USING EMPLOYEE LEVEL DATA
IN A FIRM LEVEL ECONOMETRIC STUDY

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Econometric Study
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ABSTRACT

In this paper, we make the general point that econometric studies of the firm can be effectively and substantially enriched by using information collected from employees, even if only a few of them are surveyed per firm. Though variables measured on the basis of the answers of very few employees per firm are subject to very important sampling errors, they can be usefully included in a model specified at the firm level.

In the first part of the paper, we show that in estimating parameters of interest in a regression model of the firm, the biases arising from the sampling errors in the employee based variables can be assessed, as long as we have a large enough sub-sample of firms with at least two or with more (randomly chosen) surveyed employees.

As an illustration in the second part of the paper, we consider the estimation of the relationship between the firm average wage (directly obtained from the firm accounts) and estimates of the proportion of female workers based on the gender of one, two or three surveyed employees per firm. As a test, we compare the estimates that we find in this way with those using the "true" proportion of female workers (i.e., based on all the employees), which we could also directly obtain at the firm level from a firm survey. The analysis is performed on two linked employer-employee samples of about 2500 firms in the French manufacturing and services industries in 1987 and 1993, with one, two or three surveyed employees per firm (for respectively 75%, 15% and 10% of the firms).

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1. INTRODUCTION

One of the main reasons explaining the rapid development of micro-econometric analyses over the last twenty years, and in particular the rise of panel data econometrics, is a negative one: the discontent with the small number of observations in annual (or even quarterly) aggregate data, the high degree of collinearity of macro-variables, and hence the poor precision of estimates and lack of power of statistical tests. Over the years, however, applied econometricians have become increasingly aware that large sample sizes are not enough, even if crucial for the use of some of the more recent sophisticated techniques. They have discovered (or rediscovered) that the quality of the measurement of the variables is an important factor, but also that the sheer existence or availability of certain variables is often an even more critical concern, setting drastic limits on the questions that can be considered and the ways in which they can be investigated. To push away such limits and go beyond what can be done with the more traditional sources of information, such as the firm accounts, population census or consumption and employment surveys, empirical economists are tending to put more efforts in conceiving and constructing new data bases of their own, or in helping official statistical offices to do so. A prominent example of such promising evolution is the recent very rapid development of employee-employer matched data. Labor economists are the driving force in this construction, trying mainly to complement the available information on the individual characteristics and wages of workers, with information on the firms and professional environment in which they work. What we propose here is in a sense the dual attitude.

In this paper, we make the general point that using information collected from employees can effectively and substantially enrich econometric studies of the firm. More specifically, we try to make the case that this is so even if only very few employees are surveyed per firm, provided they are randomly chosen in the firm. Though variables measured on the basis of very few employees per firm are subject to very important sampling errors, they can be usefully included in a model specified at the firm level.

The variables that can be estimated on the basis of the answers of the employees surveyed in the firm may be of very different types. They may be quantitative and continuous, as we

assume in the errors in variables regression framework presented in this paper. But very frequently they will also be in the nature of a proportion based on the employee 'yes' or 'no' answer to a qualitative question, as in the application considered in the paper, or more generally in the nature of a vector of proportions based on the employee assignment to given categories. They may correspond to some objective and simple enough characteristics, such as the age of the interviewed employee, or the number of years of job experience, or the sex, or the fact that he or she uses a computer at work, etc.. But they may also be related to more subjective features, possibly concerning the firm itself as a whole that will be defined from employee's answers to a set of questions. Examples of such features range from the autonomy at work and on the job satisfaction of employees to the managerial ability of executives, the organizational flexibility of the firm or its social climate, etc.. Variables of this sort raise problematic definitional issues but they could be of particular interest in many analyses of firm behavior and performance; being difficult, both conceptually and practically, to comprehend and measure directly at the firm level, they have to be constructed from employee surveys, and one will have to analyze them in an error in variables framework similar to the one presented here.

In the second section of the paper, we show that in estimating parameters of interest in a regression model of the firm, the biases arising from the sampling errors in the employee based variables can be assessed, as long as we have a large enough sub-sample of firms with at least two or with more (randomly chosen) surveyed employees.

As an illustrative exercise in the third section of the paper, we consider the estimation of the relationship between the firm average wage (directly obtained from the firm accounts), and estimates of the proportion of female workers based on the gender of one, two or three surveyed employees per firm. For the sake of our demonstration, we also compare the estimates that we find in this way with those using the "true" proportion of female workers, (i.e., based on all the employees), which we could also directly obtain at the firm level from a firm survey. The analysis is performed on two linked employer-employee samples of about 2500 firms in the French manufacturing and services industries in 1987 and 1993, with one, two or three surveyed employees per firm, for respectively 75%, 15% and 10% of the firms.

In the conclusion, we stress again the usefulness of the method in showing that it can also be applied in the context of firm panel data, and end with a few words of advice on how to proceed in matching an employee survey to firm data.

2. ASSESSING THE BIASES FROM USING EMPLOYEE LEVEL VARIABLES IN THE ESTIMATION OF A FIRM LEVEL MODEL

2.1 - A simple sampling errors in variables model

We consider the following simple regression model <u>specified at the firm level</u>:

$$y_i = \alpha \, x_i^* + \varepsilon_i$$

for $i = 1$ to N, where i is the subscript for the i th firm in the sample of N firms considered, where y_i is "explained" by x_i^* and α is the parameter of interest. As usual ε_i denotes the disturbance term in the regression, summarizing all sources of "errors", which we assume to be uncorrelated with x_i^*.[1] However, unlike the dependent variable y_i, the explanatory variable x_i^* is not known at the firm level, either simply because it is "unobserved" or more deeply because it should be thought of as an "unobservable" latent variable: that is either a variable which is not recorded in the firm information available for the analysis, but could be in principle measured and included in future investigation, or a variable which is too costly or too problematic, or both, to define and directly measure at the firm level.

The "true variable" x_i^* can however be estimated or proxied by the firm level empirical average x_i of an employee survey based variable. If there is n_i surveyed employees in the i th firm and if h denotes the h th surveyed employee among the n_i surveyed employees, we have

$$x_i = (\sum_{h=1}^{n_i} x_{ih}) / n_i$$

where the variable x_{ih} directly corresponds to the answer of the surveyed employee h in the firm i to an appropriate question or can be constructed from his or her answers to a relevant set of questions, and where the summation is over all the n_i surveyed employees in firm i.[2] As we already stress in the introduction, the scope of firm level variables x which can be constructed from employee level variables is extremely large; evidently, however, all firm variables do not fall in this category. In particular it should clear that we do not need to

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[1] We also assume that ε is i.i.d., with $E(\varepsilon_i) = 0$ and $Var(\varepsilon_i) = \sigma_\varepsilon$, and we delete the constant in the regression for simplification without real loss of generality.

[2] For simplicity and since our model of interest is specified at the firm level, we use the notation x_i rather than the usual notation $x_{i.}$ (where the dot subscript indicates over which index the mean of x_{ih} is computed). Note also

assume that this is the case for the dependent variable y (or for other variables than x in the equation), although it will be in our application in the next section.[3]

Depending on the number n_i of surveyed employees per firm, the observed x_i is more or less affected by sampling errors, and using it to approximate the "true" x_i^* in the model will cause the ordinary least squares estimator of α to be more or less severely biased. It is easy to see that we are in a classical case of random errors in variables, but fortunately in a case where we can estimate the error variance and hence compute a corrected least squares estimator, which will be consistent.

Assuming first that the n_i surveyed employees are randomly drawn among all the employees of firm i, then x_i is a consistent (and unbiased) estimate of the "true" x_i^*, and its variance is decreasing with n_i . This assumption will evidently be fulfilled by construction, in the case where the employee data set is obtained by choosing at random the surveyed employees in each of the firm of the firm sample to be considered. But it is also fulfilled in the more usual case where the employee and the firm data sets to be linked are independently constructed, and where the persons surveyed in the employee sample are randomly chosen in the total population or labor force. This is the case of our application in the next section.[4]

Assuming further that the individual answers x_{ih} of the surveyed employees in firm i are independently distributed, the variance of x_i is in fact just that of x_{ih} divided by n_i .[5] More precisely, we can write:

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that we simply use x_i rather than the more precise $\bar{x}_i$ or $\hat{x}_i$ (with the overbar or the overhat reminding that it is an estimate over the random sample of the n_i surveyed employees in firm i).

[3] In our application all the firm variables can be viewed as employee variables aggregates, y being the log of the average firm wage per employee (not though the average log wage), x the proportion of female employees and the control variables z the proportions of employees according to three types of skills (or occupations). In fact the wage equation we estimate, although we consider it at the firm level, can be simply viewed as resulting of the agregation of underlying employee level wage equations (see for example Haegeland and Klette in this volume for an explicit derivation). However, this of course does not need to be. We could have considered for example a productivity equation, where the production function is directly defined as a firm (or plant) level relationship and where the productivity variable measured by output or value added per employee or the capital variable by gross book values or insurance values of fixed assets per employee cannot be really considered as employee level agregates (see again Haegeland and Klette in this volume, who estimate gender, education and experience effects for both wage and productivity equations at the plant level, or Greenan and Mairesse, 1996, who do the same at the firm level for computer use impacts).

[4] Note that in this case the number of surveyed employee per firm n_i will tend to be larger with the firm size.

[5] This will be the case if x is a continuously distributed variable as we assumed in this section. For a discrete variable, this will also be the case if in principle the surveyed employees are randomly drawn in the firm with remise, or if in practice the total number of employees in this firm is not too small. This is true for our application in the next section, where we consider a sample of firms with twenty or more employees. This should also be true, however, for firms of about 10 employees. For firms of a smaller size, one will have to make appropriate corrections in deriving the variance of x_i from that of x_{ih} .

$$x_{ih} = x_i^* + e_{ih}$$

with:

$$E(x_{ih} \mid i) = x_i^* \text{ , or } E(e_{ih} \mid i) = 0 \text{ , and } Var(x_{ih} \mid i) = Var(e_{ih} \mid i) = \sigma_i^2$$

and hence:

$$x_i = x_i^* + e_i$$

with:

$$E(x_i \mid i) = x_i^* \text{ , or } E(e_i \mid i) = 0 \text{ , and } Var(x_i \mid i) = Var(e_i \mid i) = \sigma_i^2 / n_i$$

where e_{ih} is the sampling error on x_{ih} of variance σ_i^2, and where e_i is the sampling error on x_i of variance σ_i^2 / n_i, that is by definition:

$$e_i = (\sum_{h=1}^{n_i} e_{ih}) / n_i \text{ , and } \sigma_i^2 = Var(x_{ih} \mid i) = E[(\sum_{h=1}^{n_i} (x_{ih} - x_i)^2 / (n_i - 1)) \mid i]$$

It is important to note that σ_i^2 cannot be estimated for $n_i = 1$. Note also that when needs be, in what follows, we will simply assume that σ_i^2 is independent of the x_i's and equal for all firms (i.e., $\sigma_i^2 = \sigma^2$).[6]

Considering next that the sample of firms itself arises at random from an underlying (large) population of firms, we can see that the sampling errors e_i's are uncorrelated across firms with the true values of the x_i's. More precisely, we can write:

$$E(e_i) = E[E(e_i \mid i)] = 0 \text{ , and } Cov(e_i \, x_i^*) = E(e_i \, x_i^*) = E[E(e_i \, x_i^* \mid i)] = 0$$

and hence:

$$E(x_i) = E(x_i^*) \text{ , and } Var(x_i) = Var(x_i^*) + Var(e_i)$$

where $Var(x_i)$ and $Var(e_i)$ are respectively the (across firms) variance of the estimated x_i's and that of the sampling errors e_i's, and where $Var(x_i^*)$ is the corresponding "true" variance. Note that in the usual terminology of the analysis of the variance, $Var(x_i)$, $Var(e_i)$ and $Var(x_i^*)$ are simply the "between firm" variance of the "firm-employee" variables x_{ih}, e_{ih} and x_{ih}^* respectively.[7]

Considering finally the approximate equation where one uses the estimated x_i instead of the "true" ones x_i^*, we have:

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[6] This assumption can be relaxed in different ways. It is not made in our application in the next section, where x_i is the estimated mean p_i of a binomial variable $B(p_i^*; n_i)$ and where σ_i^2 is thus equal to $p_i^*(1-p_i^*)$. See below 2.3.

[7] Note also that while expectations or variances, such as $E(x_i \mid i)$ and $Var(x_i \mid i)$, are only taken over the random sample of surveyed employees in firm i , expectations and variances like $E(z_i)$ and $Var(z_i)$ are also taken over

$$y_i = \alpha \, x_i + v_i \quad \text{with} \quad v_i = \varepsilon_i - \alpha \, e_i$$

and see that we are in the pure classical textbook case of a random uncorrelated errors in variables model.

2.2 - Correcting the least squares estimator

We know (and can easily verify) that the ordinary least squares (OLS) estimator $\hat{\alpha}$ of the parameter of interest α, in the approximate equation with the measured x_i's, is biased downward in proportion to λ, where λ is the share of the sampling error variance of the x_i's in their measured variance, or equivalently $(1- \lambda)$ is the share of the true variance in the measured variance.

More precisely, we have:

$$\text{plim}(\hat{\alpha}) = \text{Cov}(x_i \, y_i) / \text{Var}(x_i) = (1- \lambda) \, \alpha$$

with

$$\lambda = \text{Var}(e_i) / \text{Var}(x_i) = \text{Var}(e_i) / [\text{Var}(x_i^*) + \text{Var}(e_i)]$$

or

$$(1- \lambda) = \text{Var}(x_i^*) / \text{Var}(x_i) = \text{Var}(x_i^*) / [\text{Var}(x_i^*) + \text{Var}(e_i)]$$

The important point here is that as long as we have at least a (large enough) sub-sample with more than one employee surveyed per firm, we can estimate the error and true variances, and hence we can simply obtain a consistent estimate of α.

Consider first a sub-sample with a constant number n of surveyed employees per firm ($n_i = n$), we can write:

$$\text{Var}(e_i) = E[\text{Var}(e_i \,|i)] + \text{Var}[E(e_i \,|i)] = E[\text{Var}(e_i \,|i)] = E(\sigma_i^2) / \, n = \sigma^2/n$$

and

$$\lambda = \sigma^2 / [n \, \text{Var}(x_i)] = \sigma^2 / [n \, \text{Var}(x_i^*) + \sigma^2]$$

Note that σ^2 (equal σ_i^2) and $\text{Var}(x_i)$ can be respectively viewed as the sub-sample "within firm" (across employee) variance and the sub-sample "between firm" variance of the individual employee variable x_{ih} .[8]

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the (random) sample of firms. Again for the sake of easiness and in the absence of ambiguity in the present context, we do not use the more precise notations $E_i(z_i)$ and $\text{Var}_i(z_i)$.

[8] Note that the expression $n \, \text{Var}(x_i) = n \, \text{Var}(x_i^*) + \sigma^2$ can also be seen as the between -within decomposition of the total variance in the analysis of variance model $x_{ih} = x_i^* + e_{ih}$.

It is clear from these formulas that the relative bias λ decreases with n. For example, if we suppose that $Var(x_i^*) = \sigma^2$, we have λ equals one half, one third or one fourth for the sub-samples with respectively one, two or three surveyed employees. If indeed we consider separately such sub-samples, as we shall do in our application in the next section, we should be able to check that the biased least squares estimates of our parameter of interest tend to be greater (in absolute value) in sub-samples with two surveyed employees than in those with only one, and in those with three surveyed employees than in those with two.[9] Although these formulas apply for all n (including n=1), it must be remembered that σ^2 can only be estimated in the sub-samples with n larger than one.

Considering next the full sample, we can immediately generalize the above formulas by combining them for all the sub-samples with two or more surveyed employees per firm. This amounts to simply taking for σ^2 the overall within firm (across employee) variance and for n the weighted *harmonic mean* of the numbers of surveyed employees per firm, for all the firms with more than one surveyed employee.

More precisely, let us suppose that the full sample is made of S sub-samples with different numbers of surveyed employees per firm, the sth sub-sample consisting of the N_s firms with s surveyed employees per firm, the weighted harmonic mean n is such as:

$$(1/n) = \sum_{s=2}^{S} \Pi_s (1/n_s) \quad \text{with} \quad \Pi_s = N_s / [\sum_{s=2}^{S} N_s]$$

where Π_s is the proportion of firms with s more than one surveyed employees among all the firms with more than one surveyed employees.

Using now this value for n , the previous formulas apply, and we can write:

$$Var(e_i) = (\sigma^2 / n)$$

and

$$Var(x_i^*) = Var(x_i) - Var(e_i)$$

where σ^2 and $Var(x_i)$, that we can also denote σ_w^2 and σ_b^2 from now on, are respectively the overall (across employee) within firm and overall between firm variances of the individual employee variable x_{ih}.

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[9] Note that one could in principle retrieve consistent estimates of λ and α from such relations between the OLS estimated α and the observed variances of the measured x's for the different sub-samples with a constant number of surveyed employees per firm, that is just using the fact that of being able to identify these sub-samples. It is likely, however, that these estimates will be much more inaccurate than the estimates we considered here, which are also using the within firm across employees information in these sub-samples to estimate σ^2, and hence λ.

Finally one obtains a consistent corrected least squares (CLS) estimator $\tilde{\alpha}$ of the parameter of interest α by substituting in the formula of the OLS estimator $\hat{\alpha}$ the estimated true variance for the measured one, that is:

$$\tilde{\alpha} = [\hat{V}ar(x_i^*)]^{-1} [\hat{C}ov(x_i \, y_i)]$$

or

$$\tilde{\alpha} = [\hat{V}ar(x_i) - \hat{V}ar(e_i)]^{-1} [\hat{C}ov(x_i \, y_i)] = [s_b^2 - (s_w^2 / n)]^{-1} [\hat{C}ov(x_i \, y_i)]$$

Applying this corrected estimator is in practice simple enough. To do so, we only need to obtain a consistent estimate of the error variance, and hence of the true variance of the x_i's. For this we can rely on estimating the (across employee) within firm variance σ_w^2, which in turn is possible if we have at least one sub-sample with two or more surveyed employees per firm.

2.3 - Remarks and extension

It is worthwhile to make a number of remarks on the above corrected least squares (CLS) estimator, and in particular that it easily generalizes to the case of the multivariate linear regression.

1) It is interesting first to note that the usual t-ratio test of significance of α, based on the ordinary least squares estimate $\hat{\alpha}$ and its estimated standard error, remains valid. Actually under the null hypothesis of $\alpha = 0$, whatever the sampling errors, the OLS estimate $\hat{\alpha}$ is unbiased (i.e., $E(\alpha) = 0$), and the distribution of the t-ratio is unaffected (following a Student's t distribution in a small sample if the error in the equation is itself normal). Thus even if one has to use a variable which happens to be only based on the answers of one interviewed employee per firm, one can in principle find out whether this variable is significant or not as an explanatory variable.

2) In the same vein, it is always possible to use an employee based variable as the right hand side variable to be explained in a firm level regression. This simply amounts to adding another source of (uncorrelated) error to the regression, and this is not per se a cause of bias of the OLS estimator, but will affect its precision, and possibly quite severely so.

3) One has to be aware, however, that in small samples the corrected estimator (as defined) is not always a proper estimator. This will be the case if the estimated error variance $\hat{V}ar(e_i)$ happens to be larger than the observed variance $\hat{V}ar(x_i)$, implying that a non positive estimate $\hat{V}ar(x_i^*)$ of the true variance. Fuller (1987) proposes a partial adjusment

technique to take care of this case, but it remains in practise much preferable when the estimated error variance is not a very large fraction of the observed variance.[10]

4) This last remark raises the problem of the precision of the corrected estimator $\tilde{\alpha}$ as compared to that of the OLS estimator $\hat{\alpha}$. In terms of its formula, the corrected estimator can simply be viewed as an OLS estimator performed on the true equation, where one would be using the true variance $Var(x_i^*)$ of the x_i's (and since we have $Cov(x_i\ y_i) = Cov(x_i^*y_i)$)). One might thus expect the standard error of $\tilde{\alpha}$ to be larger than that of the corresponding (biased) least square estimate $\hat{\alpha}$ because of its smaller denominator, equal to $[Var(x_i^*)]^{1/2}$ instead of $[Var(x_i)]^{1/2}$, and therefore smaller by a factor of $(1-\lambda)^{1/2}$.

This is in fact too simplistic. It is better, but also not quite right, to view the corrected estimator as an instrumental variable estimator where one would be using the true x_i's (if one knew them!) to instrument the measured x_i's (since we also have $Var(x_i^*) = Cov(x_i^*x_i)$)). Thus another reason of why the standard error of $\tilde{\alpha}$ is larger than that of its least squares counterpart $\hat{\alpha}$, is a larger estimated numerator (equal to $\hat{V}ar(v_i)$), the estimated variance of v_i , the error in the estimated equation, which by definition is minimum at the least squares estimation). Yet another reason will be the fact that the error variance $Var(e_i)$ is not exactly known but is estimated with varying precision.

5) Actually the derivation of the standard error of the corrected estimator $\tilde{\alpha}$ is not too easy; and one has to use large sample theory to obtain its limiting distribution. The formula for the asymptotic variance of $\tilde{\alpha}$ (assuming normality of the sampling error e_i and the error in the equation ε_i) is the following when the error variance $\hat{V}ar(e_i)$ is exactly (very precisely) known:

$$\hat{V}ar(\tilde{\alpha}) = (N-1)^{-1} [\hat{V}ar(x_i^*)]^{-2} [\hat{V}ar(x_i)\ \hat{V}ar(v_i) + \tilde{\alpha}^2\ \hat{V}ar(e_i)\ \hat{V}ar(e_i)]$$

where the first term $(N-1)^{-1}\ [\hat{V}ar(x_i^*)]^{-2}\ [\hat{V}ar(x_i)\ \hat{V}ar(v_i)]$ is that of the instrumental variable estimator as just suggested. When the error variance is estimated, the formula includes an additional third term $(n)^{-1}(N-1)^{-1}\ [\hat{V}ar(x_i^*)]^{-2}\ [2\tilde{\alpha}^2\ \hat{V}ar(e_i)\ \hat{V}ar(e_i)]$, which decreases in proportion to n , the average number of surveyed employee per firm (and can be neglected relatively to the other terms for large n).[11]

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[10] Note that one must have in fact the following condition, which is more restrictive than $\hat{V}ar(e_i) < \hat{V}ar(x_i)$:
$Var(\varepsilon_i) = Var(y_i - \tilde{\alpha}\ x_i)$ positive, that is $[Cov(x_iy_i)]^2 < \hat{V}ar(y_i)\ [\hat{V}ar(x_i) - \hat{V}ar(e_i)]$.

[11] The formula for a known error variance is the one given in Fuller 1987, theorem 1.2.1. See theorem .2.2.1 for a more general formula in the multiple regression case and when the error variance-covariance matrix is

6) The results so far directly generalize to the multivariate linear regression model. This is the usual extension in the case of a regression with only one employee survey based variable x_i and a number of firm level measured variables z_i. If we just want to focus on the coefficient of the employee based variable x, we can rely on the so-called Frisch-Waugh procedure. That is first compute the residuals from the least squares projections of y (to be explained) and of x on the z (including the constant or a set of industry dummies), and then consider the simple regression between these residuals. We are back to the previous one explanatory variable specification, and the main change in the above formulas amounts to taking the partial or net variances of x and y, remaining unexplained by z, and the corresponding net covariance. One can see in particular that the relative bias λ can be much larger; it is now equal to the share of the unchanged error variance to the net observed variance of the x_i's, and is thus equal to the previous λ in the equation without the additional control variables z, divided by $(1-R_{xz}^2)$, where R_{xz}^2 is the multiple correlation coefficient of the regression of x on the z.

7) The extension to the multivariate regression where there are several employee variables x is also straightforward. In practice one has first to compute an estimated variance-covariance matrix of the sampling errors in the (across employee) within firm dimension as before, and hence compute by difference with the observed variance-covariance matrix of the x_i's an estimate of the true variance-covariance matrix; then one has simply to substitute the estimated true matrix for the observed one (in the overall variance-covariance matrix of the x_i's and z's) to obtain a consistent corrected least squares estimator of all the regression parameters.[12].

8) Until now, we have assumed that $\sigma_i^2 = Var(x_{ih}|i)$ is independent of the x_i's ; this is not true, however, in our application in the next section, where the underlying process $x_{ih} = p_{ih}$ is one of a zero-one binomial variable of observed mean p_i, with true mean p_i^* and variance $\sigma_i^2 = p_i^* (1-p_i^*)$ for a given firm i.[13] Looking at this case of a binomial variable, we can see that in fact the only difference with what precedes is in the expressions of the error and true variances. We can write as before for the given firm i:

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estimated in a situation as ours (that is independently from the variance-covariance matrix of the x_i's , but with a precision increasing with the size N of the sample).

[12]Note that in principle non-linear terms in the employee based x variables can be included in the regression. One must be must be aware, however, that non-linear errors in variables models raise important additional difficulties. See Chapter 3 in Fuller 1987; see also the note by Griliches and Ringstad, 1970.

$$p_i = p_i^* + e_i$$

with

$$E(p_i | i) = p_i^* \quad \text{or} \quad E(e_i | i) = 0$$

and

$$Var(p_i | i) = Var(p_i^* | i) + Var(e_i | i) = Var(p_i^*) + \sigma_i^2/n_i = Var(p_i^*) + p_i^*(1-p_i^*)/n_i$$

from which we can directly derive that for the full sample of firms:

$$Var(p_i) = Var(p_i^*) + Var(e_i) = Var(p_i^*) + E[p_i^*(1-p_i^*)/n_i]$$

or

$$Var(p_i) = Var(p_i^*) + [p^*(1-p^*) - Var(p_i^*)]/n = (n-1)Var(p_i^*)/n + p^*(1-p^*)/n$$

where p^* denotes the full sample true mean, and where n is now defined as the weighted harmonic mean of the number of surveyed employees per firm for the full sample (and not only for the sub-samples with more than one surveyed employee as before). If there is only one surveyed employee per firm for all the firms in the sample, we see, as could be expected, that n=1 and $Var(p_i) = p^*(1-p^*)$, and hence the true variance $Var(p_i^*)$ cannot be estimated. However, if we have at least a sub-sample with more than one surveyed employee, n is larger than one and the true variance can simply be expressed as:

$$Var(p_i^*) = [nVar(p_i) - p^*(1-p^*)] / (n-1)$$

and thus be consistently estimated on the basis of the full sample empirical variance $\hat{V}ar(p_i)$ and empirical mean $\bar{p}$ (and the value of n).[14]

3. LOOKING AT THE RELATION BETWEEN THE FIRM AVERAGE WAGE AND THE PROPORTION OF FEMALE EMPLOYEES

3.1 Variables, sample and sub-samples

Mainly as an illustration of our formal analysis, we consider the estimation of the relationship between the firm average wage (directly measured at the firm level from its current accounts)

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[13] Note that the problem is the same for a multinomial variable defined over a given set of categories, corresponding to the extension from one binomial variable to a vector of interrelated binomial variables (i.e., one for each category).

[14] We also verify, as before in the continuous variable case, that the difference between the observed and true variances (i.e., the sampling errors variance) decreases in inverse proportion to n, when n increases.

and the proportion of female employees which we can obtain at the firm level by matching an employee survey to the firm data bases maintained by the French statistical office INSEE. The survey is "l'enquête sur les Techniques et l'Organisation du Travail", known as TOTTO, which has been conducted in 1987 and in 1993, by the French "Ministère du Travail". TOTTO concerns a sample of individuals who have been working during the year, randomly drawn from the French labor force.[15] TOTTO is a rich source of knowledge on the organisation of work and use of new technologies in the firm. It provides in particular unique information on computer use at work, which we have already matched to firm information in Greenan-Mairesse (1996), in an attempt to assess computer impacts on firm productivity.

We start here from the same matched samples as in this previous study, but for our present purpose we prefer to focus on the regressions of the firm average wage on the proportion of female workers, for which we expect moderately to strongly negative coefficients, depending on whether we (roughly) control for skill composition or we do not. The main reason for the choice of this example is that we can also know the average proportion of female employees among all the firm employees from a regular firm survey, "l'Enquête sur la Structure des Emplois"(ESE). The obvious interest is of course in allowing us to compare the estimates using the proportion MFEM of female workers in the firm, as estimated on the basis of the gender of the very few interviewed employees per firm in TOTTO, and the true proportion PFEM, or if not exactly true much more accurate proportion, as known by ESE. Also, we will be able to regress MFEM on PFEM, and thus directly verify whether a number of implications of the classical random (non correlated) errors in variables framework, as developed in this paper, are indeed verified.

We linked the ESE firm surveys for 1987 and 1993 to the INSEE firm data sets, providing the usual accounting data from which we constructed the firm average wage variable LW (in logs) considered here.[16] The ESE firm survey also allowed us to obtain the variables of the general skill composition of labor in the firm, which we use for controls in our firm wage regressions. We have estimated all the regressions with and without including the three skill variables PCA, PCP and PEA. These are defined respectively as the proportions in the firm total

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[15]TOTTO is conducted as an occasional supplement to the regular survey on employment "L'Enquête Emploi", which gives a selection probability of 1/1000 to each person in the French labor force, that is a sample of about 20 000. TOTTO proper concerns all the respondents who have been working during the year.

[16] These data sets come from SUSE ("Système Unifié de Statistiques d'Entreprises"), which combines the information of the firm annual surveys ("Enquêtes Annuelles d'Entreprises, EAE") and the firm fiscal declarations ("Déclarations de Bénéfices Industriels et Commerciaux, BIC").

number of employees of the managers and executives in "administrative" occupations ("admistrateurs"), of the managers and executives in "productive" occupations ("ingénieurs"), and of the employees in admistrative subordinate positions or white-collars ("employés"). The remaining category, that of the blue-collars ("ouvriers"), is the left out category in the regressions; its proportion PEP adds up to 100% with PCA, PCP and PEA and is still the largest in many industries and overall.

Quite obviously the main restriction on our final sample size results from the need to match the employee and firm data files. This we did by first tracing the SIREN identification number of the firm on the basis of its name and address as declared by the interviewed employees in TOTTO, and then using the SIREN to do the matching with the firm files. At both stages, important losses occur in the numbers of interviewed employees and firms that can in fact be linked. In the first stage this is in particular the case of self-employed persons; in the second one, this is mainly true for the interviewed employees working in the smaller firms. For that last reason, we excluded from our samples the firms with a total of less than 20 employees.[17] In total, if we consider the population of the French firms of 20 and more employees in the Manufacturing and Services industries, any strong (non random) selectivity in the sample construction seems rather unlikely; we can be fairly confident that we obtain two random samples of firms in 1987 and 1993, and more importantly we can maintain that the interviewed employees are taken at random within these firms. Note in that respect that the probability that the individuals surveyed in TOTTO (since they are randomly drawn) would be employed in a given firm is increasing with its size; and indeed the median sizes of the firms in our sub-samples with one, two and three interviewed employees are respectively about 120, 330 and 730 employees. In all our regressions, we include three size dummies (two in addition to the constant), as well as seven industry dummies (six and the constant).

In the end, we have two samples of respectively 2563 and 2213 firms in 1987 and 1993, each consisting of three sub-samples of about respectively 75 percent of firms with only one interviewed employee, 15 percent with two, and the remaining 10 percent with three.[18] To simplify matters, we have in fact abstracted from sub-samples with more interviewed

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[17] We have also excluded public enterprises and-non profit organizations, and we have not considered the Building, Construction, Energy, Transportation and Telecommunications industries, because of their specific features and/or because of the relatively small number of private firms concerned.

[18] Because of the new match with the ESE survey, the size of these samples is about 10% smaller (in number of firms) than that of our previous samples in Greenan and Mairesse, 1996.

employees per firm, by keeping only three interviewed employees chosen at random in the firms where there were four or more. To fully control for the actual differences between sub-samples (in size and industry composition and otherwise), and ascertain that the differences between the sub-samples estimates arise from the different number of interviewed employees, we have also considered what we call "restricted sub-samples" with one or two interviewed employees. These are constructed from the sub-samples with three interviewed employees by keeping only one or two of them at random, and similarly from the sub-samples with two interviewed by keeping only one of them at random.

The Table in the Appendix gives the average and standard deviations of the log wage LW, and of the estimated and true female proportion variables MFEM and PFEM, for the full samples, sub-samples with one, two or three interviewed employees (sub-samples 1,2 and 3 with respectively NS=1, 2 or 3), and the corresponding restricted sub-samples with one or two interviewed employees (sub-sample 2 with NS=1 and sub-sample 3 with NS=1 or 2). We see that the average wage is (in average) about the same across all sub-samples, increasing by nearly 30 percent in absolute terms between 1987 and 1993.[19] Our estimated and true proportions of female workers MFEM and PFEM are also about the same across all different sub-samples, and stayed about 35 to 40 percent in the two years. But mainly we verify that the averages of the two variables are, as expected, very close, within 2 or 3 percent. We can also see, as expected too, that the standard deviations of the error-ridden MFEM are much larger than that of the true PFEM, from roughly the double in the sub-samples with one interviewed employee to 50 percent larger for those with three. Likewise we see that the standard deviations of MFEM are decreasing when we go from the sub-samples with one interviewed employee to the ones with two, and again, but less so, when we go from the ones with two to the ones with three.[20] Much of what we find in what follows can in fact be traced back to these simple observations.

3.2 The ordinary least squares estimates

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[19] Note that our average wage variable is really the average labor cost by employee for the firm, including social security and other employee related charges paid by the firm. It amounts at the geometric mean (or roughly the median) to about 150 000 FF in 1987 and 200 000 FF in 1993 (or roughly 30 000 and 40 000 US $).

[20] One can also note that these standard deviations decrease by a factor of about $(1.7)^{1/2}$ between the sub-samples with one and two interviewed employees, and of about $(2.2)^{1/2}$ between those with two and three. This is less than $(2)^{1/2}$ and $(3)^{1/2}$ which will the values to be found if the differences in MFEM across firms only reflected sampling errors. There is thus room left for systematic true variance in MFEM: see Table 2 below.

[Insert Table 1 in this subsection]

The ordinary least squares estimates of the gender coefficients in our firm average log wage regressions are given in Table 1, both for the estimated proportions MFEM of female workers and for the true proportions PFEM, and with and without controlling for skill composition differences. On the whole, the estimates agree remarkably well with what we expect.

First, nearly all of our estimates are significantly negative, but much smaller when we control for skill composition. The only non significant estimates we find are in fact obtained for the restricted sub-samples (of a relatively small size) with one interviewed employee per firm, when using the estimated MFEM (i.e., 0 or 1 on the basis of the gender of this interviewed employee).

Second, the estimates using the estimated proportions MFEM are quite low relatively to the ones based on the true proportions PFEM, confirming that indeed they are severely biased downward due to sampling errors. For the full sample, for which these estimates are much more precise, the order of magnitude of the biases is roughly about 75 percent, which is what we could expect from the fact that the standard deviation of MFEM is twice that of PFEM.

Third, the estimates based on MFEM tend, as also expected, to increase when we go from the restricted sub-samples with one interviewed employee to the corresponding ones with two and with three interviewed employees. This evidence, however, is rather weak because of the lack of precision of the estimates on the sub-samples with two and three interviewed employees, due to their relatively small size.[21]

3.3 The corrected least squares estimates

[Insert Tables 2 and 3 in this subsection]

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[21] In our previous study (Greenan and Mairesse, 1996), the similar evidence concerning our estimates of the impact coefficients of computer use on the firm productivity (and average wage) is stronger. One reason is that we constructed our sub-samples with one and two interviewed employees differently, by taking the firms with exactly one or two interviewed employees (as we do here), but also taking the firms with more interviewed employees and keeping one or two at random among them. The consequence is that the size of these sub-samples (and the corresponding restricted sub-samples) is larger. In particular the size of the sub-samples with two interviewed employees is about double, and hence the precision of the estimates on these sub-samples is appreciably better. The drawback, however, is that the sub-samples with different number of interviewed employees so defined overlap, and the estimates on them are not independent anymore. With our present definition, the sub-sample estimates are independent and can be combined easily.

We show in Table 2 the estimates of the sampling error variances and true variances of the estimated proportion MFEM of female employees in the firm, for the sub-samples with two or three interviewed employees where we can compute them. Table 2 also gives the estimates of the observed variances of MFEM and the ratios (1- λ) of the true variances to the observed ones for these sub-samples, as well as the observed variances of MFEM for the sub-samples with only one interviewed employee. For comparison, it also reports the observed variances of PFEM, which should not differ much from the true variances since PFEM can be taken as the true measure of the proportion of female workers in the firm, or at the least a very accurate measure compared to MFEM. In Table 3 we present the corrected least squares estimates of the gender coefficients in the firm wage regressions for the sub-samples with two or three interviewed employees, which are based on the estimates of the sampling error variances and true variances of MFEM given in Table 2. For an easy comparison, we also show the similar OLS estimates using PFEM already given in Table 1.

From Table 2 we see that the estimated error variances amount to the major part of the observed variances of MFEM, but with an order of magnitude of about 2/3 smaller in the sub-samples with three interviewed employees than in the ones with two, which is precisely what we expect. In contrast, but also as expected, the estimated true variances for these two sets of sub-samples fall, at the second decimal place, in a same range of values: from 0.04 to 0.05 in1987 and 0.03 to 0.04 in 1993. These values agree at least very roughly with the observed variances of PFEM, which is again what we hope. If anything, however, we find a rather clear tendency for them to be smaller, with specially large differences for the sub-samples with two interviewed employees (where the estimated true variance of MFEM compared to the observed variance of PFEM is of about 0.04 as against 0.06 in 1987, and 0.03 as against 0.05 in 1993). One can view that as an indication that PFEM is not really a perfect "true" measure and is in fact also affected by some significant random errors of measurement, much smaller of course than the sampling errors in MFEM.[22] One can also suspect that such differences may well be very largely accounted by the relative lack of precision of our estimates of the true

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[22] Following this interpretation, the ratio λ of the error variance to the true variance would be roughly of an order of magnitude in the range of 20% for PFEM as compared to 80%, 70% or 60% for MFEM depending on the sub-samples (with respectively 1, 2 or 3 number of surveyed employee per firm). Although PFEM is in principle a most simple variable to define and measure, it is in fact very plausible that it is indeed affected by to some degree by errors of measurement, because of specific difficulties in the implementation of the ESE. However, a "noise to signal" ratio λ of 20% seems quite high. The values for λ that we found for our computer use indicator in Greenan and Mairesse, 1986, are in the same range as the ones we obtain here for MFEM.

variances of MFEM. Indeed, considering that the true variance estimates are obtained as the differences between the (independent) estimates of two variances, and given that in the present application these are actually based on fairly small sub-samples (of about 300 firms), one cannot hope for very precise results.

Compared to the corresponding OLS estimates in Table 1, the estimates in Table 3 correcting for the downward biases from sampling errors are indeed much larger (in absolute values), as they should be. They are in fact larger by a higher factor than the $(1-\lambda)^{-1}$ that can be computed from Table 2. This magnification occurs because we control for industry and size dummies in our first set of regressions, and also for skill composition in the second set (and what matters are the net variances conditioned on the control variables, as indicated in sub-section 2.3.6).[23] While the discrepancies between the OLS estimates with MFEM and those with PFEM are very important and significant, the corrected estimates using MFEM come much closer, on the whole, to the ones based on PFEM. Actually if one takes into account the large standard errors shown in Table 3 for these estimates, and if one also keeps in mind that the two sets of standard errors computed for corrected estimates with MFEM are in fact both underestimated (as explained in sub-section 2.3.4), most of the differences between them do not appear statistically significant (at the 5% conventional level of confidence). But again, despite such large standard errors, one may find some evidence in the numbers that the corrected estimates with MFEM are somewhat higher than those with PFEM. These differences of course reflect the ones we just noted in the estimated true variances of MFEM and observed variances of PFEM, and are consistent with the existence of some sizeable errors of measurement in PFEM.

Our corrected estimates of wage gender differentials are quite large on the whole but consistent with other comparable estimates in the literature. Taking them at their face value (with an average estimate of –0.4 with skill controls and one of –0.8 without), and considering for example a cross-sectional difference of 20% in the firm proportion of female employees (that is about the true between firm dispersion $[(Var(p_i^*)]^{1/2}$ that we find), they amount to

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[23] This magnification of the sampling errors reflects an order of magnitude of the R^2 of the auxiliary regressions of MFEM on the control variables which remains relatively modest (in a range of about 0.15 to 0.20 including only the industry and size dummies, and about 0.20 to 0.25 including also the skill variables). Such magnification will be much more pronounced in an application in which the employee based variables will be strongly correlated with the other explanatory variables.

accounting for about a quarter of the observed cross-sectional dispersion in the firm average wage to about half, with and without controlling for the firm skill composition.

3.4 A direct check of the sampling errors in variables framework
[Insert Table 4 in this subsection]

In this illustrative application where we have both the sampling error-ridden employee-based variable and the true firm level variable (or at least a rather good measure of it), we can in fact directly regress the former on the latter. We thus can check whether in such regressions the slope coefficients φ are indeed about equal to one as expected. If this is the case, the regression correlation coefficients R^2 will give us new estimates of the ratios $(1- \lambda)$ of the true variances to the measured ones, or equivalently the regression mean square errors (MSE) will give us new estimates of the sampling error variances. [24] We can then verify whether these estimates of $(1- \lambda)$ and of the error variances are about equal to the ones independently computed on the basis of the (across employee) within firm variance of the employee based variable.

Our estimates of the slope and correlation coefficients φ and R^2 in the regressions of MFEM on PFEM are shown in Table 4 for the full sample and the different sub-samples. What we see is clearly what we expected. The estimated slope coefficients are not significantly different from one. The R^2 agree roughly, on the whole, with the corresponding estimates of $(1- \lambda)$ in Table 2. They tend, however, to be higher, which again points in the direction of a modicum of random errors in PFEM: respectively 0.42 as against 0.31, and 0.34 as against 0.25 for the sub-samples with two interviewed employees in 1987 and 1993; and similarly 0.49 as against 0.39, and 0.39 as against 0.39 in the sub-samples with three surveyed employees. [25]

4. CONCLUSION

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[24] Note that if the OLS estimated φ are about equal to one, the estimated slope coefficients in the reverse regressions of the true variable on the observed one are the regression R^2 (and therefore less than one).

[25] Note that, although they reflect the same evidence, the corresponding differences in terms of the regression MSE and of the estimated error variances seem more pronounced; they are the following: 0.08 as against 0.04,

We hope to have convincingly shown in this paper that information collected from employees can be a great help in overcoming some of the major data difficulties increasingly encountered in firm econometric analyses, whether simply due to the unavailability of an easy measured variable or more deeply related to intrinsic problems in defining the relevant variables. We have also tried to convey the optimistic idea that this can be done by only surveying a few randomly chosen employees per firm, and would be very worthwhile even at the limit when one has only sub-samples with two or three surveyed employees, as in our illustrative application. We have also explained that the method to be followed, in the usual case of a linear regression model, is easy enough to implement, consisting of an application of the classical errors in variables framework, when one can obtain an independent estimate of the error variance-covariance matrices.[26]

Our framework and method, as we have presented and illustrated them here, can be in fact extended or generalized in various other contexts. We have considered them in particular in the case of a cross-sectional analysis of firms, but they can be similarly applied to a panel data analysis. In a panel data application we will not need that the surveyed employees be the same (or even be the same number) for the same firm in the different years of the panel (as long as being randomly chosen each year). The real problem will be in fact the basic one of the magnification of random errors of measurement in variables, and in the present instance the sampling errors in the employee-based variables, when one typically turns to within firm or differencing transformations in an attempt to control for unobserved correlated firm effects.[27]

We have also considered that the employee based variable (x_i) is a mean variable and estimated as such (as the firm average of the individual x_{ih} for the surveyed employees in the firm), but in principle this variable could also be for example a variance or any given quantile

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and 0.09 as against 0.03 for the sub-samples with two interviewed employees in 1987 and 1993; and similarly 0.06 as against 0.04 in the sub-samples with three surveyed employees in both 1987 and 1993.

[26] Besides the application of our framework in this paper and previously in Greenan and Mairesse, 1996, the only application which is to our knowledge quite comparable is that by Cockburn and Griliches, 1988. In their firm level investigation of the stock market's valuation of R&D and patenting activities, the two authors try to take advantage of error-ridden indicators of appropriability at a detailed industry level (not the firm level), which are based on the answers of the surveyed firms by industry (not the surveyed employees by firm) in the "Yale survey on industrial R&D". They find, however, contrary to us, that in many cases their estimates of the true variance of these indicators are about zero (with estimated error variance being as large as the observed variance conditional on the other variables in the analysis), implying that these indicators do not bring new information beyond that already captured by the other variables.

[27] For a recent exposition of the problem in the context of the estimation of a production function, see Griliches and Mairesse, 1998.

and estimated accordingly (by the firm variance and quantiles of the x_{ih}). Here also the problem will be the magnitude of the sampling error variance (involving for example in the case of a variance the within firm fourth moment of x_{ih}).

Our framework can be extended as well in contexts where the units of observation can be different from that of the employee and the firm as considered here. Indeed it has been already used in such contexts. One which is now well known in practice is that of so called pseudo-panel, where the units are "cohorts" defined by some common characteristics (like age, sex and occupation). In this case all the aggregate variables measured for the observed cohorts are error-ridden estimates of the true values for the full cohorts; and an errors in variables approach like the one considered here can be implemented to correct for the problem when of importance (i.e., when the number observations within cohort is small).[28]

In fact both our approach and the pseudo-panel approach for correcting errors in variables biases go back to a much earlier literature on either using repeated observations on the error-ridden variables in the equation of interest, or in grouping observations and estimating the equation on the group means.[29] These two methods are technically equivalent, but they differ in terms of the requirement they put on the data, and in terms of exact interpretation of the estimated equation. Both can be applied the context of a cross-section, a single time-series or a panel.[30] The originality of our approach like that of pseudo-panels is not really in the technique but in its potential domains of application. In recent years the development of pseudo-panels has been fruitful in providing new sources of data and in extending the possibilities of investigation in consumer or labor economics in particular; we hope that our approach will have a similar success in allowing for the construction and use of more comprehensive data sets in econometric studies of the firm.

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[28] See Deaton, 1985, for an original exposition of the method, and Verbeek, 1996, for a survey. For an interesting related application to an analysis of wage differentials in which in particular the authors extend the method to wage quantiles estimated on cells by age, education, sex and race, see Card and Lemieux, 1996.

[29] See Tukey, 1951, and Madansky, 1959, for using repeated observations in an errors in variables model and Malinvaud (chapter 10), 1970, for grouping observations.

[30] One of the advantage of a panel with repeated observations for the error-ridden variables, as we just suggested above, or a pseudo-panel with group observations is of course in allowing to directly control for unobserved correlated fixed effects and therefore in helping to correct for both errors in variables and omitted variables biases.

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Table 1 : Ordinary Least Squares estimates of the coefficients of the estimated and true female proportions

LW on	MFEM		PFEM		MFEM		PFEM	
	Without Controls for Skills				With Controls for Skills			
	87	93	87	93	87	93	87	93
FULL SAMPLE								
	-0.14	-0.12	-0.48	-0.48	-0.09	-0.08	-0.39	-0.40
	(0.01)	(0.01)	(0.03)	(0.03)	(0.01)	(0.01)	(0.02)	(0.02)
SUB-SAMPLE 1								
NS = 1	-0.13	-0.12	-0.45	-0.47	-0.08	-0.09	-0.39	-0.41
	(0.02)	(0.02)	(0.03)	(0.03)	(0.01)	(0.01)	(0.03)	(0.03)
SUB-SAMPLE 2								
NS = 1	-0.14	-0.04	-0.51	-0.49	-0.11	-0.01	-0.39	-0.37
	(0.03)	(0.04)	(0.06)	(0.08)	(0.03)	(0.03)	(0.06)	(0.06)
NS = 2	-0.21	-0.11	idem	idem	-0.14	-0.05	idem	idem
	(0.04)	(0.05)	"	"	(0.04)	(0.03)	"	"
SUB-SAMPLE 3								
NS = 1	-0.08	-0.11	-0.63	-0.63	-0.03	-0.06	-0.36	-0.42
	(0.03)	(0.04)	(0.08)	(0.10)	(0.02)	(0.03)	(0.06)	(0.08)
NS =2	-0.14	-0.18	idem	idem	-0.06	-0.08	idem	idem
	(0.04)	(0.05)	"	"	(0.03)	(0.04)	"	"
NS =3	-0.14	-0.21	idem	idem	-0.08	-0.10	idem	idem
	(0.05)	(0.08)	"	"	(0.03)	(0.04)	"	"

MFEM : estimated female proportion; PFEM : 'true' female proportion ; and LW : log of the firm average wage.

All regressions include industry and size dummies.

The regressions in the two last columns also control for skill composition differences as measured by : PCA , PCP and PEA.

The number of firms N is in the Full Sample :   N=2563 in 1987 and N=2213 in 1993;

in the First Sub Sample (with one interviewed employee) :   N=1882 in 1987 and N=1667 in 1993;

in the Second Sub Sample (with two interviewed employees) :   N= 363 in 1987 and N= 314 in 1993;

in the Third Sub Sample (with three or more interviewed employees) :   N= 318 in 1987 and N= 232 in 1993.

idem means unchanged: PFEM being the true variable, the OLS estimates do not vary with the number of interviewed employees, for a given subsample.

Table 2 : Observed variance, estimated error and true variances, and estimated true variance ratio (1-lambda) for the estimated female proportion and observed variance of the true female proportion.

		MFEM		PFEM	
		87	93	87	93
FULL SAMPLE					
	Obs. Var.	0.207	0.209	0.060	0.059
SUB-SAMPLE 1					
NS = 1	Obs.Var.	0.237	0.238	0.060	0.061
SUB-SAMPLE 2					
NS = 1	Obs.Var.	0.241	0.232	0.064	0.054
NS = 2	Obs.Var.	0.139	0.132	0.064	0.054
	Error Var.	0.096	0.099	0.0	0.0
	True Var.	0.043	0.033	0.064	0.054
	$(1-\lambda)$	0.310	0.250	1.0	1.0
SUB-SAMPLE 3					
NS = 1	Obs.Var.	0.239	0.230	0.050	0.045
NS = 2	Obs.Var.	0.145	0.133	0.050	0.045
	Error Var.	0.094	0.100	0.0	0.0
	True Var.	0.051	0.033	0.050	0.045
	$(1-\lambda)$	0.350	0.250	1.0	1.0
NS = 3	Obs.Var.	0.109	0.107	idem	idem
	Error Var.	0.066	0.065	"	"
	True Var.	0.043	0.042	"	"
	$(1-\lambda)$	0.390	0.390	"	"

MFEM : estimated female proportion; PFEM : 'true' female proportion.

See Table 1 for the numbers of firms N in the full sample and the three sub-samples in 1987 and 1993.

idem means unchanged: PFEM being the true variable, the observed and true variances are identical for a given subsample.

Table 3: Corrected Least Squares estimates of the coefficients of the estimated female proportion and Ordinary Least Squares estimates of the coefficients of the true female proportion

LW on	MFEM		PFEM		MFEM		PFEM	
	Without Controls for Skills				With Controls for Skills			
	87	93	87	93	87	93	87	93
SUB-SAMPLE 2								
NS = 2	-0.90	-0.73	-0.51	-0.49	-0.72	-0.41	-0.39	-0.37
	(0.08)	(0.12)	(0.06)	(0.08)	(0.07)	(0.09)	(0.06)	(0.06)
	[0.12]	[0.15]	n.r	n.r	[0.11]	[0.11]	n.r	n.r
SUB-SAMPLE 3								
NS = 2	-0.66	-1.28	-0.63	-0.63	-0.35	-0.86	-0.36	-0.42
	(0.08)	(0.01)	(0.08)	(0.10)	(0.07)	(0.12)	(0.06)	(0.08)
	[0.11]	[0.24]	n.r	n.r	[0.08]	[0.22]	n.r	n.r
NS =3	-0.70	-0.84	idem	idem	-0.48	-0.47	idem	idem
	(0.10)	(0.11)	"	"	(0.08)	(0.09)	"	"
	[0.13]	[0.14]	"	"	[0.10]	[0.11]	"	"

MFEM : estimated female proportion; PFEM : 'true' female proportion ; and LW : log of the firm average wage.

The first set of regressions (first four columns) include industry and size dummies as in Table 1.

The second set of regressions (last four columns) also control for skill composition differences (measured by : PCA , PCP and PEA), as in Table 1.

The standard errors shown in parentheses and in brackets are respectively the OLS and IV standard errors;

both are underestimated for the corrected estimates with MFEM; the latter are not relevant ("n.r.") for the OLS estimates for PFEM.

idem means unchanged: PFEM being the true variable, the OLS estimates do not vary with the number of interviewed employees

(for a given subsample) and do not need to be corrected.

See Table 1 for the numbers of firms N in the three sub-samples in 1987 and 1993.

Table 4 : Regressions of estimated female proportion on true female proportion : slope coefficient Phi and R^2 (= true variance ratio (1-lambda) if Phi =1)

MFEM on PFEM	1987		1993	
	Phi	R^2 (=1-lambda)	Phi	R^2 (=1-lambda)
FULL SAMPLE	0.99	0.28	1.00	0.28
	(0.03)	[0.148]	(0.03)	[0.151]
SUB-SAMPLE 1 NS = 1	1.00	0.25	1.02	0.27
	(0.04)	[0.177]	(0.04)	[0.175]
SUB-SAMPLE 2 NS = 1	1.07	0.30	0.83	0.16
	(0.09)	[0.168]	(0.11)	[0.195]
NS = 2	0.95	0.42	0.91	0.34
	(0.06)	[0.081]	(0.07)	[0.087]
SUB-SAMPLE 3 NS = 1	0.98	0.20	0.93	0.17
	(0.11)	[0.193]	(0.13)	[0.191]
NS = 2	1.05	0.38	0.83	0.24
	(0.08)	[0.091]	(0.10)	[0.102]
NS = 3	1.03	0.49	0.96	0.39
	(0.06)	[0.056]	(0.08)	[0.065]

MFEM : estimated female proportion; PFEM : 'true' female proportion.

The regressions do not include industry and size dummies and do not control for skill composition;

they differ only slightly from the regressions with industry and size dummies and skill composition variables

Standard errors are shown in ( ) and mean square errors (MSE) in [ ].

For other footnotes see Table 1.

Appendix : Averages and standard deviations of firm average log wage, and estimated and true female proportions

	LW		MFEM		PFEM	
	87	93	87	93	87	93
FULL SAMPLE (N=2563, 2213)	5.04 (0.33)	5.29 (0.33)	0.39 (0.45)	0.38 (0.46)	0.38 (0.24)	0.37 (0.24)
SUB-SAMPLE 1) NS = 1 (N=1882, 1667)	5.03 (0.33)	5.27 (0.34)	0.38 (0.49)	0.39 (0.49)	0.38 (0.25)	0.38 (0.25)
SUB-SAMPLE 2 NS = 1 (N=363, 314)	5.03 (0.33)	5.32 (0.31)	0.4 (0.49)	0.36 (0.48)	0.39 (0.25)	0.37 (0.23)
NS = 2 (N=363, 314)	idem "	idem "	0.38 (0.37)	0.36 (0.36)	idem "	idem "
SUB-SAMPLE 3 NS = 1 (N=318, 232)	5.1 (0.29)	5.35 (0.31)	0.39 (0.49)	0.35 (0.48)	0.37 (0.22)	0.36 (0.21)
NS =2 (N=318, 232)	idem "	idem "	0.4 (0.38)	0.37 (0.36)	idem "	idem "
NS =3 (N=318, 232)	idem "	idem "	0.4 (0.33)	0.38 (0.33)	idem "	idem "

LW is the log of the average firm "wage", precisely the average labor cost per employee for the firm (in 1000 FRF).
MFEM the estimated female proportion; PFEM the 'true' female proportion.
idem means unchanged: PFEM being the true variable, its averages and standard deviations are identical for a given subsample.