameters to become $S^* = \tilde{\gamma}\tilde{Z} + \tilde{\upsilon}$. Following Maddala (1983), we can compute the conditional expected wages:

$$E(w_s|S = 1) = \beta_s X + \sigma_{u_s\upsilon}\frac{\phi(\tilde{\gamma}\tilde{Z})}{\Phi(\tilde{\gamma}\tilde{Z})}, \tag{4a}$$

$$E(w_d|S = 0) = \beta_d X - \sigma_{u_d\upsilon}\frac{\phi(\tilde{\gamma}\tilde{Z})}{1 - \Phi(\tilde{\gamma}\tilde{Z})}, \tag{4b}$$

where $\phi(\tilde{\gamma}\tilde{Z})$ and $\Phi(\tilde{\gamma}\tilde{Z})$ are the density function and the distribution function of the standard normal evaluated at $\tilde{\gamma}\tilde{Z}$. Including $+\sigma_{u_s\upsilon}\frac{\phi}{\Phi}$ and $-\sigma_{u_d\upsilon}\frac{\phi}{1-\Phi}$ when estimating the respective wage equation will control for selectivity and yield estimates of the covariances. If we estimate the wage equations (1a) and (1b) without controlling for selectivity we will get biased estimates if the covariances are nonzero. Most probably, we will tend to underestimate the shift premia.

The third problem is logical inconsistency. This problem may arise if we pool the data. Suppose that we capture the wage differential for shift workers by a dummy variable when estimating the wage equation. The question now is if this premium should be attributed to the job or to the worker. If, on the one hand, it is connected to the job, all workers have the possibility to get this premium which is identical for all. In this case there will be no variation in the premium across workers. Consequently, it is not possible to identify the impact of the wage premium when estimating a choice equation.

If, on the other hand, the premium should be attributed the worker there will be variation across workers. Shift workers get the premium while day workers do not. The model is:

$$\text{wages:} \quad w = \beta X + \alpha S + u, \tag{5a}$$

$$\text{shift choice:} \quad S^* = \gamma Z + \delta\alpha S + \upsilon, \tag{5b}$$

where α is the wage premium. However, Maddala (1983, p. 118) presents a lemma. We use the notation of (5a) and (5b):[10]

[10]Heckman (1978, p. 936) also provides a proof of this proposition.

Lemma 1. *Suppose S^* is an unobserved variable, with the corresponding observed variable $S = 1$ if $S^* > 0$ and $S = 0$ if $S^* \leq 0$. Then a model of the form $S^* = \gamma Z + \delta\alpha S + \upsilon$, where Z is a variable, and γ is a parameter, is logically inconsistent unless $\delta\alpha = 0$.*

The proof is as follows: $\Pr(S = 0) = 1 - F(\gamma Z)$ while $\Pr(S = 1) = F(\gamma Z + \delta\alpha)$. The probabilities sum to one, $1 - F(\gamma Z) + F(\gamma Z + \delta\alpha) = 1$. But this holds only if $\delta\alpha = 0$.

Logical consistency requires that the shift premium plays no role for the choice of shift work, i.e., $\delta = 0$. Alternatively, there should be no shift premium, $\alpha = 0$.

The wage equations (1a), (1b) and the choice equation (2) is a switching regression model with endogenous switching. We can use it to estimate if there are shift premia and if shift premia affect shift choice. At the same time, the model provides a unified framework for testing selectivity, pooling, and logical consistency. The model can be estimated using full information maximum likelihood. Alternatively, the structural probit method can be used. This approach has three steps:

1. Estimate the reduced form choice equation (3) using probit to get $\hat{\hat{\gamma}}$. Compute $\phi(\hat{\hat{\gamma}}\hat{\hat{Z}})$ and $\Phi(\hat{\hat{\gamma}}\hat{\hat{Z}})$.
2. Estimate the selection models corresponding to (4a) and (4b) using a two–step procedure to get $\hat{\beta}_s$, $\hat{\beta}_d$, $\hat{\sigma}_{u_s\upsilon}$, and $\hat{\sigma}_{u_d\upsilon}$. Compute $(\hat{w}_s - \hat{w}_d) = (\hat{\beta}_s - \hat{\beta}_d)X$ for each worker.
3. Estimate the structural form choice equation (2) using probit to get $\hat{\delta}$.

How do we test selectivity, pooling, and logical consistency? If $\hat{\sigma}_{u_s\upsilon}$ and $\hat{\sigma}_{u_d\upsilon}$ are significant in the wage equations, we know that this correction for sample selection was indeed needed. We test pooling in two ways. Maddala (1983) suggests an empirical specification where the expected wage is:

$$E(w) = \beta_d X + (\beta_s - \beta_d)X\Phi(\hat{\hat{\gamma}}\hat{\hat{Z}}) + (\sigma_{u_s\upsilon} - \sigma_{u_d\upsilon})\phi(\hat{\hat{\gamma}}\hat{\hat{Z}}). \tag{6}$$

The wage equation (6) can be estimated using a two–step procedure. Suppose that all $(\beta_s = \beta_d)$ for all X except the constant. This model is sometimes called the treatment effects model. It can be viewed as a restricted version of the selectivity controlled wage equations, in the sense that all the coefficients, except the constants, are the same. Equation (6) then collapses to:

$$E(w) = \beta X + \alpha\Phi(\hat{\hat{\gamma}}\hat{\hat{Z}}) + (\sigma_{u_s\upsilon} - \sigma_{u_d\upsilon})\phi(\hat{\hat{\gamma}}\hat{\hat{Z}}), \tag{7}$$

where α equals the difference in β–coefficients for the constant. This captures the effect of shift work on the wage rate. Pooling for the whole model can be tested by an F–test of the treatment effects model vs. the separate wage equations. If pooling for the whole model is rejected, we can then test pooling variable by variable by estimating (6). The impact of a variable will differ between shift wages and day wages if the estimated coefficients $(\beta_s - \beta_d)$ are significant.

There will be no problem of logical inconsistency if pooling is rejected. If data should be pooled, consistency requires either that there is no shift premium, $\alpha = 0$, or that the shift premium does not affect shift choice, $\delta = 0$. In the pooling case, the estimation of the treatment effects model provides a test of $\alpha = 0$ while the structural form probit gives us the test of $\delta = 0$.

3 Evidence: Wages, shift premia, and shift choice

Reduced form choice equation. We start by estimating the reduced form probit for shift choice, this is equation (3).[11] The marginal effects are reported in Table 1, column 1, the corresponding absolute z–values in column 2. The first group of exogenous variables are those that we consider to determine the workers decision to work shift but are not included as explanatory variables in the wage equations. The results for these variables are reported in the top rows of Table 1. The second group of variables are the explanatory variables of the wage equations (X). The bottom rows of Table 1 report the results for these variables.

Kostiuk (1990) uses the shift rate within the industry as the main instrument to control for industry differences in shift work. He claims that this variable serves at least two purposes. First, it provides a way of incorporating industry differences in the frequency of shift work. Second, it might reflect preferences, shift work averse workers may avoid working industries where shift work is common. This variable is also highly significant here.

Previous shift work studies suggest that business cycles are important.[12] The argument is that employers try to increase capital utilization during expansions. Increased activity may be correlated with employee remuneration by profit sharing schemes. The estimation, however, shows that the impact of increased activity at the plant during the last five years is only borderline significant.

We include a dummy variable measuring if the firm offers bonuses to compensate for the negative job characteristics. In general, these bonuses are the outcome of industry level collective agreements. Hence, they cover all establishments in specific industries but only some of workers depending on the job characteristics. This variable is meant to control for worker preferences to officially and legally be compensated for such job characteristics.

[11] Appendix A presents the data.

[12] Cette (1995) discusses shift work and capital working time in France.

Table 1: Shift choice, probit models, marginal effects.

	reduced form		structural form	
shift premium			0.871	(4.23)
shift rate within the industry	1.16	(13.9)	1.13	(13.7)
increased activity at plant	0.0455	(1.94)	0.0618	(2.66)
compensating bonus	0.177	(6.43)	0.176	(6.36)
hired during the year	0.143	(2.76)	0.190	(3.95)
children, dummy	0.0522	(1.83)	0.0465	(1.70)
annual income of other household members, FF thousands	-0.00191	(3.07)	-0.00158	(2.57)
age	-0.0207	(1.93)	-0.00255	(1.76)
$\text{age}^2/100$	0.0268	(1.96)		
married	0.0318	(1.02)	0.0396	(1.28)
foreign citizen	0.0450	(0.92)	0.0239	(0.51)
schooling, years	-0.0080	(1.79)	-0.0068	(1.53)
years of job tenure	-0.0038	(0.73)		
years of job $\text{tenure}^2/100$	0.0015	(0.09)		
works in manufacturing	0.0038	(0.15)	0.0706	(2.35)
plant size, logarithm	0.0523	(5.99)	0.0159	(1.39)
service worker	-0.0551	(2.02)	0.0638	(1.53)
works in the Paris area	-0.193	(5.87)		
log likelihood	-1,009.2		-1,020.8	
χ^2	573.3		551.2	
significance level	0.000		0.000	
pseudo R^2	0.221		0.212	
number of observations	1,998		1,998	

Notes. Absolute z–values within parentheses.

Baudelot and Gollac (1993) argue that workers are only compensated for bad working conditions when the bad quality of the job is publicly recognized. The variable is highly significant in our estimations.

Now let us turn to side variables. Controlling for if the worker was hired during the survey year may capture that some workers previously were unemployed. They may be more willing to accept bad working conditions or find it more difficult to refuse shift work. The estimation shows that it has a positive and significant impact on shift choice.[13] We have also included some individual characteristics that are not directly related to the job. Having children, which is not correlated with wages in the sample, is borderline positively significant for shift choice.[14]

We have included the annual income of other household members as an explanatory variable. Workers in high income households could be less likely to choose jobs that offer compensation for bad working conditions. This idea is confirmed by our data. The annual income of other household members has a negative impact on shift choice. It should be stressed that this variable is not directly available in our data sources. The survey reports the annual remuneration of workers and the total household income, the latter only in income classes. We estimate an ordered probit model with household income class as dependent variable. The explanatory variables are the worker's annual income, if the spouse is working, if the household has capital income and public transfer income, the number of household members, if there are children, and if the worker is a foreign citizen. The estimation is reported in Appendix B, Table 4. The estimated model is used to predict household income for each household. The worker's income is then deducted from the household income.

The results for the explanatory variables also used in the wage equations are as follows. The age variables are borderline significant, the probability of shift work has a minimum at age 39. Marital status, citizenship, schooling, and job tenure do not seem to affect shift choice significantly.

There are three job related variables that are significant for shift choice. The size of the plant has a positive impact while being a service worker and working in the Paris area have negative effects. The remaining job related variable—working in manufacturing—is not significant.

We will return to discuss the results from the structural form probit. But to do this, we first need wage equations.

Wage equations. The results from the reduced form probit can be used to control for sample selection when estimating wage equations for shift and

[13] Note, however, that Altonji and Shakotko (1987) shows that this variable usually is negatively correlated with wages. Hence, its interpretation as an identification restriction can be questioned.

[14] Using the large ECMOSS, Araï et al. (1996) also find that there is no correlation between having children and wages.

day workers. Table 2, column 1 and column 2, reports the results of these estimations.

The age variables are significant in both wage equations. For shift workers the age effects peak at age 42, for day workers at age 43. Being married is significant for day workers but not for shift workers. Returns to schooling and job tenure are significant in both equations while citizenship is not.

Working in manufacturing has a negative and significant impact for shift workers. Plant size is significant for both shift and day workers. Service workers, compared to laborers, have lower wages when working shift while they have higher wages when being day workers. Working in the Paris area gives higher wages when being a day worker while there are no geographical differences for shift workers.

The selection term coefficients suggest that there is a negative selection into shift work and a positive selection into day work. Workers select themselves into day work because of preferences or comparative advantage. This is consistent with what Kostiuk (1990) finds. Kostiuk also finds that there is no effect of self–selection of workers into shift work. In contrast, our results are more surprising. Shift workers seem to prefer to avoid shift work. However, they seem to have chosen it because of the wage premium, not because of preferences or because they would be less suited for day work. This is consistent with the structural probit result, reported below, that the estimated expected wage premium is significant for shift choice.

Table 2, column 3, reports an estimation of the treatment effects model (7). Comparing with the separate wage equations, we have calculated an F–test of the hypothesis that the wage equation coefficients are the same for shift and day workers. The $F(11, 1972)$–statistic is 8.76, which corresponds to a significance level of 0.000. The hypothesis that the coefficients are the same can be rejected. This suggests that data cannot be pooled. Consequently, the problem of logical inconsistency cannot arise in this case.

Which of the explanatory variables differ in the impact on shift and day wages? In Appendix B we report the results from an estimation of the empirical specification 6. This way we test the cross equation restrictions for each variable, see Table 5. It turns out that the coefficients of the variables directly related to the individuals do not differ between the two wage equations. Age, marital status, citizenship, schooling, and job tenure have the same impacts for day and shift workers.

Working in manufacturing, being a service worker, and working in Paris have significantly lower impacts on wages for shift workers than for day workers. The plant size effect, on the other hand, is significantly higher for shift workers.

The conclusion is that it is crucial to adjust for selectivity for these data and that data for shift and day workers should not be pooled. The problem of logical consistency cannot arise in this case as data should not be pooled.

The two wage equations for shift and day workers can be used to compute

Table 2: Wage equations, sample selection models.

	shift workers	day workers	all workers
age	0.030	0.041	0.038
	(3.93)	(7.33)	(8.38)
$\text{age}^2/100$	-0.036	-0.048	-0.046
	(3.79)	(6.76)	(7.84)
married	0.026	0.048	0.042
	(1.27)	(3.19)	(3.36)
foreign citizen	-0.027	-0.030	-0.043
	(0.75)	(1.20)	(2.07)
schooling, years	0.010	0.011	0.011
	(2.99)	(4.65)	(5.85)
years of job tenure	0.015	0.008	0.010
	(4.27)	(3.28)	(5.08)
years of job $\text{tenure}^2/100$	-0.010	-0.005	-0.006
	(0.98)	(0.59)	(0.86)
works in manufacturing	-0.091	-0.018	-0.039
	(4.84)	(1.23)	(3.36)
plant size, logarithm	0.053	0.022	0.031
	(6.58)	(4.24)	(7.01)
service worker	-0.055	0.083	0.040
	(2.48)	(5.62)	(3.22)
works in the Paris area	0.004	0.144	0.113
	(0.12)	(8.17)	(7.04)
shift worker			0.213
			(5.68)
selection term	-0.109	-0.086	-0.107
	(3.76)	(3.45)	(1.52)
constant	3.11	2.83	2.86
	(20.8)	(27.6)	(35.6)
σ_{u_i}	0.22	0.22	0.23
R^2	0.45	0.31	0.35
RSS	32.15	64.43	101.30
number of observations	703	1,295	1,998

Notes. The dependent variable is the log hourly wage rate.
Absolute t–values within parentheses.

the shift premium for each person in the sample. The average shift premium in the sample is 15.7 percent. The t–statistics for this mean is 70.9.

Model selection is crucial. Suppose that we erroneously pool the data and do not correct for selectivity, the shift premium is then underestimated to 3.8 percent.[15] If instead we correct for selectivity but still erroneously pool the data, the shift premium is overestimated to 21.3 percent. This is the treatment effects model, see Table 2, column 3.

Structural form choice equation. Table 1, column 3, reports the marginal effects of the structural probit model (2). The corresponding absolute z–values are in column 4. The shift premium is highly significant. This confirms that shift choice is a result of wage differentials, not shift preferences. According to the estimation, the probability of working shift increases by 0.87 percentage points when the shift premium increases by 1 percentage point.

Analogous to the reduced form probit, there are two remaining groups of explanatory variables. The results for the variables only appearing in the choice equation are reported in the top rows of Table 1. The estimation results for this group are very similar to those from the reduced form probit.

The bottom rows in Table 1 report the results for variables also appearing in the wage equations. These are age, marital status, citizenship, years of schooling, works in manufacturing, plant size, and being a service worker. The impacts of these variables are not strong, only work in manufacturing is significant.

4 Concluding remarks

Economists expect that people who have difficult working conditions are compensated by higher wages. Workers may choose shift because of compensating wage differentials but it is also possible that they have preferences for shift work. The empirical evidence is mixed. We study if there premia paid for shift work in the French private sector. We estimate a switching regression model with endogenous switching using a sample of male full time blue collar workers from The Labor Cost and Wage Structure Survey (ECMOSS). It turns out that it is crucial to adjust for selectivity and that data for shift and day workers should not be pooled.

Our main results are

1. There is a significant shift premium, the wage rate for shift workers is 16 percent higher than for day workers. This is a higher shift premium than previously reported in the literature.

[15] This estimation is reported in Table 6 in Appendix B. Other explanatory variables that have coefficients that change a lot when controlling for sample selection are "married", "plant size", "service worker", and "works in the Paris area".

2. Shift choice is the result of wage differentials, not shift preferences. The shift premium is significant for the choice to work shift. A 1 percentage point increase in the shift premium increases the probability of shift work by 0.87 percentage points.

Model selection is crucial. Suppose that we erroneously pool the data and do not correct for selectivity, the shift premium is then underestimated to 4 percent. If instead we correct for selectivity but still erroneously pool the data, the shift premium is overestimated to 21 percent.

These are cross section results. Hamermesh (1999) reports that evening and night work has declined considerably in the U.S. between the 1970s and the 1990s. It is an important topic for future research to extend the analyses of the shift premia in France to the development over time.

Appendix A. The data

We use two data sets from The Labor Cost and Wage Structure Survey, ECMOSS (*Enquête sur le Coût de la Main–d'Oeuvre et la Structure des Salaires*) for the nonagricultural sector 1992 collected by INSEE, the French National Statistics Institute:

1. Large ECMOSS. The sample is 14,000 establishments from the nonagricultural private sector. They respond to a questionnaire describing many workplace characteristics and give information about a random sample of their employees. This resulted in an additional employer-employee survey of some 150,000 employees. This data sets has many observations and a large variety of employer characteristics which could be used as interesting instruments (demand side effects), but almost no "supply side" instruments.

2. Small ECMOSS. When conducting the large ECMOSS survey, INSEE has sent a supplementary questionnaire to a sub–sample of the 150,000 people in ECMOSS. The advantage of this questionnaire is that it can be merged with the full ECMOSS allowing us to use individual data together with variables from ECMOSS for 9,800 people.

Our starting sample is the small ECMOSS sample of 9,800 people. There are, unfortunately, many missing values so we risk losing many observations. We have, therefore, restricted our selection of variables from the small ECMOSS to a limited number. The rest of the variables are from the large ECMOSS.

The variables we use are listed below. Unless otherwise indicated the variables are from the large ECMOSS and employer–reported:

shift work Dummy variable for those who do not work an ordinary time schedule. Those working uncommon hours, in rotating teams, during night etc. are among those who are considered as being shift workers.

shift rate within the industry We have calculated the proportion of shift workers in 36 industries, according to the 2-digit French Industry classification, using the ECMOSS sample of 150,000 people.

increased activity at plant Dummy variable for those who work at plants where the activity has increased during the last five years.

compensating bonus Dummy variable for those who work at plants where the employer says that compensating bonuses are part of the wage package.

hired during the year Dummy variable for workers who entered the establishment in 1992, the year for which the survey applied.

children Dummy variable for workers who are known to have children.

total annual household income, FF Seven brackets.

$\leq$ 50,000

$>$ 50,000 – $\leq$ 75,000

$>$ 75,000 – $\leq$ 100,000

$>$ 100,000 – $\leq$ 130,000

$>$ 130,000 – $\leq$ 200,000

$>$ 200,000 – $\leq$ 300,000

$>$ 300,000

gross annual remuneration

working spouse Dummy variable for workers with working spouses.

capital income Dummy variable for those in households which have earned capital income.

public transfer income Dummy variable for those in households which have received transfers from the public sector.

number of household members

annual income of other household members Expected total annual income is computed by, first, using the ordered probit reported in Table 4 to compute the probability to be in each bracket and, second, then multiply this probability by the mid income in the bracket. Third, the workers own annual remuneration is deducted from this amount.

hourly wage rate, logarithm Gross annual remuneration divided by the annual number of paid for hours.

age

married Dummy variable for married workers. Reference is single, widowed, or divorced.

foreign citizen Dummy variable.

schooling, years Actual number of years of schooling, employee–reported from small ECMOSS.

job tenure, years

works in manufacturing Dummy variable for those working at plants belonging to the manufacturing sector. Reference is works in the service sector.

plant size, logarithm Size is measured as total number of people employed at the plant.

service worker Dummy variable for service workers, reference is laborer.

works in the Paris area Dummy variable for those working in the Paris area, reference is the rest of France.

Table 3: Sample statistics.

variable	shift workers	day workers	all workers
shift worker	1	0	0.352
shift rate within industry	0.358	0.234	0.277
	(0.114)	(0.154)	(0.154)
increased activity at plant	0.479	0.432	0.448
compensating bonus	0.865	0.598	0.692
hired during the year	0.104	0.103	0.104
children	0.596	0.499	0.533
annual household income, FF:			
$\leq$ 50,000	0.021	0.042	0.035
$>$ 50,000 – $\leq$ 75,000	0.113	0.142	0.131
$>$ 75,000 – $\leq$ 100,000	0.212	0.199	0.203
$>$ 100,000 – $\leq$ 130,000	0.270	0.230	0.244
$>$ 130,000 – $\leq$ 200,000	0.305	0.298	0.300
$>$ 200,000 – $\leq$ 300,000	0.074	0.082	0.079
$>$ 300,000	0.004	0.009	0.007
gross annual remuneration, FF	116,395	106,122	109,737
	(43,298)	(41,685)	(42,533)
working spouse	0.508	0.534	0.525
capital income	0.165	0.162	0.163
public transfer income	0.407	0.378	0.388
number of household members	3.30	3.12	3.19
	(1.40)	(1.32)	(1.35)
annual income,	19,736	23,618	22,252
other household members, FF	(21,458)	(21,864)	(21,795)
hourly wage rate, FF	63.91	58.14	60.17
	(19.77)	(18.47)	(19.13)
age	37.0	36.1	36.4
	(10.2)	(9.69)	(9.74)
married	0.677	0.617	0.638
foreign citizen	0.067	0.073	0.071
schooling, years*	10.9	11.3	11.2
	(2.61)	(3.01)	(2.88)
job tenure, years	11.7	9.43	10.2
	(9.12)	(8.64)	(8.88)
works in manufacturing	0.425	0.297	0.342
plant size	516	316	387
	(848)	(825)	(839)
service worker	0.195	0.293	0.258
works in the Paris area	0.071	0.183	0.144
number of observations	703	1,295	1,998

Notes. Standard deviations for continuous variables within parentheses.
* from the small ECMOSS, otherwise from the large ECMOSS.

Appendix B. Additional estimations

Table 4: Household income, ordered probit model.

gross annual remuneration, FF thousands	0.0106	(17.5)
working spouse, dummy	0.758	(15.5)
capital income, dummy	0.548	(8.56)
public transfer income, dummy	-0.113	(2.20)
number of household members	0.172	(8.83)
children, dummy	-0.217	(3.95)
foreign citizen	-0.325	(3.86)
threshold 1	-0.246	(2.67)
threshold 2	0.821	(9.40)
threshold 3	1.632	(18.0)
threshold 4	2.384	(25.2)
threshold 5	3.645	(34.4)
threshold 6	4.827	(34.2)
log likelihood	-3,035.9	
χ^2	785.5	
significance level	0.000	
pseudo R^2	0.115	
number of observations	2,067	

Notes. Absolute z–values within parentheses.

Table 5: Wage equation, pooling tests, sample selection model.

	day workers	interaction between $\Phi(\hat{\hat{\gamma}}\hat{\hat{Z}})$ and	difference between shift workers and day workers
age	0.035	age	0.003
	(4.55)		(0.16)
age^2/100	-0.041	age^2/100	-0.004
	(4.16)		(0.16)
married	0.065	married	-0.060
	(3.14)		(1.13)
foreign citizen	0.001	foreign citizen	-0.052
	(0.04)		(0.65)
schooling, years	0.011	schooling, years	-0.002
	(3.67)		(0.27)
years of job tenure	0.013	years of job tenure	-0.006
	(3.93)		(0.72)
years of job tenure^2/100	-0.024	years of job tenure^2/100	0.040
	(2.18)		(1.57)
works in manufacturing	0.010	works in manufacturing	-0.127
	(0.43)		(2.54)
plant size, logarithm	0.003	plant size, logarithm	0.086
	(0.34)		(4.12)
service worker	0.148	service worker	-0.355
	(7.25)		(6.44)
works in the Paris area	0.226	works in the Paris area	-0.567
	(9.57)		(6.25)
constant	2.88	constant	0.359
	(20.4)		(3.25)
$\phi(\hat{\hat{\gamma}}\hat{\hat{Z}})$	-0.201		
	(0.56)		
σ_{u_i}	0.22		
R^2	0.38		
RSS	96.39		
number of observations	1,998		

Notes. The dependent variable is the log hourly wage rate.
Absolute t–values within parentheses.

Table 6: Wage equations, without sample selection terms.

	shift workers	day workers	all workers
age	0.030	0.033	0.033
	(4.12)	(6.53)	(7.79)
age^2/100	-0.035	-0.039	-0.039
	(3.89)	(5.92)	(7.20)
married	0.038	0.055	0.050
	(1.98)	(3.98)	(4.34)
foreign citizen	-0.032	-0.039	-0.046
	(0.95)	(1.66)	(2.40)
schooling, years	0.010	0.009	0.010
	(3.02)	(4.31)	(5.44)
years of job tenure	0.013	0.009	0.011
	(3.95)	(3.88)	(5.50)
years of job tenure^2/100	-0.008	-0.009	-0.008
	(0.73)	(1.24)	(1.30)
works in manufacturing	-0.090	-0.017	-0.038
	(5.04)	(1.27)	(3.52)
plant size, logarithm	0.068	0.033	0.044
	(10.7)	(8.62)	(13.0)
service worker	-0.060	0.071	0.030
	(2.82)	(5.22)	(2.58)
works in the Paris area	-0.033	0.123	0.095
	(0.97)	(7.86)	(6.55)
shift worker			0.038
			(3.55)
constant	2.93	2.98	2.95
	(21.0)	(31.5)	(37.2)
σ_{u_i}	0.22	0.22	0.23
R^2	0.43	0.29	0.33
RSS	37.26	73.32	115.80
number of observations	791	1,480	2,271

Notes. The dependent variable is the log hourly wage rate.
Absolute t–values within parentheses.

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