Panel analysis for French Employment Survey 2018 : Wages and risks of accident in the industry.

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Abstract

This paper aims to estimate the existence and the amount of wage compensation arising from the risk of occupational accidents in French industry. For this, it takes data from the 2018 French employment survey to assemble a panel composed 4 quarters of observations for employed individuals. With this, an indicator of propensity to accidents at work is estimated by a transformation of the number of days of absence from work assuming a "sickness" component and an "accident" component. Starting from the classical Mincerian equation (1958), controls for sex and economic activity (industrial or not) are added to estimate random effects models per individual and positive correlations are found for all except sex, for which it is negative. In the process, the relevance of geographical variables and the type of hiring is discarded. Finally, it is found that occupations declared as risky present a reduction of e 4.8 euros per hour in the French industrial sector and that, therefore, this is not a compensation for the risk assumed by the worker but a penalty.

1 Introduction

In the neoclassical paradigm, labour is a productive factor and can therefore be traded on the market in exchange for remuneration: The wage. In itself, this remuneration must account for the scarcity or excess of work in the specific area or sector in which it is contracted (and thus the level of competence required for its execution) and cover the risks incurred by the bidder (both in terms of contractual stability and occupational risks). This paper will seek to estimate the impact of "risk" signalling, meaning the likelihood of workplace accidents or health impacts in the medium to long term, on the determination of the wages offered in these jobs.

Although the literature studying wage determinants is extensive and detailed, Mencer (1958) is a seminal paper. It presents an equation for wage determination that depends on years of education and years of experience (linear and squared) as the main factors of monthly income. However, as labour economics has produced in its theory, other sub-disciplines, such as development economics or gender economics, have delved deeper into the causes of the gaps, which prevents the above equation from being carried out accurately. In this article, the notion of risk becomes one of these disruptive factors. On the one hand, job seekers seek to find jobs that maximise their temporary Inter-temporal utility, and thus the risk taken seeks to be minimised so that they can work for a lifetime. This translates into employees having to generate feedback incentives for job seekers to accept risky jobs. On the other hand, employees seek to cover the risk of unforeseen absences of workers or to assume the costs of recovering the risk either by saving a part of the wage budget for insurance or by creating a mechanism for insurance coverage. Thus, industry, as an economy sector full of machines and chemicals, is one of the sectors that could witness a high frequency of occupational accidents.

On this occasion we especially mention Lalive, Ruf and Zweim¨uller (2006), who ask how important is wage compensation for occupational hazards within the wage. To answer this, the authors start with risk estimation through accident and occupational safety variables presented in the Swiss employment survey, and further generate fatality rates considering the recovery time of accident protagonists. By relating risk variables to income variables using a fixed effects model for firms they find a strong positive correlation, adding up to the creator of 64000USD per year. Next, they also ask whether more productive workers move into jobs considered "safer", but find no correlation.

The following replicates some of the process that the authors followed and draws on it for the construction of accident rates by occupation. However, the panel models for the analysis of the French employment survey data are mostly random-effect by individual.

2 Data

The 2018 French employment survey presents a list of 4 quarters observed for individuals classified in households. In this sense, the unique identifier of each individual is a combination between the code identifying the household and the number assigned to the individual within the household. This adds up to 516 732 observations with 720 variables. To estimate the relationship between occupational accident risk and wages. We formed a panel with a year-quarter time indicator, generating 4 observations per individual that was not balanced. We retained only potentially relevant variables regarding personal information, worker status, economic activity and contract characteristics, employer characteristics. We retained only those individuals who declared themselves as full-time workers for whom we found one observation for each quarter and at least 1 observation corresponding to income.

For the construction of the wage variable, we used the variable SALMEE, which reports the monthly income derived from the main professional activity, and the variable VALPRE, which records the additional income throughout the year. The latter were divided into 12 months to obtain a monthly distribution and added to the regular monthly income. This income was divided, with the help of the variable HHC (number of hours worked per week on average, counting additional hours) and a value per hour of work was obtained.

The measure of risk of accidents at work is a variable that does not exist as such in the survey. This is why we proceeded to generate a rough accident rate, but as accurate as possible with the available information. For its calculation, the variable EMPANH was used, which denotes absences from work in the reference week measured in days. Although these absences may be due to illness, such as flu, some of them may be due to injuries occurring at work. The number of absences by occupation (CSP variable) was then calculated and divided by the number of individuals reported as working in that specific activity. Given the asymmetry in the populations belonging to each profession, we proceeded to normalise this ratio (this process was also attempted for the sum of absence durations, but the regressions were not significant with this ratio).

This is to say:

$$TotalIncome_{hour} = \frac{SALMEE + \frac{VALPRE}{12}}{4HHC}$$

$$Ratio_{accident} = scale(\frac{count(EMPANHreported)}{NumIndividuals_{occupation}})$$

It is important to mention that a crucial factor in the definition of wages as well as in the exposure to the risk of occupational accidents is the occupation. This information is contained in the CSP variable which denotes 16 occupations in France. As can be seen in table 1, the skilled and unskilled industrial workers who represented 5.76% and 3.36% of workers in France in the first quarter of 2018 and who were slightly decreasing throughout the year.However, what seems more interesting is the distribution of our risk indicator. Although it is not a perfect indicator, and, for example, farmers in medium-sized farms have an indicator of 1 (probably due to the low frequency of workers in this occupation), the indicator shows high levels, for example, for the military, which makes sense. In contrast, the indicator shows very low levels for professions in which absence for personal reasons is complicated, such as being a chauffeur or working in the liberal professions. Although we include illness in this indicator, the normal rate of absence for this reason can be taken as the median (0.38), so anything above this limit can be considered as the result of occupational accidents, and, in this sense, the indicator captures this well for most occupations. Thus, skilled and unskilled industrial workers score 0.4 and 0.44 respectively. Just by looking at these last two figures, for example, it can be presumed that unskilled workers carry out more risky work and therefore the indicator could be, at least, consistent.

Table 1: Distribution of Occupations and Risk associated.

(percentages)	2018-1	2018-2	2018-3	2018-4	rat-accident
Agriculteurs sur petite exploitation	0.12	0.12	0.29	0.36	0.30727894
Agriculteurs sur moyenne exploitation	0.02	0.02	0.02	0.02	1.00000000
Agriculteurs sur grande exploitation	0.10	0.10	0.10	0.10	0.38132045
Artisans	0.26	0.26	0.26	0.26	0.29039635
Commerçants et assimilés	0.29	0.31	0.43	0.48	0.33580834
Chefs d'entreprise 10 salariés ou +	0.22	0.22	0.19	0.19	0.09525172
Professions libérales	0.36	0.36	0.36	0.36	0.14832252
Cadres de la fonction publique	2.76	2.76	2.81	2.81	0.18532174
Professeurs, professions scientifiques	3.96	3.91	3.87	3.84	0.27257437
Professions: info., arts et spectacles	0.72	0.70	0.65	0.62	0.17061924
Cadres admin. et comme. d'entreprise	6.36	6.36	6.34	6.39	0.30235072
Ingénieurs et cadres tech. d'entreprise	6.43	6.41	6.31	6.46	0.26035884
Professeurs écoles, institut.et assimil.	4.03	4.03	4.01	4.01	0.35980146
Professions interm. santé/travail social	4.90	4.80	4.61	4.66	0.28902612
Professions interm. admin. fonction pu	2.59	2.50	2.52	2.47	0.38859516
Professions interm. admin. comm. entrep.	8.57	8.31	8.36	8.00	0.38035855
Techniciens	5.93	5.76	5.71	5.45	0.30963264
Contremaîtres, agents de maîtrise	2.83	2.86	2.81	2.76	0.40980119
Empl. civils et agents service fonction pub.	9.29	9.08	8.72	8.72	0.48946079
Policiers et militaires	2.45	2.35	2.30	2.26	0.51933569
Employés administratifs d'entreprise	5.57	5.52	5.45	5.33	0.41526723
Employés de commerce	3.70	3.51	3.31	3.22	0.50560623
Personnels services dir. aux particuliers	4.37	4.32	4.25	4.08	0.39021368
Ouvriers qualifiés de type industriel	5.76	5.81	5.69	5.45	0.42635369
Ouvriers qualifiés de type artisanal	6.27	6.10	5.93	5.93	0.39695505
Chauffeurs	3.10	3.12	3.07	3.07	0.19625143
Ouvriers qualifiés: manu., maga., transp.	2.52	2.33	2.28	2.26	0.23433570
Ouvriers non qualifiés de type industriel	3.36	3.34	3.27	3.12	0.44799744
Ouvriers non qualifiés de type artisanal	2.06	1.94	1.92	1.78	0.37106341
Ouvriers agricoles	0.84	0.82	0.79	0.74	0.49264723

Two additional variables were created: experience was constructed as the result of subtracting from 2018 (current time) the date when the individual received his/her last diploma (DatDIP variable), under the assumption that individuals work since receiving their diploma uninterruptedly. And finally, the education variable is a quantification of the CITE2011A variable that specifies the highest diploma obtained. With this information, the standard number of years needed to obtain the diploma in question is associated with each individual who holds it.

Given that, in many cases, the declared monthly income SALMEE and hours worked HHC were not complete for all 4 quarters, we proceeded to fill in the missing values with the closest value (either the previous or the next quarter) with the huge assumption that the wage does not adjust with a regularity of less than 4 quarters, that individuals do not change occupation quickly and that their working conditions are more or less stable over time. The final database consisted of 16 660 observations, i.e. 4165 individuals.

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in question is associated with each individual who holds it.

Table 2: Descriptive statistics.

	incomeTotal_hour	rat_sum_nom	exp	educ	salmee	valpre	empanh	hhc
Min.	0.4286	0.000	0.00	0.000	60	0.0	0.00000	0.50
1st Qu.	10.0000	0.289	12.00	0.000	1500	0.0	0.00000	35.00
Median	12.3810	0.380	22.00	2.000	1850	0.0	0.00000	37.50
Mean	14.5127	0.354	22.23	1.735	2193	313.6	0.01441	38.76
3rd Qu.	16.2500	0.415	32.00	3.000	2500	0.0	0.00000	40.00
Max.	2050.0000	0.519	55.00	8.000	31000	200000.0	7.00000	99.50
NA's			1575					

Table 2 shows the descriptive statistics of the numerical variables used. As expected, variables such as HCC, despite having a large range, present comparatively even distributions centred on the 38 h which is the minimum working day in France, without, of course, leaving aside exceptional cases who work almost 100 hours accumulated in the last quartile. Something similar may apply for education, which presents the first two quartiles at 0, suggesting that they barely finish their BAC. Experience, on the other hand, seems to be the most normally distributed variable centred on 22 years, which is to be expected in a country with a life expectancy of 82 years (almost half). Let us now analyse the variables of interest: on the one hand, the wage, measured by total hourly income, is centred at 12.3 EUR, a figure not far from the minimum wage, and which integrates a distribution that seems normal (2 EUR difference in each quartile). Risk, on the other hand, requires assessing 2 variables: EMPANH, as expected, shows values greater than 0 very infrequently and only at the highest percentiles. The ratio that was calculated, in contrast, allowed to increase the frequency of the variable by associating the indices by profession. This allowed for a normal distribution of the index.

3 Model

Studying the relationship between exposure to occupational hazards and wages is a complex process given the immense number of unobservable variables involved and the inaccuracy that a panel survey such as the French employment survey brings. This is why this paper proposes a simple approach to the problem by means of three types of evaluations:

The first one looks at the pure correlation between workers' exposure and wages. We expect that by unconditionally evaluating these two variables, the model will be able to separate an average wage and an adjustment for risk taken. However, it is clear that this estimation may be biased by the number of omitted variables. This is why we now propose to take the Mincerian model (Mincer, 1958) and add to it a sex dummy (which takes the value of 1 when the gender is "Not male") and a ratio calculated for occupational risk. Finally, a dummy is added to indicate that the worker works in the economic sector "industry" (based on the variable NAFG004UN as this is the research area of this paper). Thus the main equation, which will be estimated for the 3 types of panel, is presented below:

$$log(Total_{Income}) = \beta_0 + \beta_1 Educ + \beta_2 Exp + \beta_2 Exp^2 + \beta_3 Sexe + \beta_4 Rate_{Accident}$$

Secondly, it is proposed to assess whether the presence of risk remuneration itself is different within the industrial sector and outside it. In this sense industries, which include manufacturing, extraction, agro-industry, and so on, allow for the use of heavy machinery and interaction with materials that may be considered Hazardous. While they do not involve the level of danger that professions such as the military may pose, the calculated indicator of occupational risk propensity is above the median and therefore the industry was identified as a "hazardous" sector. That said, the comparison between the economic sectors should at least show a difference in order to corroborate the significance of the remuneration.

Third, it is proposed to revise two biases: First, the geographical distribution of wages in France will be assessed by including "rural/urban" variables or variables associated with the administrative divisions of the national territory. This would expose the fact that factories in the capital region pay their employees better and compensate them more since there is a greater supply of labour in the area and the risk is something that is in itself useful for the worker. Second, the impact of the legal definition of the contract would be assessed by expecting higher wages for CDIs, for example, but in particular by seeking to decipher whether it implies different risk compensation structures.
Finally, a regression that completely isolates the effect of risky work in the industrial sector (an interaction of variables) will allow us to generate a quantitative approximation of the amount of risk compensation on the wages of French industrial workers.

$$log(TotalIncome_{hour}) = \beta_0 + \beta_1 Educ + \beta_2 Exp + \beta_3 Exp^2 + \beta_4 Sexe$$

$$+\beta_5 Industry + \beta_6 Risk + \beta_7 Risk * Industry$$

4 Results

4.1 Unconditional Correlations

Table 3 shows the results of the unconditional correlation estimation for the income variables, the industry dummy and the occupational accident rate. Columns (1), (2) and (3) of the table show the possible panel regression models: Fixed effects, Random effects and Within estimator. As expected, the fixed effects have problems fitting the model to our study variables and do not suggest any sign of significance beyond the intercept. This makes sense when the panel contains a large number of individuals but very few time periods. This is even more complex insofar as the absence of responses for quarters 2, 3 and 4 forced us to perform repeated data imputations for these periods, in this sense the fixed effects operate on time invariant variables and therefore their fit does not allow us to observe anything relevant.

However, this raises questions about the independence of the errors with respect to the predictor variables. Assuming that the errors are not independent, the within estimator allows us to assess within-individual intertemporal differences. The random effects estimator allows us to generate an indicator for each individual that presumably captures the particular differences of each of them, something that is considered convenient in a case like this given the high number of individuals but the low variability among the data recorded for them over the 4 quarters.

With respect to the within estimator, it presents the highest fit when estimating the unconditional correlation and results in significance for both the accident rate and the industry dummy. However, the absence of an "expected income" related intercept may be loading on the accident rate variable. In such a case the income variable is potentially influenced by the risks involved and, in general, the industry sector shows an increase in wages.

When the Mincerian model and the gender variable are aggregated for a multi-industry evaluation, the random effects indicator (column (5)) has a higher efficiency showing a much higher adjusted r than the rest and significance for all variables. As expected, education and experience have positive effects on income. Likewise, not being male represents a reduction. Finally, the probability of risk seems to be rewarded by the labour market.

4.2 Conditional correlations

Table 4 presents again models with random effects model because of its best fit and because of the nature of the panel, an unconditional ((1) and (3)) and conditional ((2) and (4)) model was estimated for separate samples of Industry and "all others". This time a dummy was used as a measure of

Table 3: Unconditional correlation.

Lg(Incm$_{Tot}$)	(1)		(2)		(3)		(4)		(5)		(6)	
Intercept	-0.0117	***	7.5798	***			-1.20e-2	***	7.33e+0	***		
	(0.0004)		(0.007)				(4.79e-4)		(1.63e-2)			
Rate_accid.	-0.0029		0.0040		0.0121	**	4.90e-5		1.56e-2	**	2.07e-2	***
	(0.0041)		(0.004)		(0.0043)		(4.55e-3)		(4.83e-3)		(4.78e-3)	
Educ							3.18e-3		9.23e-2	***	-2.62e-3	
							(6.12e-3)		(2.95e-3)		(5.70e-3)	
Exp							-1.43e-5		1.20e-2	***	1.60e-3	
							(2.28e-3)		(1.12e-3)		(2.11e-3)	
Exp_sqr							-6.33e-6		-1.16e-4	***	-5.60e-5	
							(8.63e-5)		(2.75e-5)		(7.84e-5)	
Industry	0.01060	.	0.0342	***	0.0267	***						
	(0.0056)		(0.005)		(0.0055)							
Sexe									-1.69e-1	***		
									(1.24e-2)			
Panel	Balan		Balan		Balan		Unbal		Unbal		Unbal	
n	4165		4165		4165		3783		3783		3783	
Effects	fd		rand		with		fd		rand		with	
Total Sum Sq:	32.557		33.445		24.747		29.023		34.797		21.986	
Res. Sum Sq:	32.548		33.345		24.661		29.022		30.384		21.947	
R-Squared:	0.0002		0.0029		0.0034		4.71e-5		0.1268		0.0017	
Adj. R-Sq:	0.0001		0.0028		-0.3288		-0.0003		0.1265		-0.3327	
(P-Value)	F 0.1716	Xsq	1.63e-11	F	3.66e-10	F	0.9701	Xsq	<2.22e-16	F	0.0004	

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1. Rate of accident is count of EMPANH normalisied

risk, suggesting as "risky" any career whose accident rate exceeds the median value. While both unconditional regressions suggest that the Risk variable is significant at 1%, both do so with a negative value, suggesting that risk does, in fact, reduce wages. This impact appears to be stronger in industry, whose indicator is higher. The unconditional regressions continue to show a high degree of significance. However, the significance of the Risk parameter falls outside the accepted 5% range in economics for the other economic sectors. This result might suggest that while risk impacts on wages, in the industrial sector there is indeed a trade-off (negative or positive) of risk on wages. This counter-intuitive result might suggest that lower paid jobs have higher risks and therefore this relationship would be somewhat spurious.

4.3 Geographical and legal impact

As a final exercise, Table 5 presents regressions to check the relevance of other variables. So far, evidence has already been provided to suggest that wages depend on gender, and industry (in addition to the Mincerian variables), which can be seen in regression (1), and it is now proposed to assess whether the type of contract is a determinant of wage determination (regression (2)). While the values for apprenticeship contracts and for those who did not report any type of contract turned out to be significant and negative, most of the contract types did not pass the 5% confidence level and therefore it is concluded that contract type is not an effective explanatory variable for earnings. Also, it was asked whether the values could vary due to geographical location. This can be understood as a relationship between "urban and suburban" and "rural". But it is presumed that modern industry occupies space and consumes resources that would block it from being in the cities and in the open countryside and that therefore most of it is accommodated in the suburban perimeter of the cities which would not allow to observe a significant difference for the case of industry. Another way to understand it is to analyse its variation across the regions of France (regression (3)). In this case, however, only 1 of the regions showed a significant result suggesting that, regardless of the geographical location of the industries, the outflows are more or less homogeneous across the country. This, perhaps as a result of the high specialisation of some of the industrial workers,

Table 4: Conditional correlation.

	Industry				Other sectors			
Log(IncomeTotal)	(1)		(2)		(3)		(4)	
Intercept	2.662053	***	2.2132e+00	***	2.5642177	***	2.1869e+00	***
	(0.015634)		(4.6986e-02)		(0.0073309)		(2.0937e-02)	
Risk	-0.105695	***	-6.4580e-02	***	-0.0458489	***	-2.0890e-02	*
count-Norm	(0.018293)		(1.9390e-02)		(0.0080196)		(8.7023e-03)	
Educ			1.0988e-01	***			1.0316e-01	***
			(7.7745e-03)				(3.4243e-03)	
Exp			2.2221e-02	***			1.6824e-02	***
			(3.8709e-03)				(1.6294e-03)	
Exp_sqr			-2.4954e-04	**			-1.7874e-04	***
			(8.4735e-05)				(3.6022e-05)	
Sexe			-1.6819e-01	***			-1.0007e-01	***
			(2.8689e-02)				(1.2787e-02)	
Panel	Unbalanced		Unbalanced		Unbalanced		Unbalanced	
n	747		747		3502		3502	
Effects	random		random		random		random	
Total Sum of Squares:	22.59		22.658		117.7		113.19	
Residual Sum of Squares:	19.821		17.627		114.61		100.8	
R-Squared:	0.12263		0.22205		0.026451		0.10956	
Adj. R-Squared:	0.12232		0.22051		0.026381		0.10921	
Xsq (P-Value)	7.5598e-09		<2.22e-16		1.0837e-08		<2.22e-16	

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Table 5: Robustness

Log(IncomeTotal_hour)	(1)		(2)		(3)		(4)	
Intercept	2.1999e+00	***	2.2611e+00	***	2.2001e+00	***	2.1960e+00	***
	(1.9154e-02)		(5.5778e-02)		(1.9734e-02)		(1.9201e-02)	
Risk	-3.0255e-02	***	-3.0783e-02	***	-3.1322e-02	***	-1.9484e-02	*
	(7.4972e-03)		(7.4785e-03)		(7.8064e-03)		(8.4021e-03)	
Educ	1.0272e-01	***	9.9566e-02	***	1.0195e-01	***	1.0292e-01	***
	(3.1371e-03)		(3.1491e-03)		(3.1190e-03)		(3.1376e-03)	
Exp	1.6657e-02	***	1.7382e-02	***	1.6654e-02	***	1.6724e-02	***
	(1.5079e-03)		(1.4973e-03)		(1.4994e-03)		(1.5079e-03)	
Exp_sqr	-1.7394e-04	***	-1.8946e-04	***	-1.7565e-04	***	-1.7492e-04	***
	(3.3448e-05)		(3.3203e-05)		(3.3231e-05)		(3.3447e-05)	
Industry	5.5374e-02	***	6.1137e-02	***	5.8431e-02	***	7.3156e-02	***
	(9.4813e-03)		(9.4727e-03)		(9.9018e-03)		(1.1371e-02)	
Sexe	-1.1030e-01	***	-1.1494e-01	***	-1.0929e-01	***	-1.1089e-01	***
	(1.1680e-02)		(1.1558e-02)		(1.1591e-02)		(1.1682e-02)	
Region			Not signif.					
Contract					Not signif			
Industry-risk							-4.8549e-02	***
							(1.7139e-02)	
Panel	Unbalanced		Unbalanced		Unbalanced		Unbalanced	
n	3783		3783		3783		3783	
Effects	Random		Random		Random		Random	
Total Sum of Squares:	131.06		132.26		131.83		131.03	
Residual Sum of Squares:	119.39		119.29		119.35		119.31	
R-Squared:	0.089023		0.098038		0.094664		0.089471	
Adj. R-Squared:	0.08866		0.09672		0.093943		0.089048	
Chisq(P-Value):	<2.22e-16		<2.22e-16		<2.22e-16		<2.22e-16	

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

4.4 Estimation of the wage compensation on risk exposure

Finally, equation (4) of Table 5 presents the same model adding an interaction between the industrial dummy and the risk dummy. This interaction will allow us to estimate how much the explained variable changes when both conditions are simultaneously met: having a risky job and working in the industrial economic sector. The result was a significant negative coefficient of -4.8549e-02. This coefficient means that when the job is considered risky and the employer is classified as "industry", the wage decreases on average by 4% hour compared to non-accident-prone and non-industrial jobs.

5 Conclusions

As could be observed, the structure of the wage equation proposed by Mincer (1958) is valid for the French case today. Although with high probability the data presented here contains abundant measurement errors, the quantification and transformation of the variables of the French employment survey for the year 2018 allowed to complete a panel for 4 quarters and more than 6000 individuals. These data allowed to evaluate the significance of years of education (positive), years of experience (positive), gender (negative for any "non-male") and economic sector (positive for the industrial sector).

In addition, a risk indicator calculated through the frequency of absences from work in a week of residence for each profession allowed us to establish that this indicator would also be influential in wage determination. In view of this, it was possible to calculate that the most accident-prone jobs are not compensated for this risk but, on the contrary, suffer a loss in hourly wages of 4,8%. This result may suggest that employees who take on risky jobs are often less skilled (which seems unlikely given that the risk indicators for "skilled industrial workers" and "unskilled industrial workers" are not significantly different), or that employers cover themselves against casual absences and related costs by keeping a part of the wage budget to cover these occasional and random expenses. Providing evidence as to which of the two theories is true would require further research, which, at least for now, remains to be done.

References

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