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This study provides new evidence on the debate surrounding international trade and the gender wage gap in a developing country context. It asks whether increased competition from trade has any causal effect on the district-level gender wage gap in India. Changes in competition from trade are measured using changes in imports from China, owing to the dramatic rise in Chinese imports into India in recent years. An instrumental variable (IV) based estimation strategy is used following Autor, Dorn, and Hanson (2016), to delineate causality. Results indicate a positive and statistically significant impact of an increase in Chinese imports on the gender wage gap over time. In addition to the economy-wide sample of workers, this effect holds true for the sub-samples of casual laborers and rural sector workers where the majority of women workers in India are concentrated. Unlike previous studies using industry-level data, the district-level focus of this study allows us to capture micro-level effects, as well as the net effects of trade in the surrounding district.

Keywords: International trade; Gender wage gap; Competition; Imports; China; District

JEL Code: F16, D63, J16, J31

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A district-level analysis

Abstract

This study provides new evidence on the debate surrounding international trade and the gender wage gap in a developing country context. It asks whether increased competition from trade has any causal effect on the *district-level* gender wage gap in India. Changes in competition from trade are measured using changes in imports from China, owing to the dramatic rise in Chinese imports into India in recent years. An instrumental variable (IV) based estimation strategy is used following Autor, Dorn, and Hanson (2016), to delineate causality. Results indicate a *positive* and statistically significant impact of an increase in Chinese imports on the gender wage gap over time. In addition to the economy-wide sample of workers, this effect holds true for the sub-samples of casual laborers and rural sector workers where the majority of women workers in India are concentrated. Unlike previous studies using industry-level data, the district-level focus of this study allows us to capture micro-level effects, as well as the net effects of trade in the *surrounding district.*

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1. Introduction

The gender wage gap is a simple measure of inequality between the sexes. It is defined as the difference between male and female wages and is often expressed as a proportion of male wages. Even though it has recorded a decline over the years, it is still pervasive across the world and has till today remained a crucial object of study for labour economists. Globally, in 2015 it was estimated to be 23 percentage points (I.L.O, 2016). In the set of all OECD countries, the gender wage gap has recorded a secular decline from 1995-2017. It declined from about 19.59 per cent in 1995 to 13.45 per cent in 2017. Recent estimates from India record a similar overall decline. According to the India Wage Report, released by the ILO in 2018 (I.L.O, 2018), the gender wage gap in India declined from 48 per cent in 1993-94 to 34 per cent in 2011-12. According to the Periodic Labour Force Survey 2017-18, the gender wage gap for regular salaried rural workers stood at 33.83 percentage points while for urban workers, it stood at 19.06 percentage points.[1]

Literature surrounding the gender wage gap typically focuses on two definitions – the 'raw' or 'unadjusted' wage gap, and the 'residual' wage gap. The former is expressed as the simple raw difference in male and female wages. The 'residual' wage gap, on the other hand, is that part of the 'raw' wage gap that remains after controlling for differences in observable skills between men and women. This component is taken as a proxy for 'discrimination', but may also reflect differences in unobservable characteristics between the two groups. The residual wage gap is arrived at through the application of several decomposition techniques – such as the one proposed by Oaxaca and Blinder in 1973 (Blinder, 1973; Oaxaca, 1973).

Several studies, in the Indian context, have found that this 'unexplained' component of the wage gap has been increasing over time, in spite of the overall gender wage gap recording a

[1] Figures are sourced from the Annual Report on Periodic Labour Force Survey 2017-18 (NSO, 2019)

decline (Deshpande, Goel and Khanna, 2018; I.L.O, 2018)[2]. According to trends observed in the US, the 'residual' wage gap increased substantially over 1980-2010 but has reached a plateau since then (Blau and Khan, 2017). Over time, as women started catching up to men in terms of observable skills such as 'education', there was a gradual shift in focus towards the pursuit of newer explanations behind the still persistent 'discriminatory' wage gap.

Among many of these newer explanations was also the focus on market mechanisms like increasing competitive forces. One channel through which competition increases is through openness to international trade - which is the point of focus of this study.

In contextualizing the debate on trade and gender wage gap, I observe the existence of several opposing theoretical perspectives. The gender wage gap may change in response to trade because of technology-related theories such as the 'skill-biased technical change' theory. Trade, being accompanied by positive technical change, will lead to a rise in the demand for skilled workers. Given that in developing countries such as India, women tend to sort into low-paying, less skilled jobs relative to men, trade results in a rise in male relative to female wages. In contrast, the Heckscher-Ohlin-Samuelson (HOS) model framework predicts a rise in the demand for unskilled relative to skilled labour following trade, since India is an unskilled labour abundant country. The gendered implication of this prediction is that trade will lead to an increase in the relative wages of women workers. Lastly, trade-induced changes in the gender wage gap may also be caused by the discriminatory practices of employers. While the neo-classical approach (in line with Becker, 1971) predicts a fall in costly discrimination following an increase in competitive pressures from trade, the monopsonistic approach argues in favour of

[2] Both these studies have in turn cited Madheswaran and Khasnobis (2007) and Mukherjee and Majumder (2011) as studies that have found evidence in this regard.

a persistence of discrimination owing to labour market imperfections and employers wielding more 'monopsonistic' power over female relative to male workers.

There have been multiple studies documenting both positive and negative effects, in the context of international trade and gender wage gap. While some studies point to an increase in gender wage gap following trade, others point to a decline. However, sound empirical evidence is sparse in the context of developing economies (Fontana, 2009). This study, in particular, asks whether increased competition from trade has any causal effect on the gender wage gap in India. In doing so, it conducts a *district-level* analysis on the same. In the Indian context, the regional dimension has remained unaddressed in the study of the link between trade and gender wage gap.

The rationale behind exploring geographical differences in the gender wage gap is that there are certain factors (institutional, demographic) specific to each geographical region that might significantly contribute to these differences. This has been confirmed by several cross-country studies. However, as opposed to cross-country studies, regional studies control for unobservables better as regional labour markets within a country tend to share the same institutional features.

Industry level studies on trade and the gender wage gap in India have largely been limited to the formal manufacturing sector, whereas it is in the informal sector where most women labourers in India work (Fontana, 2009). In contrast, this study extends beyond this narrow focus and conducts a district-level analysis that covers the economy-wide sample of workers.

In addition to this, the district-level focus allows us to capture both the direct effects of trade shocks on import-competing industries, as well as the net effects in the surrounding region.

Further, this study uses increasing imports from China to measure the variation in competition from trade. The focus on China is justified on account of the dramatic rise in share of Chinese imports, which alone is driving the rise in imports that India experiences across the sample period. Moreover, China's accession to WTO in 2001 (which marks the beginning of our sample period) can be seen as a 'quasi-natural' experiment that might help aid our causal inference. This is alluded to in greater detail in a later section.[3]

The rest of this paper is organized as follows. Section 2 presents a review of literature. Section 3 explains the factual background and descriptive statistics. Section 4 talks about the model specification and empirical strategy. Section 5 describes the estimation results and Section 6 concludes this study.

2. Review of Literature

While industry-level and cross-country studies have been popular in exploring the link between trade and the gender wage gap, studies conducted at the sub-national level have been limited in scope[4].

Among cross-country studies, Oostendorp (2004) conducts an analysis using 83 countries and focusses on the 'within occupation' gender wage gap as a measure of 'discrimination'. The cross-country database used is the ILO October Inquiry, spanning the years 1983-1999. Both OLS and IV-2SLS estimation techniques are used to analyse the impact of trade and FDI on the

[3] The focus on imports requires us to ignore the effect arising out of Indian exports to China and the effect arising out of import competition in the common export markets of India and China. Since Indian imports from China greatly exceed Indian exports to China, the impact of the 'export channel' is relatively low. Controlling for import competition in the common exports is however important, given the similar product specializations of India and China. This is looked at as scope for future research work.

[4] Mostly due to lack of reliable data at the regional level

‘occupational gender wage gap’. The results indicate that this measure of the wage gap decreases with trade and FDI in richer countries, but no significant effect is found for poorer countries.

Berik, Rodgers and Zveglich (2004) explore the link between trade and the industry-level residual wage gap in Taiwan and Korea. They use OLS on long-differenced cross-sectional data, as well as GLS on yearly panel data. Their results show that an increase in trade competition from imports (in case of Taiwan) and exports (in case of Korea) over time is associated with an increase in residual wage gaps in ‘concentrated’ versus ‘competitive’ industries. Concentrated industries are the ones which are ‘relatively more insulated from the pressures of domestic competition’ and are therefore more exposed to competition from trade. Their findings do not support Becker’s neoclassical theory.

Following the same methodology, Menon and Rodgers (2009) similarly find results that are contradictory to what standard neo-classical theory predicts in the case of the urban manufacturing sector in India. Their regression specification follows a difference-in-difference methodology wherein they compare the behaviour of industry level residual wage gaps across ‘concentrated’ versus ‘competitive’ industries before and after the liberalization reforms of the 90s, over the time period of 1983-2004. Their results indicate a widening of the residual gap with increasing competitiveness in concentrated industries, thereby refuting Becker’s theory. They also find some evidence of skill-biased technical change.

In a similar context Reilly, Dutta, et.al. (2008) find no significant effect of trade openness on the (residual) gender wage gap in India across 39 industry groups over the time period spanning the years 1983, 1993 and 2000.

Aguayo Tellez et.al (2014) and Juhn, Ujhelyi, and Villegas Sanchez (2014) exploit the massive tariff reductions associated with signing of the NAFTA by Mexico in the 90s. The former uses household level data and follows an industry level analysis, while the latter uses establishment or firm level data. Both indicate how trade liberalization positively impacted female labour market outcomes.

Juhn, Ujhelyi, and Villegas Sanchez (2014) use a panel dataset of firms for the years 1991 and 2000. Their results indicate that export tariff reduction in firms is associated with larger increases in the female-male relative employment and wage ratio for blue collar occupations in the manufacturing sector. This is consistent with their adopted theoretical framework where exporting firms experiencing larger tariff reductions undertake technology upgradation which is less 'physically demanding'. This new technology is therefore skill-biased towards female workers and helps improve their outcomes. This effect is not prevalent in case of white-collar occupations where the importance of 'physically demanding' skills is less. Additionally, they find no effect with input tariffs in their study.

Among regional level studies, Benguria and Ederington (2017) studies the link between increasing imports from China and the gender wage gap across 558 Brazilian micro-regions during 2000-2010. After decomposing the wage gap into the 'explained' and 'unexplained' components, they find that rising imports from China lead to a fall in the 'explained' portion of the gender wage gap. There was no significant impact on the 'unexplained' portion or the residual wage gap. They further decompose the 'explained' portion into three components – the parts explained by differences in education, occupation and age between male and female workers. Running the regression specification on each of these three components reveal that the fall in the 'explained' portion of the wage gap was mainly driven by differences in occupational employment between men and women.

In the Indian context, Deb and Hauk (2020) study the impact of Chinese imports on the skilled-unskilled wage gap, as well as the gender wage gap. Their study is at the industry level and covers three rounds of the Employment-Unemployment Surveys conducted by the NSSO – Namely, 55^{th} (1999-00), 61^{st} (2004-05) and 66^{th} (2009-10). They find a positive and significant effect of Chinese import exposure on the gender wage gap, but the effect on skilled-unskilled wage gap is found to be insignificant altogether.

The rest of this section explores studies that are relevant to this paper in terms of their methodological contributions.

Autor, Dorn, and Hanson (2016) talk about the impact of rising import competition from China during 1990-2007 on local labour markets in the US. To delineate causality, this study instruments Chinese import growth in the US using Chinese import growth in other high-income countries. Variation in exposure to Chinese imports across local labour markets is created using variation in 'initial' industry specialization across these labour markets. Their results reveal a fall in both wages and employment, as a result of rising trade with China.

Exploring the regional dimension in the Indian context, Topalova (2007) and Topalova (2010) studied the impact of the 1991 trade reforms on poverty and inequality across districts in India. These studies rely on an identification strategy that compares districts that were more or less exposed to trade because of tariffs being imposed at varying levels and varying times. Both these studies use household survey data from various 'thick rounds' of the NSSO, which is then aggregated to create district level measures. In Topalova (2007), the poverty gap increased in rural districts that were composed of industries that were relatively more exposed to the trade reforms of 1991.

The regression models underlying Topalova (2007, 2010) and Autor, Dorn, and Hanson (2016) belong to the class of 'shift-share' regression models. This paper borrows the instrumental variables based empirical strategy from Autor, Dorn and Hanson (2016) and uses a shift-share model set-up. In a shift-share model set-up, a regional outcome (district-level gender wage gap) is usually regressed on a weighted average of sectoral shocks (in this case, industries within a district differentially exposed to the Chinese imports). The weights used are regional sectoral shares (in this case, district-industry relative employment shares). The specifics of this set-up are explained in further details in the methodological section of this paper.

3. Factual Background and Descriptive Statistics

3.1 Data and Sample

3.1.1 Data Sources

Relevant trade data on imports has been obtained from WITS at ISIC Revision 3 product classification. This data on imports has then been converted from dollars to rupees using data on exchange rate (average annual rupee/US dollar) from the Reserve Bank of India (1999-00-2011-12). Following this, imports have been adjusted for inflation using GDP deflator (base year 2011), data for which has been obtained from the World Bank.

Labour market data has been obtained from the employment-unemployment survey (EUS) rounds of the NSSO and the Economic Census. Specifically, three rounds of the NSSO have been used - 55th (1999-00), 61st (2004-05) and 68th (2011-12)[5]. Unit level data from

[5] Data (on wages) shown in graphs for the different EUS rounds of the NSSO are available in published reports ((NSSO), 2001, 2006, 2014)

NSSO is at the individual level, which has been aggregated to the district level for the purposes of this study (using relevant weights given in the survey)[6].

Census data for the years 2000 and 2011 have been used to procure data on employment in industries within a district. Data on both 'Main' and 'Marginal' workers have been used. Main workers are the ones who have worked for the major part of the reference period (6 months or more) and marginal workers are the ones who have worked for less than 6 months. This data is used to create the district-level import exposure variable across the years 1999-00, 2004-05 and 2011-12. The data for district-industry employment figures in 2004-05 is taken as an average of Census 2000 and 2011 figures.

However, Census data on such employment weights do not include data on agricultural laborers. Therefore, I substitute employment weights for the agricultural sector using data from the corresponding NSS rounds[7].

In this context, it is important to mention that a uniform coding for industries has been arrived at by concording NIC 2008 codes (Census 2011) to NIC 1998 codes (Census 2000). This particular classification has been chosen since the product classification codes for our data on imports (ISIC Rev 3) is its closest match.

[6] Previous district-level studies using NSSO data have focused either on district-level poverty (Dreze and Murthi (2001), Topalova (2007, 2010)) or district-level (casual) wages (Imbert and Papp (2015), Mahajan and Ramaswami (2017)).

[7] This is done following Topalova (2007) and Topalova (2010) who construct these employment weights in a similar way

3.1.2 Construction of district-level dataset (final sample):

The relevant sample of individuals from the NSSO include all 'workers' earning positive weekly wages in the age group of 15-64. Individual level data on wages is then aggregated to the district level using multiplier weights given in the survey. The district-level average wage, for example, is the population-weighted average of the individual weekly wages of all the workers living within a district.

Other district-level outcomes that have been constructed using unit-level NSSO data have been provided in Table 1 of Section 4.1, under the list of all *control variables* used in this study. Some of these variables include the share of educated male (female) workers (as a percentage of total male (female) workers), share of workers in manufacturing sector (as a percentage of total workers) and labour market density (total number of workers/total population in each district).

The final data set comprises of a total of 366 districts, nested across 18 of the major states of India[8]. To arrive at a uniform district coding across all data sets (Census and NSSO) and across all years, districts were rearranged and coded according to the list given in Census 1991. Between 1991 and 2012, there have been many instances of district reorganization wherein new districts have been carved out of old ones. For example, the state of Orissa comprised of 13 districts in 1991, which increased to 30 in 1993. In cases like this, the districts created anew were subsumed into the coding used for the older districts that they were carved out of. In this way, a panel data set of 366 districts was created for the years 1999-00, 2004-05 and 2011-12.[9]

[8] The states in question are Bihar, Jharkhand, Madhya Pradesh, Chhattisgarh, Uttar Pradesh, Uttarakhand, Assam, Orissa, Rajasthan, West Bengal, Punjab, Haryana, Gujarat, Maharashtra, Andhra Pradesh, Kerala, Karnataka, Tamil Nadu

[9] Note that given the sampling methodology of NSSO in the earlier rounds, there are concerns regarding representability of district-level estimates for the urban sector. However, due to the growing significance and use of district-level estimates, there was a change in the sampling methodology for

3.2 Measure of competition: Why China?

The choice of choosing to measure increased competition from trade in India using imports from China is justified on the following counts. Firstly, the rise in imports that India experienced over the sample period under study is driven mostly due to the dramatic rise in share of Chinese imports across this period. Secondly, China's accession to WTO in 2001 led to a period of rapid trade liberalization in China. This episode constitutes as a global 'external shock' that may have been driving Chinese exports across the sample period (1999-2012) and is often used as a 'quasi-natural experiment' in literature.

Given the sample period under study, Chinese import growth has been the most dramatic, surpassing India's export growth in China. While the share of Chinese imports in total imports grew from about 1.28 in 1993 to 11.06 in 2012 (760.9 per cent), the Chinese share of total exports grew from 0.013 in 1993 to 0.051 in 2012 (303.26 per cent). This suggests that variation in competition from the 'export channel' is relatively low[10].

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the *urban sector* in the 'later rounds' of the NSS that allayed such concerns regarding representability (The change involved making district the 'primary strata' for urban sector, in line with rural sector sampling in later rounds of the NSS. Previously, the primary strata in case of the urban sector were taken to be 'NSS Regions' instead (See National Academy of Statistical Administration (NASA), n.d.). In case of the Employment-Unemployment surveys, there was a change in sampling methodology for the urban sector only after the year 1999-00. Therefore, in so far as representability is concerned, the district-level estimates for the urban sector for the 61st round (1999-00) should be interpreted with caution in this study.

[10] Nevertheless, in the Robustness Checks section, I incorporate competition from 'exports' and construct a net import exposure variable. The qualitative nature of our results remains the same.

The top 5 importing partners of India as of 2012 include China followed by UAE, Saudi Arabia, Switzerland and USA. Comparing the growth in share of imports from China with that of India's other top importing partners, we see how China stands out in terms of its growing importance over the sample period under study.

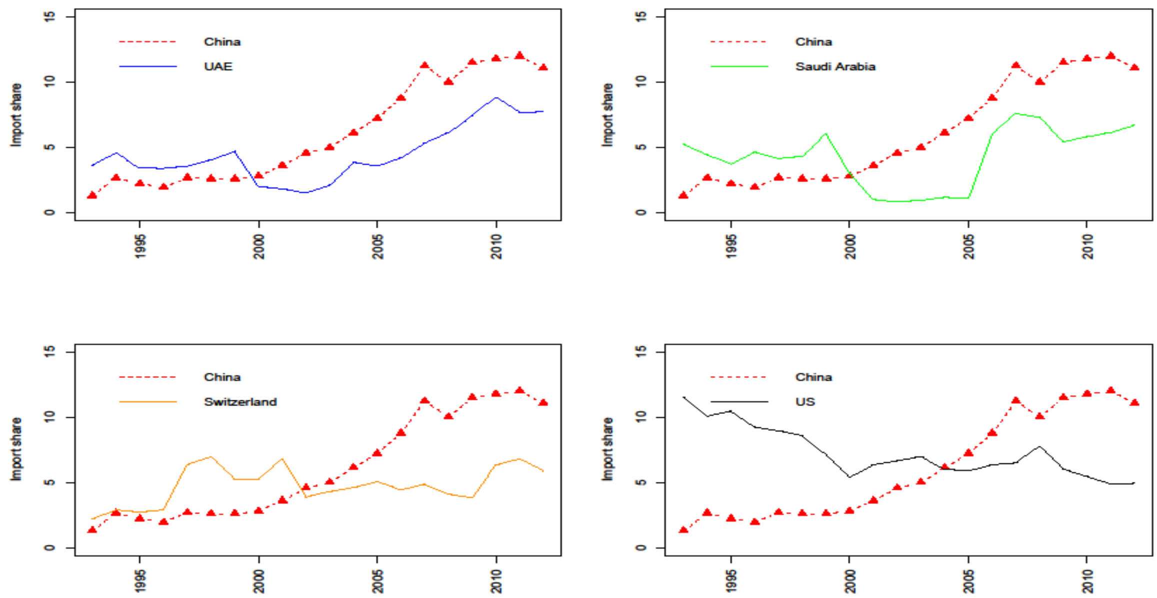

Figure 1: Trend in India's share of total imports from China and other top importing partners

3.3 Measure of gender inequality: The Raw and Occupational Gender Wage Gap

There are two measures of district level gender wage gap used in this study. One is the 'raw/unadjusted gender wage gap'. This is calculated as the simple difference in district-level average wages[11] of all male and female workers residing in a district. Over the sample period under study, this measure registered an overall decline from 0.68 to 0.58 log points, while registering a slight increase in the first time period (1999-00 to 2004-05) from 0.68 to 0.74.

[11] Data on individual wages from NSSO have been log transformed and then averaged across districts using multiplier weights given in the survey.

The 'occupational gender wage gap' measure is borrowed from Oostendorp (2004), where it is argued how it is a better proxy for discrimination than the 'residual' gender wage gap in case of cross-country studies. The author argues how after controlling for occupation, the explanatory power of human capital differences in explaining the gender wage gap is very minimal, especially for developing economies.

Given the regional focus of this study, this measure can be regarded as a reasonable 'proxy' for 'discrimination' in our context. Such a measure abstracts away from occupational segregation among male and female workers. Recent literature on the gender wage gap regards occupational segregation as explaining a major part of the observed gap in wages. The district level occupational gender wage gap is defined as:

$$\sum_{i=1}^{10} S_i^f (\overline{\log W_i^m} - \overline{\log W_i^f}); i = occupation \tag{1}$$

Here, $\overline{\log W_i^m}$ and $\overline{\log W_i^f}$ denote average male and female wages within occupation 'i'; S_i^f denotes the share of female workers in occupation 'i'.[12]

In this study, this measure is constructed using data from the NSSO across three rounds - 55th, 61st and 68th. 'Occupation' is defined according to the NCO (National Classification of Occupations) classification codes. In order to construct this particular measure of the wage gap, I rely on the one-digit NCO occupation codes although the highest level of disaggregation available is at the 5-digit level. This is done to ensure maximum representability of aggregate wages at the 'district-occupation' level. The behaviour of the all-India average occupational gender wage gap as observed over time is depicted as under.

[12] Note: The raw wage gap can be expressed as a summation of the occupational gender wage gap and $\sum_{i=0}^{n}(S_i^m - S_i^f)\overline{lnW_i^m}$ (defined as the inter-occupational component in Oostendorp (2004))

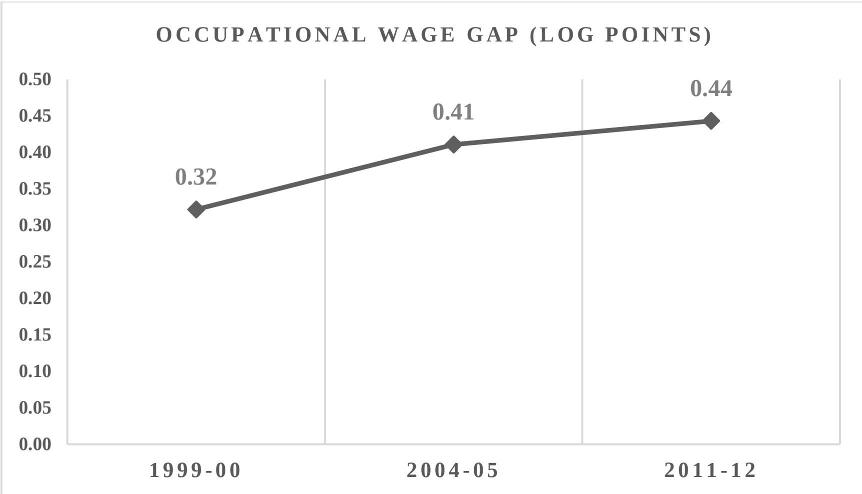

Figure 2: Trend in the occupational gender wage gap over time

Unlike the raw gender wage gap, this measure shows an overall increase across the sample period under study.

4. Model Specification and Empirical Strategy

4.1 Econometric Model

The purpose of adopting a shift share regression design is to study the impact of a set of "shocks" (shifters) on districts that are differently exposed to them. The shock episode here is increasing imports from China. The district-level import exposure variable is arrived at by constructing a weighted average of imports per worker in each district. The weights used are national district-industry employment shares.

Given below is our main estimating equation:

$$\Delta Y_{iT} = \gamma_T + \alpha_S + \beta \Delta IMP_{iT} + X'_{iT}\delta + \epsilon_{iT}; i = district, s = state, T(time\ period) = 1,2 \quad (2)$$

In equation (2) above, T = 1 refers to the time interval 1999-2005 and T = 2 refers to the time interval 2005-2012. The relevant dependent and independent variables are therefore stacked as differences over these two time intervals. ΔY_{iT} is the main dependent variable which measures the change in the gender wage gap of district ‘i’ in time period T. It is defined as under:

$$\Delta Y_{iT} = \Delta\left(\log(\frac{\overline{W^m}}{\overline{W^f}})\right)_{iT} \tag{3}$$

Here, the individual `weekly' wages (log transformed) are averaged for male and female workers separately in each district, using multiplier weights given in the survey. The gender wage gap is then defined as the raw difference in average male and female wage in a district. In other words, it is the log of the ratio of geometric means of male to female wages in a district.

ΔIMP_{iT} is the main independent variable of interest. This is the 'shift-share' measure which depicts the change in import exposure from China faced by district ‘i’ in India, over time period T. Import exposure, at the district level, is measured as the weighted sum of imports from China with the weights being equivalent to the national employment shares of industries within a district. It is constructed as under.

$$\Delta IMP_{iT} = \sum_j \frac{L_{ijT}}{L_{IiT}} \frac{\Delta M_{jT}}{L_{iT}}; i = district, j = industry, T(time\ period) = 1,2 \tag{4}$$

The first part of the fraction in (4) refers to the 'national industry employment share' where each industry's share of employment in district 'i' (L_{ijT}) is normalized by its national employment share (L_{IiT}). For each time period T, the employment weights used are that of the beginning year of that period (For T=1 (1999-2005), for example, the employment figures are from the year 2000). The second part of the fraction refers to Chinese imports per worker in district 'i' in India over time period T. Here, the change in Chinese imports accruing to industry j over time period T (ΔM_{jT}) is normalized by the number of workers residing in district i (L_{iT}).

γ_T refers to the time-period fixed effects. α_S refers to state-fixed effects, which controls for the state-specific linear time trend in the outcome variable.

X_{iT} include district level control variables that have the potential to affect the gender wage gap (Y). These are level outcomes that correspond to the beginning year of each time period (1999-00 for T=1 and 2004-05 for T=2). On controlling for these variables, I ensure that changes in the gender wage gap are a function of initial conditions. The variables and their data sources are listed in the table below.

Table 1: Control Variables[13] and Data Sources

Variable Name	Data Sources
• Share of educated[14] male workers • Share of educated female workers • Share of workers in low-skill[15] occupations • Share of workers in manufacturing sector • Share of 'full-time'[16] workers • Share of married female workers • Share of workers who are 'Hindus' or 'SC/ST' • Labour Market Density (total number of workers/total population)	NSSO Employment and Unemployment Surveys (Unit level data): 55th (1999-00) and 61st (2004-05) rounds

[13] See Fuschs et. al. (2019) for an explanation of the theoretical arguments that may help explain the possible direction of impact of these variables on the regional gender wage gap. Fuschs et al (2019) outlines factors affecting regional differences in the gender wage gap in the context of Germany. To the best of my knowledge, there is no comparable study in the Indian context.

[14] 'Secondary' and above

[15] Here low-skill refers to 'elementary' and 'service' occupations, as classified under G.O.I (2005)

[16] In accordance with NSSO data, full-time workers are those workers who have worked for more than 5 days in the one-week recall period

Population Density[17]	Economic Census
Total Fertility Rate	Guilmoto and Rajan (2013)

4.2 Empirical Strategy

As is inevitable, the given regression specification suffers from the problem of endogeneity. This prevents us from uncovering the true **causal** effect of a rise in Chinese imports on the raw and occupational gender wage gap. In particular, Indian imports from China may be correlated with industry level labour demand shocks causing 'simultaneity' in the regression model (That is, $cov(\Delta IMP_{iT}, \epsilon_{iT}) \neq 0$) This makes it difficult for us to separate out the effect arising from increased competition. Following Autor et al (2013), this paper follows an Instrumental Variables (IV) strategy to overcome this problem of identification. The proposed IV involves replacing Chinese imports into India with Chinese import growth in other low and low middle income countries[18]. This is done to separate out the exogenous component of Chinese import growth (that is common to India and the set of comparison countries), so as to make it act as a supply shock from the Indian perspective. The IV used is described below:

$$\Delta IMX_{iT} = \sum_j \frac{L_{ijT}}{L_{IiT}} \frac{\Delta MO_{jT}}{L_{iT}}; i = district, j = industry, T(time\ period) = 1,2 \quad (5)$$

Therefore, ΔM_{jT} (change in Indian imports from China) is replaced with ΔMO_{jT} (change in Chinese import growth in the set of low and low middle countries). There are two caveats in

[17] Number of people living within a district per square kilometre

[18] The selected set of countries include: Pakistan, Bangladesh, Philippines, Nicaragua, Senegal, Morocco, Zambia, Zimbabwe. These countries were selected on the basis of their similarity with India with respect to income level, import basket and other structural parameters such as GDP composition across agriculture, industry, services, as well as Chinese import share.

the use of this particular IV. One relates to the use of employment figures (which are inherently a function of wages) to apportion imports. This fails to rule out the effect arising out of unobserved supply shocks in industries within a district which might be driving our outcomes of interest.[19] Note that the inclusion of state fixed effects in our estimating equation controls for the effect of these unobserved shocks (with a linear trend) to some extent, if not do away with it completely. The other relates to the use of *start-of-period* employment figures in the IV, which may cause simultaneity in the regression equation. The solution would be to use lagged employment figures instead. For the use of lagged employment shares, however, I would need NSSO data on these weights for the agricultural sector prior to 1999-00, to substitute in place of the Census data. Because of the lack of district identifiers in past NSSO Employment-Unemployment rounds, this data was not available. Therefore, I make use of the IV without the lagged employment weights.

5. Estimation Results and Discussion

The estimation for our model in question has been conducted using both Ordinary Least Squares (OLS) and Instrumental Variables Two Stage Least Squares (IV-2SLS)[20] techniques. To help aid causal inference, imports from China have been instrumented with Chinese import growth in other low and lower middle income countries. There are two assumptions underlying the

[19] In line with Goldsmith Pinkham et.al. (2018), the proper identification of such IVs rests on the exogeneity of the initial employment figures.

[20] The IV-2SLS techniques proceeds as follows. In the first stage, ΔIMP_{iT} is regressed on ΔIMX_{iT} and all the other district-level variables in X_{iT}. In the second stage, ΔY_{iT} is regressed on the fitted value of ΔIMP_{iT} from the first stage regression ($\Delta\widehat{IMP}_{iT}$). Therefore, the first stage estimation extracts out the exogenous component of the explanatory variable of interest and ensures that $cov(\Delta\widehat{IMP}_{iT}, \epsilon_{iT}) = 0$ in the second stage.

working of any instrument – instrument relevance and exclusion restriction[21]. Results from the first stage regression of IV-2SLS, validating the first assumption, are depicted in the graph below. Threats to the validity of the second assumption are discussed in the 'Robustness Checks' section of the Appendix.

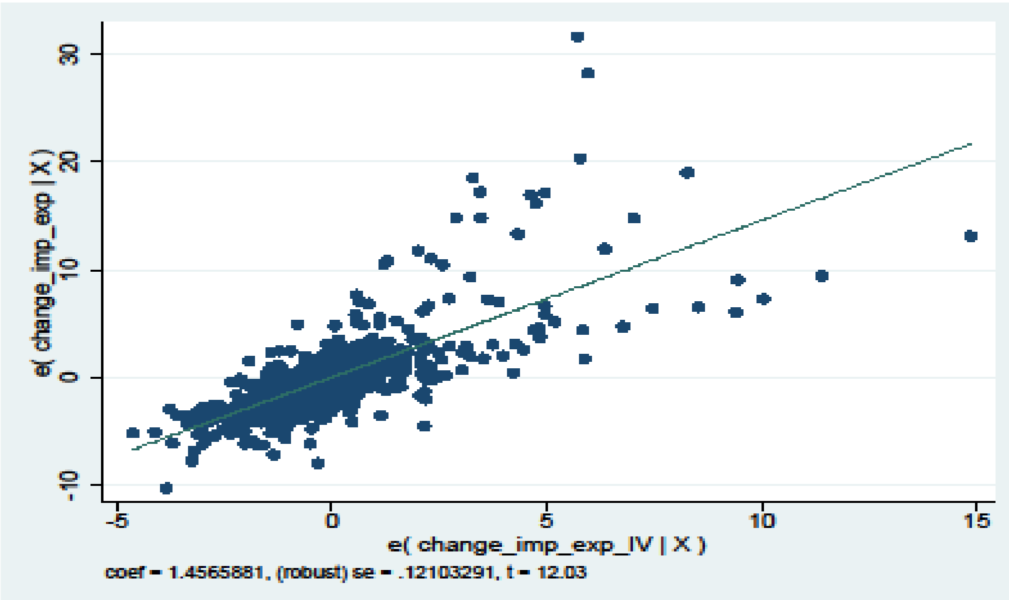

Figure 3: First stage IV-2SLS regression results

It is evident that the instrument used has very high predictive power of India's import exposure from China, making it relevant for our use. The value of the coefficient tells us that a 1000Rs. increase in low and low-middle income country imports from China (IV) leads to an increase of Rs.1456 in measured Indian imports from China.

5.1 Main Results

The results shown below correspond to the main estimating equation (that is, equation (2)). The controls used are state and 'time-period' fixed effects along with the entire set of time-varying

[21] The first requires $cov(\Delta IMP_{iT}, \Delta IMX_{iT}) \neq 0$. The second requires $cov(\Delta IMX_{iT}, \epsilon_{iT}) = 0$. The challenge lies in testing whether $cov(\Delta IMX_{iT}, \epsilon_{iT}) = 0$ since the error term is unobservable.

district-level characteristics. The standard errors used have been adjusted for heteroskedasticity and are robust to estimation.

In addition to the economy-wide analysis, the estimation has been carried out for various sub-samples of workers within the economy. This includes Rural and Urban sector workers, Regular Wage Salaried (RWS) workers and Casual Labourers.[22]

5.1.1 Impact on the Raw Gender Wage Gap

The table below depicts the impact of rising Chinese imports on the district-level 'raw' gender wage gap across various sub-samples.

Table 2: Impact of the 'China shock' on the raw gender wage gap

	OLS	IV-2SLS
Economy-wide sample	0.012** (0.005)	0.030** (0.014)
RWS workers	0.016** (0.007)	0.032** (0.014)
Casual Labourers	0.013* (0.008)	0.029** (0.013)
Rural Sector	0.023*** (0.007)	0.050*** (0.016)

Note: * p<0.10, ** p<0.05, *** p<0.01, + p<0.001; Robust Standard Errors are given in parentheses; Regressions are weighted using the square root of the working-age population in each district.

The results above show how rising imports from China positively impacts the district-level gender wage gap in India. In case of the economy-wide sample, a 1000Rs increase in Chinese imports causes the gender wage gap to increase by 3 percentage points over time. The

[22] Detailed regression table for the economy-wide sample has been provided in the Appendix. The regression output pertaining to the various sub-samples of workers will be available on request.

observed increase in the gender wage gap is also the greatest among rural sector workers (5 percentage points).

A rural-urban break-up reveals significant estimates for the rural sector only. This may be because the mechanisms linking trade and gender wage gap in case of the urban sector cancel each other out, and therefore we see no overall impact. This could also point towards the issue of representability of district-level estimates for the urban sector, given the sampling methodology of NSSO for the year 1999-00 (as outlined before).[23]

5.1.2 Impact on Occupational Gender Wage Gap

The results pertaining to the impact of rising Chinese imports on the occupational gender wage gap are depicted in the table below.

Table 3: Impact of the 'China shock' on the occupational gender wage gap

	OLS	IV-2SLS
Economy-wide sample	0.012** (0.005)	0.021** (0.009)
RWS workers	0.021** (0.008)	0.030** (0.014)

Note: * p<0.10, ** p<0.05, *** p<0.01, + p<0.001; Robust Standard Errors are given in parentheses; Regressions are weighted using the square root of the working-age population in each district.

[23] In view of this issue of representability, it is useful to gauge the robustness of results obtained using NSS Regions (collection of districts that share the same agro-climatic and socioeconomic features) instead. This counts as scope for future research.

This measure, by definition, applies only to the full sample and RWS workers since these workers are engaged in a variety of different occupations[24]. Estimate for the urban sector, in this case, is insignificant as well.

Similar to the raw gender wage gap, Chinese imports positively impact the occupational gender wage gap as well. The effect size in case of the full-sample is 2.1 percentage points (weighted IV) and 3.0 percentage points (weighted IV) in case of RWS workers

5.2 Discussion of Results

The results found so far indicate that a rise in imports from China causes a rise in both the raw, as well as the occupational gender wage gap.

While this study cannot provide definitive proof of any theory, it can give insights into the mechanism by which the Chinese import shock may have caused a rise in the gender wage gap. In so far as I observe an increase in the gender wage gap, I can provide insights with respect to the skill-biased technical (SBTC) theory and the non-neoclassical or monopsonistic theory on discrimination.[25]

SBTC theory: As predicted by this theory, there is some evidence of a skill premium in response to increased imports from China. The change in skilled[26] wages display a positive

[24] Both casual labourers and workers in the rural sector are disproportionately employed as ‘agricultural labourers’.

[25] The various theoretical arguments linking trade and gender wage gap has been alluded to in the introductory section.

[26] ‘Skilled’ wages refer to wages of workers with a skill level equivalent to secondary education and above

association[27] with change in import exposure from China, while change in unskilled wages turn out to be insignificant altogether. This increase in skilled wages does not, however, translate into a male-skill bias as predicted by the SBTC Theory. Instead, further results from this study indicate that a rise in imports from China *causes* a decline in the district-level average *female* wage over time. The change in district-level average male wage displays insignificant IV-2SLS estimates.[28]

Non-neoclassical approach to discrimination: Since rising trade causes a decline in female wages, female workers seem to be the disproportionate bearers of cost-cutting strategies in the presence of competition - as predicted by this hypothesis. This hypothesis is based on the premise that female workers are segregated into low-paying, lower-status jobs, by virtue of which they have lower bargaining power. This fact is corroborated by the data used in this study.

Among RWS workers, female workers are disproportionately employed either as teachers or domestic servants (low-skill)[29] throughout the sample period under study. The latter share registers a consistent increase from 6.5 per cent in 1999-00 to 13 per cent in 2011-12. Among casual wage earners, female workers are disproportionately employed as 'agricultural labourers'

[27] A 1000 Rs increase in Chinese imports leads to a 0.98%(weighted OLS) increase in skilled wages over time. This effect size in case of weighted IV2SLS is 1.03% (significant only at 10% level)

[28] According to the IV estimates of the sample of RWS workers, a 1000Rs increase in Chinese imports into India causes the average female wage in a district to fall by 4.1% (significant at 1% level) over time. This fall is predicted to be 2.2% (significant at 10% level) for the economy-wide sample, 3.2% (significant at 5% level) for the sample of casual labourers, and 4.5% (significant at 1% level) for rural sector workers.

[29] Classified in accordance with NCO codes (See G.O.I (2005))

(low-skill)[30] in all the years. The share of female relative to male workers in this occupation has registered a slight increase from 0.62 per cent in 1999-00 to 0.66 per cent in 2011-12.

Our findings, therefore, point towards the predictions of the non-neoclassical theory on discrimination. However, it is important to acknowledge here that gender wage gap measures used in this study do not necessarily correspond to 'discrimination' and are at best taken as proxies for the same.

With regard to *employment effects*, I find no evidence of trade-induced changes in the ratio of female to male workers in a district ('fm-ratio'). However, imports from China is positively associated (weakly) with 'fm-ratio' in the economy-wide sample (The effect size is around 0.31 percentage points). This effect holds only in case of OLS estimation with time-period and state fixed effects, and is not robust to the inclusion of the time-varying district-level characteristics.

6. Conclusion

This study highlights the importance of gender in analysing the perceived effects of trade liberalization in general and increasing imports from China in particular. The main results of this study point to an increase in the district-level raw gender wage gap in India by a magnitude of about 3 percentage points over time, in response to a 1000Rs increase in Chinese imports. This rise is most pronounced in case of rural sector workers (5 percentage points). The district-level occupational gender wage gap also registers an increase in response to a rise in Chinese imports – the magnitude of which is higher in case of RWS workers (3 percentage points) than the economy-wide sample of workers. (2.1 percentage points).

[30] Classified in accordance with NCO codes (See G.O.I (2005))

The results therefore indicate how an increase in competition from trade leads to a rise in district-level inequality and discrimination against women wage earners in India. It is worthwhile to note that this direction of impact has been documented previously in *industry-level* studies in the Indian context. This includes Menon and Rodgers (2009) and Deb and Hauk (2020). This study, however, moves beyond the narrow focus on urban RWS workers (as in Deb and Hauk, 2020) and urban manufacturing sector workers (as in Menon and Rodgers, 2009). The findings of this study are consistent for the economy-wide sample of workers. In addition to this, I find evidence of an impact of Chinese imports on casual labourers and rural sector workers – which is where majority of female workers in India are concentrated.

The results obtained have been analysed in the backdrop of the theoretical framework that governs the interconnections between trade and gender wage gap. In making this analysis, however, it is important to acknowledge the limitations[31] faced in the data and framework used for this study. A more in-depth analysis and representative data is required to draw policy implications. However, it is advisable to build a stronger social safety net for women which might improve their access to high paying, high skilled occupations that men usually have better access to. Given that travel costs for women are higher than for men (which in turn fuels employer's ability to engage in 'monopsonistic discrimination' at the district level[32]), provision of better (and safer) transportation services for traveling long distances is advisable in this regard.

The contribution of this study is two-fold. First, it uses district level data to analyse the gender wage gap in India. This allows us to capture micro-level effects, compared to previous

[31] For example, concerns regarding representability of district-level estimates for the urban sector - as explained in footnote 9.

[32] Spatial duopsony model, Hirsch (2009)

studies using aggregate data at the industry or firm level. Second, it uses an IV based empirical strategy to delineate causality in such a set-up. Given that 'instrument relevance' holds and some of the threats identified to the working of the IV have been ruled out[33], our findings hold some validity in terms of the direction and magnitude of impact.[34]

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Disclosure Statement

No potential conflict of interest was reported by the author.

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Data Availability Statement

The data that support the findings of this study were derived from resources available in the public domain which are listed under section 3.1 (Data and Sample) of Section 3. The data sets used will be available upon request from the corresponding author.

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[33] See Appendix I: Robustness Checks

[34] In analysing the results obtained, however, it is important to recognize the limitations faced in the data and the framework used for this study

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Appendix I: Robustness Checks

The robustness of the model set-up is assessed in terms of validating the IV strategy, as well as considering alternate measures of import exposure. The results are summarized below.[35]

Validating the IV strategy

Within the context of this study, possible threats to the exclusion restriction include:

- Export displacement effects: Indian exports to the selected set of low and low middle income countries might crowd out Chinese exports to these same countries. However, our results show imports from China clearly outweigh imports from India in all the 'comparison' countries, across the sample period under study.

- Correlated import demand shocks across India and the set of comparison countries: Even though the IV vouches to rule out the threat of industry level demand shocks in India, demand might still contaminate the true effect if demand shocks across India and the set of comparison countries for the IV are correlated. On dropping the 'suspect' products (such as 'networked' products like electric equipment) and reconstructing the import exposure variables, the estimated main effect remains qualitatively similar.

Using alternative measures of import exposure

To gauge the validity of the results obtained, two alternative measures of import exposure have been constructed. The first adjusts for exports and constructs a net import exposure (imports minus exports) variable. The magnitude of the main effect changes but the direction and sign of

[35] Detailed results will be available on request

the impact are preserved. The second measure is where total imports from China is adjusted for the import of intermediate inputs[36]. Although results are still qualitatively similar, I see a rise in the magnitude of the main effect on considering only final use imports. The productivity enhancing effect of imported intermediate inputs could affect the demand for labor, which in turn might offset the supply-side effect arising from imports in final goods

[36] Data from World Input Output Database (WIOD) provides us with information on the import of final goods, as separate from the import of goods for intermediate consumption.

Appendix II: Regression Table

Table 4: Regression Results (economy-wide sample)

	Δ (raw GWG) OLS b/se	Δ (raw GWG) IV-2SLS b/se	Δ (‘occ’ GWG) OLS b/se	Δ (‘occ’ GWG) IV-2SLS b/se
Δ (Import Exposure)	**0.012**** **(0.005)**	**0.030**** **(0.014)**	**0.012**** **(0.005)**	**0.021**** **(0.009)**
Ratio of female to male workers	-0.151 (0.221)	-0.124 (0.211)	0.228 (0.196)	0.241 (0.194)
Share of educated (>=secondary) females	0.011** (0.005)	0.011** (0.004)	0.002 (0.004)	0.001 (0.004)
Share of educated (>=secondary) males	-0.012*** (0.004)	-0.011*** (0.004)	-0.004 (0.005)	-0.004 (0.004)
Share of female RWS workers	0.002 (0.003)	0.003 (0.002)	0.001 (0.004)	0.001 (0.004)
Share of male RWS workers	-0.004 (0.003)	-0.005** (0.002)	-0.001 (0.003)	-0.001 (0.003)
Share of manufacturing female workers	-0.005** (0.002)	-0.006*** (0.002)	-0.002 (0.003)	-0.003 (0.003)
Share of male manufacturing workers	0.000 (0.004)	-0.001 (0.005)	0.002 (0.004)	0.001 (0.004)
Share of male household heads	0.002 (0.005)	0.001 (0.005)	-0.003 (0.004)	-0.004 (0.004)
Share of female household heads	0.004 (0.003)	0.004 (0.003)	0.002 (0.003)	0.002 (0.003)
Share of married female workers	0.006** (0.003)	0.006** (0.003)	0.008*** (0.003)	0.008*** (0.003)
Share of married male workers	0.001 (0.004)	0.003 (0.004)	0.007 (0.005)	0.008 (0.005)

Share of 'Hindu' workers	0.002 (0.003)	0.001 (0.003)	-0.005** (0.003)	-0.006** (0.003)
Share of 'SC/ST' workers	0.002 (0.002)	0.001 (0.002)	-0.001 (0.002)	-0.001 (0.002)
Share of workers in low-skill occupations	-0.000 (0.005)	0.000 (0.005)	-0.001 (0.005)	-0.000 (0.005)
Share of full-time workers	0.004* (0.002)	0.003 (0.002)	-0.001 (0.003)	-0.001 (0.002)
Labour Market Intensity	-0.001 (0.004)	-0.002 (0.004)	-0.005 (0.004)	-0.006 (0.004)
Log (Population Density)	-0.035 (0.034)	-0.046 (0.034)	-0.016 (0.034)	-0.021 (0.034)
Total Fertility Rate	0.030 (0.057)	0.029 (0.055)	-0.017 (0.057)	-0.018 (0.056)
state=102	-0.158 (0.221)	-0.163 (0.216)	0.124 (0.174)	0.121 (0.169)
state=104	-0.171 (0.200)	-0.161 (0.193)	0.150 (0.154)	0.155 (0.150)
state=105	-0.179 (0.187)	-0.163 (0.182)	0.109 (0.165)	0.116 (0.162)
state=107	-0.181 (0.231)	-0.145 (0.222)	0.278 (0.176)	0.296* (0.173)
state=108	-0.410 (0.265)	-0.389 (0.256)	0.509* (0.297)	0.520* (0.290)
state=201	0.065 (0.260)	0.087 (0.255)	0.103 (0.209)	0.114 (0.205)
state=202	-0.134 (0.185)	-0.120 (0.179)	0.328* (0.197)	0.335* (0.193)
state=203	-0.212 (0.218)	-0.177 (0.207)	0.079 (0.188)	0.096 (0.185)

state=204	-0.141	-0.126	0.159	0.167
	(0.186)	(0.181)	(0.223)	(0.219)
state=301	-0.314	-0.263	-0.158	-0.133
	(0.261)	(0.251)	(0.299)	(0.292)
state=302	-0.392*	-0.355*	0.204	0.222
	(0.223)	(0.213)	(0.219)	(0.216)
state=401	0.047	-0.009	0.171	0.143
	(0.204)	(0.202)	(0.177)	(0.171)
state=402	0.107	0.087	0.157	0.147
	(0.201)	(0.195)	(0.169)	(0.163)
state=501	0.001	0.014	0.128	0.134
	(0.189)	(0.186)	(0.187)	(0.183)
state=502	-0.015	-0.035	0.193	0.183
	(0.184)	(0.183)	(0.173)	(0.169)
state=503	0.161	0.152	0.258	0.254
	(0.229)	(0.224)	(0.222)	(0.216)
state=504	0.133	0.147	0.280	0.287
	(0.200)	(0.198)	(0.197)	(0.192)
year=2	-0.130**	-0.234***	-0.109	-0.159*
	(0.063)	(0.079)	(0.071)	(0.087)
Constant	-0.570	-0.444	-0.154	-0.092
	(0.716)	(0.684)	(0.731)	(0.719)
N	728.000	728.000	728.000	728.000
r2	0.127	0.119	0.057	0.055

Robust standard errors in parentheses
Regression is weighted using the square root of the working age population in a district
GWG refers to Gender Wage Gap and 'occ' refers to occupational
* p<0.10, ** p<0.05, *** p<0.01, + p<0.001