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Gender Wage Inequality and Economic Growth: Is There Really a Puzzle?—A Comment

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Summary. — Seguino (2000) shows that gender wage discrimination in export-oriented semi-industrialized countries might be fostering investment and growth in general. While the original analysis does not have internationally comparable wage discrimination data, we replicate the analysis using data from a meta-study on gender wage discrimination and do not find any evidence that more discrimination might further economic growth—on the contrary: if anything the impact of gender inequality is negative for growth. Standing up for more gender equality—also in terms of wages—is good for equity considerations and at least not negative for growth.

1. INTRODUCTION

In an influential paper [1] Seguino (2000) showed that gender wage inequality might be good for economic growth. Her hypothesis concerned semi-industrialized export-oriented countries: low wages for female workers in export industries might foster investment, exports, and also growth of the economy in general. The analysis was taken up by Mitra-Kahn and Mitra-Kahn (2008), emphasizing her results and arguing that discrimination of females was particularly growth-promoting in early stages of development. These results are in strong contrast to studies showing convincingly that gender inequality in terms of education or access to jobs is detrimental to growth. While the study by Seguino (2000) may legitimate gender discrimination as being a positive factor for economic growth in the economy, Seguino (2000) herself is only questioning export-oriented growth and industrialization strategies of developing countries: "Yet evidence presented here suggests that gender inequality is a *casual* factor in investment and economic growth for the semi-industrialized countries in the sample used here" (emphasis added by us, p. 1224).

While the theory of Seguino (2000) relates to wage discrimination: that is, paying lower wages to women with equal productivity, the data she has at her disposal are only aggregate wage gaps. We replicate the empirical analysis with internationally comparable gender wage discrimination data coming from a meta-regression on the international gender wage gap (Weichselbaumer & Winter-Ebmer, 2005) and cannot confirm her results: Using various definitions of the gender wage gap, none of the regressions show any positive impact of gender wage discrimination on economic growth.

We revise the discussion about gender inequality and growth in Section 2. Section 3 discusses our construction of gender wage discrimination measures, Section 4 describes the data used and Section 5 presents our results for the growth regressions. Section 6 concludes.

2. GENDER INEQUALITY AND ECONOMIC GROWTH

The relation between gender inequality and economic growth is complex and covers several plausible direct and indirect links. In the following, we give a short outline of previous work.

There is solid evidence that gender inequality in education is detrimental to growth. The theoretical literature suggests that gender inequality will reduce average human capital, thus harming economic growth. Given different talents of children, declining education to equally-talented females must mean that marginal returns to educating girls must be higher than that of boys, which is inefficient (Knowles, Lorgelly, & Owen, 2002). While Barro and Lee (1994) found negative coefficients for female education in growth regressions, the subsequent literature showed that this result was due to the inclusion of some outliers (Dollar & Gatti, 1999) and multicollinearity between male and female school attainment (Klasen, 2002). Moreover, female education might have positive additional effects, such as reduced fertility, lower child mortality, or higher education of the offspring, which by themselves are all fostering long-term growth perspectives of a country (Galor & Weil, 1996, Lagerlöf, 2003, Schultz, 1997).

Somewhat less robust are the results concerning females' access to employment. Klasen and Lamanna (2009) investigate the growth implications of employment gaps. In a cross-country study covering the time period 1960–2000 they point out the high costs of low female labor force participation for the Middle East and North Africa, which is found to be a major factor explaining growth differences with East Asia. Esteve-Volart (2009) shows for Indian regions that gender gaps in access to managerial positions and to employment more

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generally distort the optimal allocation of talent and reduce growth.

While there is a large amount of literature on unequal access of females to education, the labor market, and other productive assets (such as land and credit), there is less literature on direct effects of gender wage differentials or discrimination on growth. One argument in favor of gender wage equality invokes market distortions because of wage discrimination. There are efficiency losses concerning the potential of an economy's workforce: if discriminated against, women might hesitate to participate in the labor market because their reservation wage is not met (Baldwin & Johnson, 1992). Furthermore, existing wage gaps could affect human capital investment negatively.

There is another way how gender aspects might influence household decisions: a number of studies show that resources devoted to children's wellbeing rise with mother's control over these resources (Sinha, Raju, and Morrison (2007)). Wage gaps which deteriorate women's income position or discourage them from entering the labor market could negatively affect their bargaining power within the household. Therefore, human capital endowments of the next generation might suffer and restrain development. Thomas (1997), for instance, uses household survey data from Brazil containing information about labor and non-labor income. He finds that increased income for women is linked to a larger share of household budget used for household services, health, and education and results in better outcomes of child health. Another indirect effect might operate *via* fertility (Galor & Weil, 1996): Fertility decisions of households are also influenced by relative wages of women. Opportunity costs of children rise with wages, leading to lower population growth and increased level of capital per worker—and, in turn, to higher growth.

Seguino (2000), on the other hand, argues with respect to international competitiveness: gender wage differentials may act as a stimulus to growth in semi-industrialized export-oriented economies. Lower relative wages in female-dominated manufacturing industries will make investment attractive because of high expected profitability; this will boost exports and economic growth. She backs this analysis with a macroeconomic growth model (Blecker & Seguino, 2002), where lower female wages relax the balance of payment constraint faced by developing countries that require technology imports to move up the industrial ladder. These considerations conform with the labor market analysis of Standing (1999), who argues that female labor force participation has risen in countries with export-led industrialization due to a pursuit toward lower wages to gain global competitiveness.

Seguino (2000) as well as Mitra-Kahn and Mitra-Kahn, 2008—using the same data—find supportive evidence for a small sample of semi-industrialized countries. The argument is partly supported by the results of Busse and Spielmann (2005), which indicate that countries with higher gender wage gaps have higher exports in labor-intensive goods. However, the authors explicitly doubt that this mechanism can lead to faster growth and emphasize that rather than total exports the export structure is affected.[2]

3. MEASURES OF WAGE DISCRIMINATION

Following Seguino (2000), we analyze the period 1975–95 where various developing countries successfully adopted export orientation strategies to pursue economic growth. Data sources and definitions of variables can be obtained from Table 1. Average values of the key variables are presented in Table 2.

The essential difference in our work is the source of information on gender wage gaps. Seguino (2000) relies on aggregate earnings data from the International Labour Organization (ILO). Gender wage gap studies require hourly wages, but hours worked were not recorded for some countries. Seguino corrected the earnings data for hours worked in the available cases (p. 1225). Using aggregate earnings or wage data is not appropriate in such an analysis because the theoretical argument relates to wage discrimination: the female-dominated export industry[3] is boosted if there is a gender wage gap for workers with the same productivity.[4]

An estimate of gender-discrimination can only be constructed by using micro data, either by using a sex dummy from a wage regression, controlling for productive characteristics like education, training, job-experience, *etc.*, or an explicit Blinder–Oaxaca wage decomposition. In the latter, following Blinder (1973) and Oaxaca (1973), wages are estimated separately for individuals i of the different groups g (males m and females f):

$$W_{gi} = \beta_g X_{gi} + \varepsilon_{gi}, \tag{1}$$

where W_{gi} is the log wage and X_{gi} is a vector of control characteristics of an individual i of group g.

The total wage differential between men and women can then be decomposed into an explained part due to differences in characteristics and an unexplained residual. The difference in mean wages can be written as:

$$\overline{W_m} - \overline{W_f} = (\overline{X_m} - \overline{X_f})\hat{\beta}_m + (\hat{\beta}_m - \hat{\beta}_f)\overline{X_f} \equiv E + U, \tag{2}$$

Table 1. *Variable description and data sources*

Variable	Description	Data source
Raw gender wage gap	Mean gender wage differential from the original studies	Weichselbaumer and Winter-Ebmer (2005)
Unexplained gender wage gap	Discrimination component estimated in the original studies	”
Meta wage residual	Fitted values of the meta-regression	”
Human capital	Years of secondary education of the population aged 15 and over	Barro and Lee (2001)
d log K	Growth rate of gross fixed capital formation	World Development Indicators 2004 and Taiwan Statistical Data Book 2008
GDP growth	Average growth rate of GDP	”
Exports/GDP	Exports of goods and services in % of GDP	”
Manufactures exports	Manufactures exports % of merchandise exports	”
Life expectancy	Life expectancy at birth	”
Openness	Exports plus Imports divided by GDP	Penn World Tables Version 6.2
log(GDP)	Natural log of real GDP *per capita*	”

Table 2. *Average annual values of period 1975–94*

Country	Exports/GDP	Manufactures exports (%)	HK	Gender wage gaps		
				Raw	Unexplained	Meta resid.
Countries in sample A						
Brazil	9.2	43.2	0.67	0.476	0.452	0.451
Chile	26.8	10.1	1.53	0.221	0.250	0.253
Colombia	15.9	23.1	1.35	0.222	0.115	0.107
Costa Rica	33.4	24.7	1.09	0.067	0.185	0.184
Cyprus	47.8	53.0	2.19	0.592	0.370	0.309
El Salvador	24.5	32.2	0.45	0.370	0.270	0.276
Hong Kong, China	109.5	95.4	3.24	0.174	0.135	0.135
Indonesia	25.7	19.1	0.64	0.801	0.540	0.540
Korea, Rep.	31.6	90.5	3.02	0.605	0.168	0.161
Malaysia	60.6	35.7	1.42	0.402	0.250	0.254
Mexico	14.7	36.7	1.27	0.224	0.133	0.122
Philippines	25.1	29.8	1.40	0.227	0.373	0.373
Portugal	26.3	75.7	1.18	0.223	0.185	0.185
Singapore		58.1	1.93		0.040	0.040
Taiwan			2.40	0.425	0.228	0.228
Thailand	27.2	40.8	0.65	0.328	0.219	0.219
Additional countries in sample B						
China	11.3	69.7	1.46	0.225	0.258	0.253
Guatemala	18.0	24.6	0.45	0.370	0.184	0.184
Kenya	28.1	16.6	0.46	0.478	0.170	0.146
Nicaragua	23.4	11.1	0.62	0.863	0.631	0.631
Pakistan	12.7	65.7	1.06	0.354	0.266	0.266
Panama	39.3	13.3	1.62	0.221	0.189	0.189
Peru	16.3	13.8	1.50	0.246	0.223	0.226
Poland	24.5	63.4	1.27	0.292	0.345	0.345
South Africa	27.4	29.2	0.84	0.284	0.511	0.511
Tanzania	14.8	12.5	0.14		0.073	0.062
Uruguay	20.6	37.8	1.83	0.295	0.201	0.201
Additional countries in sample C						
Argentina	8.3	25.9	1.38	0.466	0.329	0.329
Australia	15.9	20.9	3.13	0.198	0.127	0.145
Austria	36.0	85.7	3.73	0.246	0.251	0.260
Barbados	57.1	60.1	2.97	0.205	0.211	0.211
Bolivia	23.1	5.0	1.20	0.473	0.380	0.380
Canada	26.8	56.1	3.95	0.283	0.212	0.214
Denmark	33.3	57.5	3.19	0.200	0.106	0.095
Ecuador	26.4	2.8	1.40	0.258	0.180	0.180
Germany	22.4	86.8	5.19	0.322	0.212	0.221
Honduras	30.3	9.3	0.60	0.211	0.293	0.296
Hungary	37.2	65.4	1.24	0.369	0.354	0.354
India	6.9	62.0	0.78	0.372	0.240	0.259
Ireland	52.8	61.1	2.29	0.185	0.170	0.161
Italy	21.4	85.7	2.10	0.180	0.108	0.091
Japan	11.8	95.7	2.69	0.664	0.404	0.395
Netherlands	52.5	54.8	2.67	0.374	0.136	0.136
New Zealand	28.4	21.2	3.03	0.188	0.196	0.196
Norway	38.6	37.0	2.96	0.237	0.185	0.203
Spain	17.1	72.4	1.60	0.256	0.207	0.184
Sudan	8.9	0.9	0.32	0.111	0.296	0.296
Sweden	30.1	80.8	3.69	0.162	0.118	0.122
Switzerland	34.9	92.2	4.16	0.343	0.199	0.231
Trinidad and Tobago	42.2	17.9	1.98	0.168	0.341	0.341
Uganda	10.9	1.4	0.28	0.331	0.312	0.296
United Kingdom	26.1	74.8	2.16	0.267	0.188	0.179
United States	8.9	69.9	4.49	0.323	0.182	0.179
Venezuela, RB	26.3	6.0	1.19	0.300	0.231	0.231

where $\overline{W}_g$ and $\overline{X}_g$ denote the mean log wages and control characteristics of group g and $\hat{\beta}_g$ represents the vector of estimated parameters from Eqn. (1). While the first term stands for the effect of different productive characteristics (the endowment effect E), the second term represents the unexplained residual U which is due to differences in the estimated coefficients for both groups and is often referred to as the discrimination effect.

Our wage discrimination data come from a meta-analysis of existing studies of Blinder–Oaxaca wage decompositions conducted by Weichselbaumer and Winter-Ebmer (2005).[5] Meta-analysis is a helpful tool to compare empirical results coming from different data sets or being obtained with different econometric methods (Stanley, 2001). This technique is particularly suitable for the examination of gender wage differentials because the literature in this area is very standardized in the way the parameter of interest—the discrimination component—is usually estimated. Meta-analysis is collecting all details of the existing studies and uses them in a meta-regression analysis to make the results comparable across studies (i.e., countries and time).

For the meta-analysis on gender wage differentials, all accessible published estimates for sex-discrimination were collected. In November 2000, Weichselbaumer and Winter-Ebmer searched the Economic Literature Index for any reference to: "(wage* or salar* or earning*) and (discrimination or differen*) and (sex or gender)". In total, 263 papers provided them with the respective estimates for differences in wages of men and women with identical characteristics in 62 countries and cover the time span from 1963 to 1997.

The meta-regression model takes the form:

$$R_j = \sum a_k Z_{kj} + \sum b_t t_{jt} + \sum d_l c_{lj} + \varepsilon_j,$$
$$(j = 1, 2, \ldots, J)\ (k = 1, 2, \ldots, M)$$
$$(l = 1, 2, \ldots L)\ (t = 1, 2, \ldots T), \tag{3}$$

where R_j represents the "gender wage residual", that is, the unexplained log wage differential, of study j, which can either be the coefficient of a gender dummy from a wage regression or the Blinder–Oaxaca unexplained residual U_j from (2), Z_{kj} are the k meta-independent variables, t_{jt} are time dummies and c_{lj} are a set of country dummies; a_k, b_t and d_l are parameters to be estimated.

To extract all the relevant characteristics of a paper and record them in the meta data set, each article was analyzed and carefully coded. The included meta-independent variables can be grouped into three categories: variables concerning the data selection, variables capturing the applied econometric method, and variables specifying the type of control variables which were (not) included in the original wage regressions. Specifically, 14 variables for data set selection (e.g., data source (administrative statistics or survey data), data set restrictions to never-married individuals, minorities, *etc.*), nine variables for econometric methods (such as Blinder–Oaxaca, dummy variable approach, use of instrumental variables, Heckman sample selection, or panel data methods), 21 variables for inclusion of specific human capital control variables (e.g., experience, training, tenure, and occupation) in the underlying log wage regressions plus a variable for the sex of the researcher were used.[6]

Such a meta-regression allows us to construct three internationally comparable estimates of gender wage gaps: The "*raw gap*" is the mean gender wage differential from the original studies, which does not control for any human capital differences between the sexes. The "*unexplained gap*" is the discrimination component estimated in the respective studies; this gap is controlling for different productivity characteristics—but in a way which is idiosyncratic to the data and econometric methods used in the study. Finally, our meta-regression analysis allows us to construct a "*meta residual*": using predicted values from the meta-regression we can estimate what each paper would have reported if a standard method and data set had been used and make the results comparable. This provides us with internationally comparable gender wage residuals for a variety of countries which are better comparable as aggregate data.

We follow exactly the specification of Seguino (2000) and restrict our estimation to a limited number of explanatory variables.[7] The function for the GDP growth rate ($d \log Y$), can be written as

$$d \log Y = \alpha + \gamma_1 d \log K + \gamma_2\ \textit{human capital}$$
$$+ \gamma_3\ \textit{gender wage gap} + u, \tag{4}$$

where $d \log K$ is the growth rate of the capital stock measured as the growth rate of gross fixed capital formation, and "years of secondary education of the population aged 15 and over" is our proxy for human capital. The coefficients of primary interest are those for our three different measures of the gender wage gap.

4. DATA

Seguino (2000) restricts her sample to 20 semi-industrialized countries which are characterized by export orientation and a large share of female employees in manufacturing industries. Due to availability problems for gender wage gaps compared to the ILO-database, we choose to construct three different samples for the regression analyses.

Sample A consists of the 16 countries in Seguino's original sample for which meta wage information is available.[8] In sample B we add low or middle income countries if they fulfill two criteria: Their exports to GDP ratio as well as the share of manufacturing in exports exceed those shares for the countries in the original Seguino sample. These additional 11 countries, therefore, extend the sample while they should be similar enough to the original countries to be consistent with Seguino's hypothesized mechanism.

Table 2 lists countries included in the different samples and the mentioned indicators. Export shares and structure vary substantially within the countries of sample A. Hong Kong stands out with the highest values in both categories, pointing out the countries' distinct export performance. With 9.2%, Brazil has the lowest average value of exports to GDP, Chile shows the lowest share of manufacturing exports with a share of 10.1% in total exports. Countries in sample B surpass these values, leading to a sample average of 21.5% in exports to GDP and 32.5% in manufacturing exports, compared to averages of 34.2% and 44.5% in sample A.

Sample C finally consists of countries from all income classes where meta wage information is available, driving the sample size up to 54 countries.[9]

5. RESULTS

Our first results in Table 3 present growth regressions for the period 1975–95 based on a cross-section of countries. Whereas the number of countries is rather small in sample A, we have more countries in samples B and C. Column (1) presents Seguino's standard model without wage inequality, while in Columns (2)–(4) we add our different measures for gender wage gaps one by one. The estimated models are largely consistent with established results in the literature: investment has a large positive effect on cross-country growth rates, human capital is in general positive, but due to the small sample size not significant. When we use the (small) sample A, all the estimates with respect to gender wage differentials are practically zero: low coefficients and low

Table 3. *Gender wage gap and economic growth (cross section)*

	(1)	(2)	(3)	(4)
Sample A				
d log *K*	0.568***	0.514***	0.565***	0.567***
	(0.103)	(0.141)	(0.106)	(0.120)
Human capital	0.006	0.006	0.006	0.006
	(0.003)	(0.005)	(0.004)	(0.004)
Raw gap		0.016		
		(0.015)		
Unexplained gap			0.009	
			(0.026)	
Meta residual				0.002
				(0.031)
Constant	0.006	0.002	0.003	0.005
	(0.010)	(0.009)	(0.010)	(0.011)
Observations	16	15	16	16
R^2	0.783	0.826	0.785	0.783
Sample B				
d log K	0.503***	0.544***	0.518***	0.527***
	(0.124)	(0.156)	(0.133)	(0.135)
Human capital	0.005	0.004	0.002	0.001
	(0.005)	(0.005)	(0.005)	(0.005)
Raw gap		−0.009		
		(0.032)		
Unexplained gap			−0.040	
			(0.032)	
Meta residual				−0.048
				(0.032)
Constant	0.008	0.008	0.021**	0.024**
	(0.008)	(0.009)	(0.009)	(0.009)
Observations	27	25	27	27
R^2	0.554	0.571	0.598	0.609
Sample C				
d log *K*	0.523***	0.538***	0.523***	0.526***
	(0.072)	(0.088)	(0.074)	(0.075)
Human capital	0.000	0.000	−0.001	−0.001
	(0.002)	(0.001)	(0.001)	(0.001)
Raw gap		−0.015		
		(0.023)		
Unexplained gap			−0.038	
			(0.025)	
Meta residual				−0.045*
				(0.025)
Constant	0.013**	0.016**	0.025***	0.027***
	(0.005)	(0.007)	(0.007)	(0.007)
Observations	54	52	54	54
R^2	0.595	0.607	0.633	0.644

Robust *t*-statistics in parentheses.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

Table 4. *Gender wage gap and economic growth (panel estimations using five-year periods)*

	(1)	(2)	(3)	(4)
Sample A				
d log *K*	0.262***	0.249***	0.256***	0.263***
	(4.702)	(4.481)	(4.521)	(4.361)
Human capital	−0.007	−0.007	−0.006	−0.007
	(−1.131)	(−1.196)	(−0.978)	(−1.098)
Raw gap		−0.002		
		(−0.0606)		
Unexplained gap			−0.035	
			(−0.887)	
Meta residual				−0.003
				(−0.0335)
Constant	0.053***	0.056**	0.060***	0.053**
	(4.242)	(2.894)	(4.001)	(2.120)
Observations	35	32	35	35
R^2	0.594	0.637	0.613	0.594
Sample B				
d log *K*	0.260***	0.253***	0.261***	0.266***
	(5.584)	(5.094)	(5.642)	(5.404)
Human capital	−0.006	−0.007	−0.004	−0.006
	(−1.270)	(−1.143)	(−0.838)	(−1.259)
Raw gap		−0.018		
		(−0.622)		
Unexplained gap			−0.025	
			(−1.120)	
Meta residual				−0.034
				(−0.465)
Constant	0.046***	0.054***	0.049***	0.054**
	(5.045)	(3.282)	(5.179)	(2.761)
Observations	51	46	51	51
R^2	0.607	0.619	0.628	0.611
Sample C				
d log *K*	0.277***	0.269***	0.277***	0.279***
	(9.025)	(8.491)	(9.040)	(8.885)
Human capital	−0.002	−0.002	−0.002	−0.002
	(−0.808)	(−0.581)	(−0.633)	(−0.780)
Raw gap		−0.003		
		(−0.225)		
Unexplained gap			−0.013	
			(−1.044)	
Meta residual				−0.010
				(−0.369)
Constant	0.031***	0.030***	0.033***	0.033***
	(4.745)	(3.403)	(4.839)	(3.756)
Observations	110	104	110	110
R^2	0.605	0.602	0.613	0.606

Robust *t*-statistics in parentheses.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

t-statistics. Using our preferred sample B, which does fulfill all the requirements from Seguino (2000) all coefficients are even negative (!), the same as in sample C. For our preferred gender wage gap measure—the "meta wage residual" which provides the most internationally comparable wage discrimination estimate—we even get marginally significant negative results. So with due caution, we can say, that more discrimination is definitely not related to higher growth rates; if anything, it tends to reduce growth rates somewhat.

The results in Table 4 show results using five-year average growth rates with a fixed effect panel regression. These results are very similar to the ones using only cross-sectional data. Here we find all nine coefficients for the gender wage estimates to be negative and insignificant. To summarize, none of the results—and also none with more extended growth models—show positive and significant relations between more discrimination of females and higher growth. [10]

6. CONCLUSION

The relationship between gender (in)equality and economic development has been discussed quite controversially. There is general agreement that keeping women away from education and the labor market in general is restricting the pool of talent and thus detrimental to development and growth. But there are also studies showing that export-led growth in semi-developed countries could be fostered by cheap female labor and gender wage discrimination, which is disturbing from an equity point of view. As previous studies did not have appropriate gender wage discrimination data at their disposal, they had to rely on aggregate gender wage gaps where different productivity of males and females cannot be accounted for. Once we use internationally comparable data for gender wage discrimination we do not find any evidence that more discrimination might further economic growth—on the contrary: if anything the impact of gender inequality is negative for growth. Standing up for more gender equality—also in terms of wages—is good for equity considerations and at least not negative for growth.

NOTES

1. The article by Seguino (2000) was cited 164 times in Google Scholar and 22 times in the SSCI—among them several UN or World Bank reports.

2. Surprisingly, in another study Seguino and Floro (2003) show with data for 20 developing countries that females have higher savings rates; thus an increase in female wages will lead to higher aggregate savings—contradicting her main argument, because high savings ratios are generally good predictors of growth rates.

3. Note that in principle gender wage discrimination data for the export sector only would be required; a restriction neither Seguino (2000) nor we can fulfill.

4. As one crude way to correct for different productivity, Seguino (2000) in another wage gap measure divides aggregate wages by mean educational attainment.

5. These data have also been used to explain international differences in gender wage gaps and the impact of competition and anti-discrimination laws at an international level (Zweimüller, Weichselbaumer, & Winter-Ebmer, 2008; Weichselbaumer & Winter-Ebmer, 2007).

6. See Weichselbaumer and Winter-Ebmer (2005) for a more detailed description and for specification and robustness checks of the same general model that we use here.

7. For instance, Seguino (2000) does not include initial conditions (i.e., log (GDP) at the beginning of the period) in her regression.

8. We are losing Greece, Paraguay, Sri Lanka and Turkey. Estimations including the raw gender wage gap have fewer observations because of missing data.

9. The construction of internationally comparable gender wage gaps is also possible using micro data from the International Social Survey Programme (ISSP). Unfortunately, these data mainly cover OECD countries, which are not appropriate for assessing the gender discrimination-growth hypothesis in export-oriented developing countries. Nonetheless, using these data for 19 (period 1975–95) or 24 (period 1985–2000) countries, we did not find any relation between gender wage differentials and growth (results are available on request).

10. In the appendix (Tables 5 and 6) we show extended regressions including initial conditions (log of GDP *per capita*), life expectancy, as well as an openness indicator; the impact of our various measures of the gender wage gap is in most cases negative and only once statistically significant– again with a negative sign.

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APPENDIX A

See Tables 5 and 6

Table 5. *Gender wage gap and economic growth—extended model (cross section)*

	(1)	(2)	(3)	(4)
Sample A				
d log *K*	0.456	0.438*	0.584*	0.535
	(1.463)	(1.982)	(1.902)	(1.698)
Human capital	0.001	0.000	0.000	0.001
	(0.241)	(0.0474)	(0.0271)	(0.119)
log(gdp)	−0.012	−0.008	−0.001	−0.005
	(−0.563)	(−0.453)	(−0.0552)	(−0.184)
Life expectancy	0.001	0.001	0.001	0.001
	(1.186)	(1.295)	(1.019)	(1.163)
Openness	0.009	0.006	0.007	0.008
	(1.696)	(0.666)	(1.344)	(1.383)
Raw gap		0.029		
		(1.394)		
Unexplained gap			0.034	
			(1.192)	
Meta residual				0.030
				(0.920)
Observations	16	15	16	16
R^2	0.842	0.869	0.865	0.855
Sample B				
d log *K*	0.307**	0.254*	0.311**	0.322**
	(2.182)	(1.737)	(2.101)	(2.175)
Human capital	0.009	0.011	0.009	0.008
	(1.462)	(1.515)	(1.421)	(1.362)
log(gdp)	−0.020***	−0.024***	−0.020***	−0.019***
	(−3.440)	(−4.366)	(−4.117)	(−4.147)
Life expectancy	0.001	0.001	0.001	0.001
	(1.044)	(0.993)	(1.072)	(1.007)
Openness	0.010*	0.004	0.010*	0.009*
	(2.044)	(0.377)	(1.993)	(1.918)
Raw gap		0.001		
		(0.0284)		
Unexplained gap			−0.002	
			(−0.0795)	
Meta residual				−0.008
				(−0.278)
Observations	27	25	27	27
R^2	0.727	0.737	0.727	0.728
Sample C				
d log *K*	0.312***	0.278***	0.322***	0.332***
	(3.899)	(3.594)	(4.076)	(4.252)
Human capital	0.005**	0.006***	0.005***	0.005***
	(2.578)	(2.841)	(2.817)	(2.750)
log(gdp)	−0.020***	−0.023***	−0.019***	−0.018***
	(−4.059)	(−4.964)	(−4.651)	(−4.635)
Life expectancy	0.001**	0.001**	0.001**	0.001**
	(2.205)	(2.624)	(2.251)	(2.124)
Openness	0.009**	0.003	0.008**	0.008**
	(2.220)	(0.518)	(2.139)	(2.086)
Raw gap		0.000		
		(0.0259)		

Table 5 (*continued*)

	(1)	(2)	(3)	(4)
Unexplained gap			−0.007	
			(−0.371)	
Meta residual				−0.015
				(−0.717)
Observations	54	52	54	54
R^2	0.748	0.753	0.749	0.752

Robust *t*-statistics in parentheses.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

Table 6. *Gender wage gap and economic growth—extended model (panel estimations using five-year periods)*

	(1)	(2)	(3)	(4)
Sample A				
d log *K*	0.266***	0.255***	0.261***	0.273***
	(4.808)	(4.623)	(4.611)	(4.671)
Human capital	−0.003	−0.001	−0.004	−0.003
	(−0.171)	(−0.0831)	(−0.209)	(−0.180)
log(gdp)	−0.018	−0.012	−0.015	−0.019
	(−0.700)	(−0.439)	(−0.556)	(−0.732)
Life expectancy	0.003	0.001	0.003	0.003
	(1.560)	(0.646)	(1.386)	(1.609)
Openness	−0.025*	−0.024	−0.025	−0.026
	(−1.846)	(−1.430)	(−1.673)	(−1.631)
Raw gap		0.006		
		(0.119)		
Unexplained gap			−0.021	
			(−0.800)	
Meta residual				−0.045
				(−0.508)
Observations	35	32	35	35
R^2	0.701	0.708	0.707	0.706
Sample B				
d log *K*	0.246***	0.251***	0.250***	0.255***
	(5.445)	(4.727)	(5.641)	(5.026)
Human capital	−0.008	−0.000	−0.004	−0.008
	(−0.661)	(−0.0183)	(−0.357)	(−0.685)
log(gdp)	−0.007	−0.009	−0.007	−0.007
	(−0.313)	(−0.341)	(−0.358)	(−0.304)
Life expectancy	0.002	0.001	0.002	0.002
	(1.296)	(0.348)	(1.181)	(1.294)
Openness	−0.020	−0.021	−0.022	−0.020
	(−1.277)	(−1.047)	(−1.337)	(−1.118)
Raw gap		−0.015		
		(−0.344)		
Unexplained gap			−0.027**	
			(−2.216)	
Meta residual				−0.051
				(−0.631)
Observations	51	46	51	51
R^2	0.673	0.673	0.698	0.681
Sample C				
d log *K*	0.266***	0.263***	0.267***	0.268***
	(9.232)	(8.284)	(9.188)	(8.822)
Human capital	0.000	0.001	0.000	0.000
	(0.107)	(0.435)	(0.0565)	(0.0957)
log(gdp)	−0.016	−0.013	−0.015	−0.016
	(−1.221)	(−0.944)	(−1.088)	(−1.193)
Life expectancy	0.001	0.001	0.001	0.001
	(1.184)	(0.781)	(1.241)	(1.188)
Openness	−0.016	−0.016	−0.017	−0.016
	(−1.118)	(−0.974)	(−1.150)	(−1.081)

(*continued on next page*)

Table 6 (*continued*)

	(1)	(2)	(3)	(4)
Raw gap		−0.002		
		(−0.136)		
Unexplained gap			−0.013	
			(−1.339)	
Meta residual				−0.015
				(−0.529)
Observations	110	104	110	110
R^2	0.651	0.641	0.658	0.652

Robust *t*-statistics in parentheses.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.