Can Policy Directly Reduce the Unexplained Gender Wage Gap?

Evidence from Switzerland

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I. Unexplained wage gap as measure of discrimination

The typical approach to study gender wage gaps uses statistical residuals to decompose the gender pay gap into explained and unexplained wage differences. Explained wage differences are mainly attributed to differences in human capital investments. Unexplained pay gaps are usually related to other individual characteristics and are commonly attributed to wage discrimination (Oaxaca-Blinder, 1973; Killingsworth, 1993; Blau and Kahn, 2007). Numerous policy interventions have attempted to guarantee equal treatment between men and women; however, gender wage discrimination still persists.[2] Why have most these policies failed to reduce discrimination?

Different hypotheses may explain this failure. First, the burden of proof against wage discriminatory practices is usually left to workers who frequently do not appeal charges. Second, even when policies require employers to be transparent regarding their wage structure, provision of information and supervision is costly.[3] Third, employers and employees often failed to recognize wage discrimination, because it is difficult to measure.

This paper provides an example of an anti-discrimination policy called *Lohngleichheitinstrument Bund (Logib)* or *Federal Equal Pay Instrument*, introduced in Switzerland in 2006, that explicitly asks employers of firms with at least 50 workers to reduce their unexplained wage gap by using a specific wage regression. This regression includes different observable measures of productivity-related characteristics and a gender dummy which quantifies the unexplained gender wage gap in the firm. Firms' compliance is evaluated based on the magnitude and statistical significance of this

2 Blau and Kahn (2007) found that 41.1% of the gender pay difference was not explained neither by education, experience, occupation, industry, union status in 1998 in the US. In Switzerland, the unexplained gender wage gap has similar magnitude and it has been stable over time. In 2014 the average wage difference between men and women in the private sector in Switzerland was on average 19.5%. Only 61% of it was explained by objective factors, while 39% remained unexplained (Source: Federal Statistical Office, based on computations using the SWSS 2014).

3 Successful examples are governmental instruments developed in Ontario, Austria, and Sweden under which employers are required to analyze payrolls for discriminatory gender wage differences.

gender estimate. An estimated gender coefficient exceeding 5% and statistically significant at 5% is considered a sign of gender wage discrimination.

This Swiss policy aims to prevent, identify, and eliminate discriminatory practices by providing employers a self-monitoring tool. Official checks are made randomly, and sanctions may lead to exclusion from public procurement; however, they are rarely implemented. Between 2003 and 2014, monitoring has been performed against 43 firms only, and no firm has been penalized.

This paper has two important contributions. First, it provides a clean test to measure the impact of a wage discrimination policy. Despite many efforts, it has been very difficult to establish the causal effect of a policy in reducing unexplained wage gaps (Beller, 1982; Altonji and Blank, 1999; Neumark and Stock, 2006). Usually policies are not enacted in isolation and therefore it is difficult to disentangle the effect of these laws from other regulations. This paper leverages the firm size cut-off of *Logib* and data before and after the introduction of this reform, to estimate its causal effect using a Difference-in-Discontinuity (Diff-in-Disc) design. Specifically, I study whether there are significant discontinuities of average unexplained wage gap for firms around the threshold of 50 employees. Then, I compare those potential discontinuities before and after the introduction of the reform and test whether they are significantly different. This design allows me to verify if discontinuities at the relevant threshold appear only after the introduction of this policy.

Second and more importantly, this paper studies an anti-discrimination policy with a very unprecedented design. *Logib* targets explicitly the reduction of the unexplained wage gap using a regression framework. Regression analysis has been widely used to quantify the contribution of human capital investments and unobservable factors to gender wage differences, but it has not been employed to design anti-discrimination policies. The Swiss *Logib* is a pioneer policy that uses statistical methods to detect gender wage differences. Following this Swiss example, Germany developed its own *logib-d* in 2009, Luxembourg its *logib-lux* in 2011, and other European countries their *equal-pacE*. The latter refers to a broader project developed in the United Kingdom to enable companies based in Europe (initially available for companies in Finland, France, Poland and Portugal) to voluntarily analyze their pay structures to reduce potential gender pay gaps. Also, *Logib* is inexpensive, and easy to implement. Firms are recommended to run this wage regression anonymously using a free online software, based on Excel, a program with which companies and employees are usually familiar.[4] Data collection for the implementation of *Logib* does not represent an additional burden for the companies. Information used in *Logib* is collected every two years from most of the companies by the Federal Statistical Office (FSO) to build the Swiss Wage Structure Survey (SWSS).

II. Background

This section provides a brief overview of key features of the Swiss regulation. *Logib* consists in a wage regression which explicitly includes log wages as dependent variable, and a very detailed set of control variables such as education, potential experience, tenure, hierarchical position, and job difficulty, in addition to the gender dummy (1 if woman, 0 if man). Education, potential experience, and tenure refer to the number of years of education or training, years of potential experience, and number of years worked in the firm, respectively. Hierarchical position and job difficulty are categorical variables that are assigned by the employers. While the former variable can take the value of (1) senior, (2) middle-management, (3) junior, (4) low management, and (5)

[4] Documentation is available in multiple languages (English, French, German, and Italian), and free access to the software can be obtained from https://www.ebg.admin.ch/ebg/en/home/services/equal-pay-self-test-tool--logib/download-logib.html

no management; the latter can be either (1) the most difficult, (2) independent work, (3) professional knowledge, or (4) simple and repetitive work (Strub, 2005).[5]

Although the Swiss government prohibits discrimination regardless of firm size, only firms with 50 workers or more are required to use *Logib* to check whether their pay practices are discriminatory. Among them, only the subsample of contractors is randomly investigated to verify that men and women receive equal pay for equal work. Firms that fail to comply with this equal pay law will be excluded from the public procurement processes, their licenses will be revoked, and/or their approved contracts will be cancelled. The causal effect of being assigned to the treatment is twofold; it combines the effect of the recommendation and the effect of monitoring, because it is not possible to disentangle both effects.[6] If the policy was effective, one would expect that after the introduction of this policy in 2006, firms with less than 50 workers have, on average, higher unexplained wage gap estimates than larger firms.

III. Data and Identification Strategy

The empirical analysis uses the Swiss Wage Structure Survey (SWSS) from 1996 to 2010, and the Swiss Business Census (BC) from 1991 to 2008. The SWSS is a biannual and representative survey, with a repeated cross-sectional structure, that collects relevant information about firm characteristics (size, geographic location, industry, etc.) and socio-demographic information about firm's workers. RDD and Diff-in-Disc estimations use this survey for the analysis. Since the sampling rates in the SWSS change by firm size, I use the BC to examine the continuity of the

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[5] Specifically, the detailed policy uses this wage equation $\ln(wage) = \beta_0 + \beta_1 educ + \beta_2 \exp + \beta_3 \exp^2 + \beta_4 ten + \beta_5 hier + \beta_6 dif + \beta_7 fem + u$, where *educ* refers to education, *exp* to potential experience, *ten* to tenure, *hier* to hierarchical position, *diff* to job difficulty, *fem* to the female dummy, and *u* to the error term.

[6] Multiple efforts have been carried out to obtain information regarding public tenders in Switzerland; however, neither the list of companies, statistics based on firm size, nor industry details of public tenders has been available. Provision of public services are compiled only by contracts and it is not possible to identify single public providers.

running variable (firm size). The BC assembles information about all firms in Switzerland, and it is collected three times per decade. It includes information of workplaces and persons employed in all companies from the industrial, trade and service sectors; however, it does not provide information about worker characteristics.

The main concern of the identification strategy is the potential sorting around the threshold. Firms close to the cut-off may change their size to avoid being affected by the federal recommendation. To assert that the treatment assignment is as-good-as-random, histograms and McCrary (2008) tests show that the distribution of firms in Switzerland is continuous at the threshold, before and after the introduction of this Swiss wage policy (Vaccaro, 2017). These can be interpreted as evidence that no firm size manipulation takes place in response to the Swiss regulation. Also, according to the Swiss Federal Office of Gender Equality (FOGE), *Logib* is the only Swiss legislation designed to affect companies based on firm size. Neither the Swiss Federal Labour Act nor any other Swiss regulation establish legal obligations that differentiate between firms with less or more than 50.

IV. Method and Results

The causal effect of the policy is identified by using a Diff-in-Disc design, a combination of a Regression Discontinuity Design (RDD) which exploits the discontinuity of the assignment of the *Logib* policy at the 50-employee threshold, and a Difference-in-Difference (Diff-in-Diff) strategy that uses data for all the period of the analysis (Grembi, Nannincini and Troiano, 2016). If firms are continuously distributed at the relevant threshold, the causal effect of this Swiss policy can be identified by an OLS model as:

$$\hat{\beta}_j = \gamma_0 + \gamma_1 f(S_j) + [S_j \geq 50]\left(\delta_0 + \delta_1 f(S_j)\right) +$$

$$[T_t \geq 2006]\left\{\alpha_0 + \alpha_1 f(S_j) + [S_j \geq 50]\left(\phi_0 + \phi_1 f(S_j)\right)\right\} \quad \text{(equation 1)}$$

Where j refers to each firm, S_j to the normalized firm size centered to the mean, $f(S_j)$ is a polynomial function of firm size, $[S_j \geq 50]$ refers to the firm size dummy of being larger than 50, and $[T_j \geq 2006]$ to the post-treatment indicator (after 2006). The Diff-in-Disc estimator will be captured by ϕ_0, which identifies the effect of the treatment $[S_j \geq 50] * [T_t \geq 2006]$. Other parameters of the regression are $\gamma_0, \gamma_{1,} \delta_0, \delta_{1,}, \alpha_0, \alpha_1, \phi_1$.The peculiarity of the design used in this paper consists in using an estimated parameter of the unexplained wage gap of individual firms $(\hat{\beta}_j)$ as the dependent variable, whose statistical significance depends inversely on the number of observations in each firm. To give greater weight to those estimates that have less uncertainty, RDD and Diff-in-Disc estimations are weighted by the inverse of their standard errors. Robustness tests include estimations on local samples and multiple polynomial specifications.

To ensure relevant gender wage gap estimates are obtained, the empirical analysis restricts the attention to firms that employ at least 5 men and 5 women. Local samples are restricted to 100 workers in the firm.[7] The resulting dataset from the local sample used for Diff-in-Disc regressions contains information on 33,300 firms.

Table 1 reports the results of RDD and Diff-in-Disc estimates from series of regressions using multiple specifications. Column (1) and (2) show RDD estimates before and after the introduction

[7] The core of RDD as local randomization method consists in comparing treated and control firms with similar characteristics. To assess smaller relevant windows around the threshold, I implemented a data driven selection procedure that evaluates different regression specifications for local samples around the treatment threshold at firm size ≥ 50 with bandwidth from 1 to 100. The local sample presented here is based on the bandwidth for which p-values of the effect are significant.

of the policy, respectively. Column (3) reports Diff-in-Disc estimates, which inform about the statistical significance of differences in discontinuities at the firm size threshold before and after 2006. While row A shows estimates without industry and sectoral dummies, row B includes these controls. Row C tests for “donut” effects (Barreca et al., 2011). This sensitivity analysis investigates if discontinuities remain after excluding firms with firm size between 47 and 53 employees to account for the possibility that firms have changed their size during the reporting period. Interestingly, RDD and Diff-in-Disc estimates indicate that the mean unexplained wage gap of firms with at least 50 workers declined by 3.5 percentage points after the introduction of *Logib*.

While RDD and Diff-in-Disc estimates can identify the effects of *Logib* on unexplained wage gaps, they do not provide evidence of the mechanisms by which wage gaps were adjusted. Caution is warranted because this policy, as other anti-discrimination laws that targeted only equal pay, may incentivize employers to fall into other forms of discrimination. In a separate manuscript (Vaccaro, 2017), I show that employers did not adjust the values of variables such as job difficulty and hierarchical position to fulfill the regulation. Also, no evidence of unintended employment effects was found.

[INSERT TABLE 1]

V. Discussion and Conclusions

Using a Diff-in-Disc design, this paper shows the effectiveness of a Swiss anti-discrimination policy (*Logib)* on reducing the unexplained wage gap. The novelty of the *Logib* design lies in (a) using a wage regression tool that facilitates treated firms the self-surveillance of their wage policies, and in (b) its very weak enforcement limited to public providers.

There is, however, no ideal policy to reduce discrimination. Policies like *Logib*, based on wage regressions, are not able to distinguish wage discrimination from the effects of other omitted characteristics. As a result, estimations of unexplained wage gaps can be biased.

Regression methods to explain wage gaps are subject to statistical limitations as they require men and women to be evenly distributed across explanatory factors in each firm. Wage regressions are also sensitive to extreme values of wage data. The variables on which this or similar regression frameworks are based may themselves be subject to discrimination, for example employees in different hierarchical positions despite identical work descriptions and responsibilities.

Even though we still have work on identifying the best anti-discrimination policy, in a nutshell, this paper provides empirical evidence about the causal effect of a very clear policy that targets the reduction of the unexplained wage gap, and a clean test to measure the impact of other wage discrimination policies.

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Table 1: The effect of the Equal Pay Self-Test Tool on the unexplained wage gap

	RDD before 2006 (1)	RDD after 2006 (2)	Diff-in-Disc (3)
A. Without industry and sectoral dummies	-0.003	-0.047***	-0.054**
	(0.023)	(0.009)	(0.018)
B. With industry and sectoral dummies	0.023	-0.073***	-0.035**
	(0.034)	(0.016)	(0.013)
Number of observations (A and B)	13104	24066	33366
C. Excluding observations at the threshold (47<N<53)	0.029	-0.082***	-0.056**
	(0.035)	(0.015)	(0.020)
Number of observations	12708	15823	32236

Notes: All models refer to local samples which include maximum 100 workers in the firms. Regressions include industry (with 2 digits of disaggregation) and sectoral dummies. Models refer to third polynomial degree specifications. Robust standard errors in parenthesis. *** significance at the 1 percent level, ** significance at the 5 percent level, * significance at the 10 percent level. Source: SWSS.