# The Gender Dimension of Industrial Diversification: What is the Role of Skills Gap?

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# The Gender Dimension of Industrial Diversification: What is the Role of Skills Gap?

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**Abstract**

Regional capabilities are considered the primary source of the industrial diversification process. Even so, the existing practice is somewhat reluctant to observe their exact nature. The present study explores one important dimension of regional capabilities, namely the gender gap in workplace skills, and considers it in accounting for the observed patterns of industrial diversification of regions. By constructing a gender skill gap indicator at the industry-region level, female-biased and male-biased skill gaps are analysed. The descriptive and empirical analyses document significant variations of the gender skill gaps across industries and regions. By employing piecewise logistic models, the study unfolds the contrasting impacts of the female-biased and male-biased skill gaps on the industrial diversification of regions.

**Keywords:** Regional Capabilities; Gender; Diversification; Skill Gap; Industries.
**JEL Classification:** J24; O18; R10; R23.

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# 1 Introduction

One of the indispensable features of the industrial diversification of regions is substantial heterogeneity in regional capabilities underpinning the diversification process. Up-to-date, the literature has generally focused on indirect measures of capabilities –usually captured by co-location-based relatedness- without observing their diverse and uneven nature (Boschma, 2017; Buyukyazici et al., 2023). This practice masks a more nuanced picture of regional potential and deficiencies. In this paper, we integrate gender into the industrial diversification framework to assess the gender dimension of regional capabilities in the form of workplace skills and knowledge. We analyse how the uneven distribution of workplace skills and knowledge between genders can partly determine the industrial diversification process of regions.

Addressing the gender skill gaps is critical at both the micro, i.e. within organisation strategies, and macro level, i.e. regional and national policies, to harness the potential of existing capabilities and productive potential to reach sustainable regional economic growth and development. In this regard, the present work seeks to improve the policymakers' understanding of gender segregation and skill gaps in industries, as well as their geographical patterns, to enhance the effectiveness of a variety of regional and industrial policies including re-skilling, up-skilling, capability-building, and gender equality.

To explore the importance of gender skill gaps in the industrial diversification of regions we focus on Italy, which is a country with significant regional differences and a fragmented industrial structure. We use a well-detailed data set, *the Italian Sample Survey on Professions* (ICP), on workplace skills and merge it with the Italian Labour Force Survey (ILFS) across 107 Italian regions (NUTS-3) and 532 (four-digit NACE) industries for the period 2013-2019. By building an indicator of the gender skill gaps at the region and industry level, we evaluate how female-biased and male-biased skill gaps influence the comparative advantages of industries. Since the Evolutionary Economic Geography (EEG) literature has shown that the diversification process is highly affected by cognitively related industries in the region (Neffke et al., 2011), we employ the skill relatedness concept (Neffke and Henning, 2013; Buyukyazici et al., 2023) to account for cognitive proximity between industries. The EEG literature has also shown that economic complexity is a relevant determinant of the diversification process (Hidalgo et al., 2018; Balland et al., 2019). In addition, prior studies underlined that gender biases are more pronounced for unskilled labour than skilled labour (Olivetti and Petrongolo, 2014). A skill complexity measure is employed to address these aspects. We first employ network methods to describe the gender dimension of workplace skills. The gendered skill space of the Italian industrial portfolio is constructed by using skill relatedness and skill complexity measures. Then, the skills in which each gender has comparative advantages are mapped on the skill space. The results show that females have comparative advantages in social-cognitive skills while males have comparative advantages in technical-physical skills. The descriptive analyses also indicate the existence of skill gaps in the raw skills data. Females have higher skill scores in almost every social-cognitive skill while males have higher scores in technical-physical skills. However, the skill gap in technical-physical skills is much larger. In order to capture the skill differences at the industry-region level, a gender skill gap indicator that allows to account for female-biased and male-biased skill gaps is created. Then logistic and piecewise logistic models are used to analyse the impact of skill gaps on the industrial entry and exit within a region. Interestingly, the empirical results document an overall positive relationship between skill gaps and industrial diversification of regions. The overall picture changes when piecewise regression is applied to account for female-biased and male-biased skill gaps. Female-biased skill gaps are found to be negatively associated with entry and negatively associated with exit while male-biased skill gaps are positively related to entry and negatively related to exit. We discuss several channels that might underpin this diverging effect including biases in wage and employment distribution, labour force participation, leadership and decision-making process, market perceptions, and access to resources.

The present study contributes to the regional economics and EEG literature. It aims to complement prior research on skills and diversification by accounting for another, yet crucial, dimension of regional capabilities: gender. It provides a detailed examination of the gender skill differences across industries and regions by providing a new indicator inspired by the gender segregation indices. In this regard, the present study is the first that considers the gender dimension of regional capabilities in explaining the industrial diversification of regions. To the best of our knowledge, the empirical practice in this paper constitutes the highest micro-level analysis in the industrial diversification literature (at the gender, skill (161 workplace skills), industry (Nace 4 digit), region (Nuts-3) and time level). Our work also contributes to the gender inequalities literature and bridges it with the EEG literature.

The remaining of the paper is constructed as follows. Section 2 briefly overviews the interdisciplinary literature on gendered skills. Section 3 introduces the data sources. Section 4 defines relative skill advantage, skill relatedness and skill complexity measures to provide descriptive analyses of the gendered skill space and skill gaps. Section 5 develops an index for gender skill gaps. Section 6 performs econometric analyses to evaluate the impact of the gender skill gaps on the industrial diversification of regions by using logistic and piecewise logistic models. Section 7 conducts the sensitivity analyses. Section 8 discusses the potential channels through which the gender skill gaps impact the diversification process. Section 8 concludes.

## 2 Roots in Economic Theory and Empirical Literature

The gender dimension of workplace skills can be traced back to the human capital theory (Becker, 1962; Mincer, 1962; Becker, 1985) which asserts that the division of labour among family members, i.e. woman and man, is defined partly by biological factors and investments in human capital. Due to the asymmetric division of housework, childbearing, and child care, women are expected to have relatively shorter and discontinuous work experience which reduces investments in female education and market-oriented skills leading to gender skill and wage gaps (Becker, 1981). Another source of the wage gap is productivity differences across genders. Kao et al. (1994) explain productivity differences with expected lifetime labour force participation which is the pre-condition of human capital investment. Little incentive to invest in female education and market-oriented skills, caused by low labour force participation among women, leads to differences in skills and thereby in the productivity of genders. Ngai and Petrongolo (2017) model productivity differences to explain gender gaps, assuming that women have a comparative advantage in services over manufacturing.

An extensive body of economic research focuses on gender differences in labour market outcomes (see Goldin (2014) and Blau and Kahn (2017) for overviews). Nevertheless, a more interdisciplinary approach can be adopted to document the gender dimension of skills since women and men are different due to biological, sociocultural, and biosocial factors (Feingold, 1994). Hence, in what follows we briefly discuss gendered skills from a *nature or nurture* perspective to grasp the voluminous and interdisciplinary literature of gender studies.

The nature dimension accounts for biological and partly biosocial factors. For instance, hormones and brain structures of women and men are not the same as shown by biology and neuroscience literature (Baron-Cohen et al., 2005; Hines, 2011; Joel, 2012). The psychology and neuroscience literature indicates that females and males differ in cognitive tasks (Maccoby and Jacklin, 1974; Feingold, 1994; Baron-Cohen et al., 2005; Woolley et al., 2010; Koenig et al., 2011), thus, they are likely to have comparative advantages in different skill types (Hyde, 2014). Indeed, it has been shown that women outperform men in social, interacting, and language skills, while men outperform women in spatial, physical, technological, and mathematical skills (see Archer (2019) for a concise review).

The nurture dimension covers sociocultural and partly biosocial factors. Due to differences in their social roles as conceptualised by the social role theory (Eagly and Wood, 1991; Eagly, 2013), females and males develop different social behaviours, therefore, genders might have alike economic preferences and psychological traits such as risk preferences (Charness and Gneezy, 2012), time preferences (Dittrich and Leipold, 2014), social preferences (Kamas and Preston, 2015), educational (Stoet and Geary, 2018; Breda and Napp, 2019) and vocational preferences (Kuhn and Wolter, 2022). Such differences can affect the knowledge diffusion process especially when there is a disproportionate allocation of females and males among occupations and industries (Martini, 2021). Indeed, a stream of the literature suggests that gender gaps in the labour market are heavily affected, or caused, by occupational and sectoral segregation (Blau and Kahn, 2000) which is quite persistent over time and is not eroded by converging labour force participation rates or equalisation of education levels (Borrowman and Klasen, 2020). For instance, Blau and Kahn (2017) underline that the share of the gender wage gap due to education and experience has declined while the share accounted by occupational and sectoral differences has almost doubled between 1980 and 2010. Despite a narrowing gender education gap in recent decades, women are still underrepresented in science, technology, engineering, and mathematics (STEM) fields and over-represented in education, humanities, and healthcare (Gemici and Wiswall, 2014). Correspondingly, the human capital formation process of genders is expected to be conditioned not only by completed years of education but also by the level of occupational and sectoral segregation in the local economy given that on-job vocational training is as crucial as formal education, if not more. On top of these factors, the living conditions of women and men are not the same in many cultures (Treas, 2008). Childbearing, child care, and housework are duties of women (Ferrant et al., 2014) generally, leaving women less time than men for career advancements and human capital development (Peto and Reizer, 2021).

The above-mentioned nature and nurture dimensions, which are intertwined and are not mutually exclusive, donate genders with different capacities in different skill types' development (van Emmerik, 2006). For instance, helping and caring for others are traditionally seen as feminine skills while mathematics and working with machines are considered masculine skills (Anker, 1997; Cejka and Eagly, 1999; Koenig and Eagly, 2014). Prior research has underlined that women have a comparative advantage in service industries which require intensive use of social and interacting skills (Ngai and Petrongolo, 2017) while men are advantageable in physical and technical skills. For instance, Bacolod (2017) show that women tend to be concentrated in jobs requiring cognitive and social skills, while men are concentrated in jobs requiring physical skills. Cortes et al. (2021) note that the increased share of women in high-paying occupations can be explained by the importance of social skills. The social psychology literature underlines that the skill polarisation between females and males is visible even in early education and field choices (Park et al., 2007; Stoet and Geary, 2018; Goulas et al., 2022). Aucejo and James (2021) find that females (males) have a comparative advantage in verbal (math) skills. They attribute females' higher presence in tertiary education to their stronger verbal skills and males' higher representation in STEM fields to their stronger math skills. All in all, there seems to be a consensus across different fields, i.e. economics, sociology, and psychology, that women are advantageous in social and verbal skills, while men are so in technical, physical and mathematical skills.

### 2.1 Connecting the Dots: Gender, Skills, and Industrial Diversification of Regions

Gender skill gaps have generally been considered in the context of labour market studies (Goldin, 2014; Blau and Kahn, 2017) in relation to gender employment gaps, wage gaps, and occupational and sectoral segregation as briefly mentioned in the previous section. However, as shown by prior research (Di Noia, 2002; World Economic Forum, 2020; di Bella et al., 2021; Cascella et al., 2022), national gender skill gaps can posit great variation across regions due to severe regional inequalities that can augment or mitigate the influence of the nurture dimension, leading to potential consequences for industrial dynamics, innovation policy (Buyukyazici, 2022), and the development of regions.

A possible explanation for regional gender skill gaps is regional differences in female labour supply in terms of both quality and quantity. Prior research has underlined that female labour supply can have a large degree of variation across spatial units (Black et al., 2014; Bacolod, 2017) which might be caused by educational differences (Weeden et al., 2020), sectoral composition of the local economy, limited social rights for birth-giving and public childcare services (Del Boca and Vuri, 2007), cultural beliefs about gender roles and family values (Fernandez and Fogli, 2009), and different personality traits and preferences between genders (Flinn et al., 2018). The differences in gender compositions of labour across regions are reflected in within-region industries augmented with widely observed occupational and sectoral segregation. In this regard, gender skill gaps are expected to vary at the industry-region level depending on the factors mentioned above, positing implications for industrial dynamics of regions. EEG literature has shown that the industrial diversification process of regions is dependent on the utilisation of regional capabilities and competencies embodied in the regional population (Neffke et al., 2011; Buyukyazici et al., 2023). Regions specialise in new activities by building on and/or by recombining regional capabilities. In this regard, disproportionate distribution of competencies among the population, i.e. between genders, firms, and industries, would lead to implicit or explicit consequences for the development paths of regions. Motivated by this reasoning, the scholars called for a more micro approach and through evaluation of regional capabilities (Boschma, 2017; Buyukyazici, 2022). Nevertheless, the existing practice to observe the true nature and impacts of regional capabilities is scarce. In the present study we explore the gender dimension of regional capabilities in the form of workplace skills and knowledge.

To the best of our knowledge, the literature has not considered the impact of gender skill gaps, nor any kind of gender inequality, on the industrial diversification process of regions thus far. Gender studies in regional science and economic geography are limited including the regional differences of gendered employment (Elhorst and Zeilstra, 2007; Elhorst, 2008; Noback et al., 2013), the gendered employment and regional resilience (Ray et al., 2017; Martini and Platania, 2022). Hence, in what follows we briefly discuss the potential channels through which gender skill gaps might affect industrial diversification of regions under two rough categories: costly gender skill gaps and cost-friendly gender skill gaps.

Costly gender skill gaps are expected to be negatively related to the industrial diversification process either by increasing the production costs of firms directly and indirectly. Skill gaps may affect the productivity of firms since knowledge creation and diffusion among the labour force are likely to be diminished by skill gaps due to cognitive distance among workers. In addition, high search and hiring costs may be faced by firms operating in sectors and regions with large gender skill gaps, leading to less profitability and investment incentives.

On the other hand, cost-friendly gender skill gaps may positively affect the industrial diversification process of regions by allowing firms to reduce their production costs or simply by imposing no extra cost. For instance, gender skill gaps can be a source of comparative advantage for an industry if the gender with lower skills is paid significantly less. Given that the literature defines comparative advantage as the over-presence of an industry within a region in terms of the number of employed people (Neffke et al., 2011), the availability of cheaper labour supply employable in that industry would increase the probability of hiring more people thereby contributes to establishing a comparative advantage. Reversing the argument, narrower gender skill gaps imply a more equal and competitive labour market in which females and males compete at every part of the skill distribution, thus earning similar wages if there is no discrimination. In this case, the possibility of hiring more labour at a low cost disappears, potentially leading to less employment and, thereby the loss of an established comparative advantage. This reasoning is in line with the prior work that underlines that gender inequality, which contributes to females' relatively lower wages, can be a stimulus to investment and economic growth (Seguino, 2000).

Based on these premises, we define the following hypothesis.

H1: Gender skill gaps negatively affect the industrial diversification process of regions.
H1a: Female-biased skill gaps negatively affect the industrial diversification process of regions.
H1b: Male-biased skill gaps negatively affect the industrial diversification process of regions.

H2: Gender skill gaps positively affect the industrial diversification process of regions.
H2a: Female-biased skill gaps positively affect the industrial diversification process of regions.
H2b: Male-biased skill gaps positively affect the industrial diversification process of regions.

## 3 Data Sources

The data used in the present study drives from three main sources: *the Italian Sample Survey on Professions* (ICP), *the Italian Labour Force Survey* (ILFS), and *Local Units and Persons Employed:*

*Size Class of Persons Employed, Economic Activities, Geographical Areas.*

ICP data, provided by the National Institute for Public Policies Analysis (INAPP), is a confidential source of detailed information on the characteristics of all professions existing in the Italian labour market. During the two waves of the survey in 2007 and 2013, almost 16.000 workers are interviewed, representing approximately 800 occupational units at the five-digit level[1]. The ICP survey concept and questions are designed based on the Occupational Information Network (O*net) that is run by the Bureau of Labour Statistics in the USA. Hence, the ICP data provides granular and detailed information on the work content and tasks of occupations, the knowledge and skills they require, and the organisational structure where the work takes place. The ICP survey consists of seven sections with different question designs and scales: knowledge, skills, attitudes, generalised working activities, values, working styles and working conditions. This study exploits the first four sections summing up to 161 skill types unfolded in Table A1. The remaining three sections have different question designs and scales than the first four sections, thus they are not combinable. Hereafter, the term *skills* is used in a broader sense to refer to the first four ICP sections. Each skill type in the sample has two dimensions: the importance and the level of the skill required by occupations[2]. These dimensions are combined to generate skill intensity variables for each skill by multiplying importance scores with level scores. This multiplicative approach increases the skill variation across occupations (Feser, 2003).

The ICP data is merged with ILFS on the four-digit occupational level. Then the skill intensity values of each gender-industry-region-year quadruplet are calculated by using the gender distribution of occupations, occupational distribution of industries, and industrial distribution of regions that are available in ILFS. Women and men may occupy different occupations in a given industry. We thus calculate skill intensity scores for each industry by taking into account occupational compositions of genders. For instance, male skill intensity scores of industry $i$ are calculated as follows. First, the number of male employees in industry $i$ and their occupations are identified. Second, the skill intensity scores of 161 skill types for these occupations are extracted from the ICP survey. Lastly, mean skill intensity scores are computed. This strategy enables us to analyse within-industry gender skill differences captured by the occupational distribution of genders. Consequently, a sample of two genders, 161 workplace skills, 532 industries at the four-digit level, and 107 regions at the Nuts-3 level for the period 2013-2019 is obtained.

*Local Units and Persons Employed: Size Class of Persons Employed, Economic Activities, Geographical Areas* data provided by Istat is used to construct the dependent variables, i.e. industrial entry and exit, for econometric analyses. In addition, data for control variables are obtained from both Eurostat (GDP per capita, business growth, churn) and Istat (population density, education, industrial ubiquity, regional diversity).

[1] In the context of the Classificazione delle Professioni (CP), which is the Italian version of ISCO classification.

[2] Importance question: *How important is this competence in carrying out your current profession?* Level question: *Among those indicated below, at what level is this competence necessary for the development of your current profession?* Importance questions are rated on a scale from 1 (not important) to 5 (extremely important), while complexity level questions are rated on a scale from 1 (least complex) to 7 (most complex). They are rescaled to be between 0 and 100.

## 4 Relative Skill Advantage of Genders across the Skill Space

A gendered analysis of industrial diversification requires the knowledge of differences between females and males across the skill space of industries which we are able to extract from the data sources employed. Accordingly, we start by characterising the skill differences of genders alongside related stylised facts with a particular focus on various skill types and their usage patterns by industries. In this regard, we define relative skill advantage, skill relatedness, and skill complexity measures by following Buyukyazici et al. (2023) to construct the gendered skill space.

**Relative Skill Advantage:** Reformulation of Balassa index. RSA is the share of the relative importance of skill $s$ to industry $i$ (the numerator) to the relative importance of skill $s$ to all industries $I$ (the denominator).

$$RSA(i,s) = \frac{icp(i,s) \setminus \sum_{s' \epsilon S} icp(i,s^{'})}{\sum_{i' \epsilon I} icp(i',s) \setminus \sum_{i' \epsilon I, s' \epsilon S} icp(i',s^{'})} \tag{1}$$

where $icp(i,s)$ is the skill intensity score of skill $s$ for industry $i$ obtained from the ICP and ILFS data sets. A higher value of RSA indicates a higher level of importance of skill $s$ to industry $i$ compared to the overall importance of skill s to all other industries. Skill $s \in S$ is effectively used by industry $i \in I$ if its relative skill advantage (RSA) is greater than 1.

RSA formula is gendered by using gendered skill intensity scores, i.e. $icp^g(i,s)$ where $g = \{female, male\}$.

**Skill Relatedness:** Based on Hidalgo et al. (2007) and Buyukyazici et al. (2023). The skill relatedness between each pair of effectively used skills is defined as the minimum conditional probability of their co-occurrences in industry classes as formulated below.

$$R(s,s^{'}) = \frac{\sum_{i \epsilon I} e(i,s).e(i,s^{'})}{max(\sum_{i \epsilon I} e(i,s), \sum_{i \epsilon I} e(i,s'))} \tag{2}$$

where effective use of skills denoted as $e(i,s) = 1$ if $RSA > 1$, and $e(i,s) = 0$ otherwise. The resulting matrix is the skill relatedness index $(MxM)$ of $N$ industries which contains proximities between two skill types $s$ and $s^{'}$. Each cell $(s,s^{'})$ represents the probability that a random industry effectively uses skill $s(s^{'})$ effectively uses skill $s^{'}(s)$ as well.

The skill relatedness formula gives skill-to-skill matrices which we use to construct the skill space. We also define a density measure to have space and industry dimensions to use skill relatedness as a control variable.

$$AverageRelatednessDensity^p_{i,t} = \frac{\sum_{s \in i} (\frac{\sum_s \phi_{s,j,t} RSA_{s,i,t}}{\sum_s \phi_{s,j,t}} \times 100)_{s,i,t}}{\sum_{s \in i} s} \tag{3}$$

where $\phi_{s,j,t}$ refers to relatedness between skill $s$ and $j$ at time $t$; $RSA_{s,i,t}$ is a binary variable that takes the value of 1 if industry $i$ effectively uses skill $s$ at time $t$, and takes the value of 0 otherwise. Accordingly, skill relatedness density around industry $i$ at time $t$ in region $p$ is defined as the sum of relatedness values between all the skill pairs that industry $i$ effectively uses, divided by the sum of relatedness between all the skill pairs available in region $p$ at time $t$. As a result, the skill relatedness density formula, located inside the parentheses in the numerator of equation 3, gives a matrix ($MxN$) whose each cell indicates relatedness density between skill $s$ and industry $i$. We use this skill relatedness density matrix to calculate the average skill relatedness density (ASRD) of industry $i$ in region $p$ as the sum of relatedness densities of skills that industry $i$ effectively uses to the sum of all skill relatedness densities available in region $p$ at time $t$. ASRD measure allows us to compare the required skill portfolios of different industries across regions and years by combining information on the use of 161 different workplace skills. ASRD will be high for a new industry if its skill space is similar to other industries in which the region has an RSA. In other words, ASRD measures how close a potential new industry is to the region's existing industry mix in terms of human capital.

**Skill Complexity:** The complexity measure used in the present study is *the method of reflections* (MOR), introduced in the pioneering work of Hidalgo and Hausmann (2009). MOR sequentially combines two measures: diversity and ubiquity. In our case, diversity ($K_{i,0}$) is the number of skills effectively used ($RSA > 1$) by industry $i$. Ubiquity ($K_{s,0}$) is the number of industries that effectively use a particular skill $s$. After sequentially combining diversity and ubiquity measures for $N \geq 1$ steps, MOR is defined as iterative linear equations that are theoretically infinite. Accordingly, skills that are effectively used by relatively fewer industries which effectively use a diverse set of rare skills are considered complex. Skill complexity is used to construct the gendered skill space as well as a control variable.

Figure 1 depicts the gendered skill space of the Italian industrial portfolio built by employing RSA, skill relatedness, skill complexity and gendered RSA measures. Each node represents a particular skill as indicated with node labels that can be traced in Table A1. Edge lengths, connecting node pairs, show cognitive proximity between skills and are defined based on skill relatedness.In other words, closer skills are generally used together by industries. The size of each node is proportional to the sophisticatedness level of the represented skill and is based on the skill complexity score. When network techniques are applied by using a force-based algorithm and community detection methods[3], the skill space forms two polarised skill clusters into social-cognitive (basic, social, management, interacting, and higher concentration of knowledge and cognitive skills) and technical-physical (physical, psychomotor, sensory, systems, and technical skills) skills. Each cluster is documented in Table A2. The skill space is gendered by colouring skills in which females and males have relative skill advantage (RSA).Purple nodes indicate skills in which females have RSA, while grey nodes represent males' RSA. Interestingly, the polarization of the skill space reflects itself also as the gender segregation of skills. Despite some exceptions, females generally have RSA in social-cognitive skills, while males have RSA in technical-physical skills. In addition, the skills females have RSA are more complex than males.

[3]The graph is created in Gephi software. Multiscale Force Atlas algorithm is used.

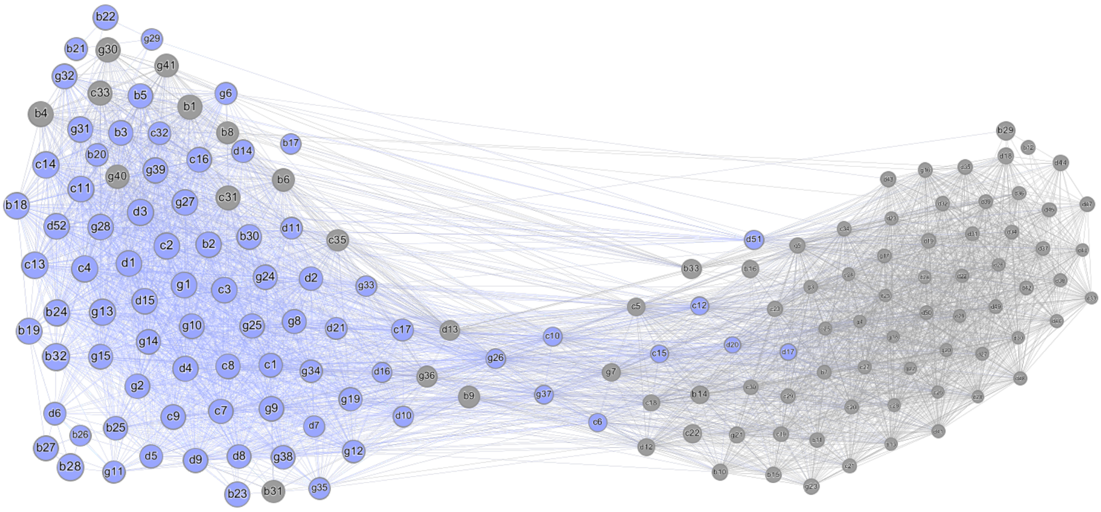


**Figure 1. Gendered Revealed Skill Advantages (RSA) on the Skill Space of Italy's Industry Mix (2013-2019).** Each node represents a particular skill. Node size is proportional to the complexity level of the skill the node represents. Edge lengths indicate the degree of relatedness between skill pairs. Nodes are coloured according to the gendered RSAs: purple for females and grey for males.

Figure 2 provides further evidence of the skill segregation of genders by depicting the raw gender skill gap. The red line represents the raw skill intensity scores of females for each of the 161 skill types that are standardised and averaged on industries, regions, and time. The blue line represents males. The left half of the figure is populated with social-cognitive skills while the right half accommodates technical-physical skills. A strict gender divergence is visible at first glance. Only three out of 161 skills intersect: monitoring (c10), evaluating information to determine compliance with standards (g7), making decisions and solving problems (g10). Females have higher skill intensity scores almost in every social-cognitive skill, while males score higher in technical-physical skills. However, the gender gap is strictly larger in the technical-physical skill cluster.

The data-driven finding that females have stronger social-cognitive skills and males have stronger technical-physical skills is in line with the prior research on gender differences (Bacolod, 2017; Cortes et al., 2021). Table A3 displays the mean skill intensity scores for each skill aggregation by gender as well as their distribution across industries.

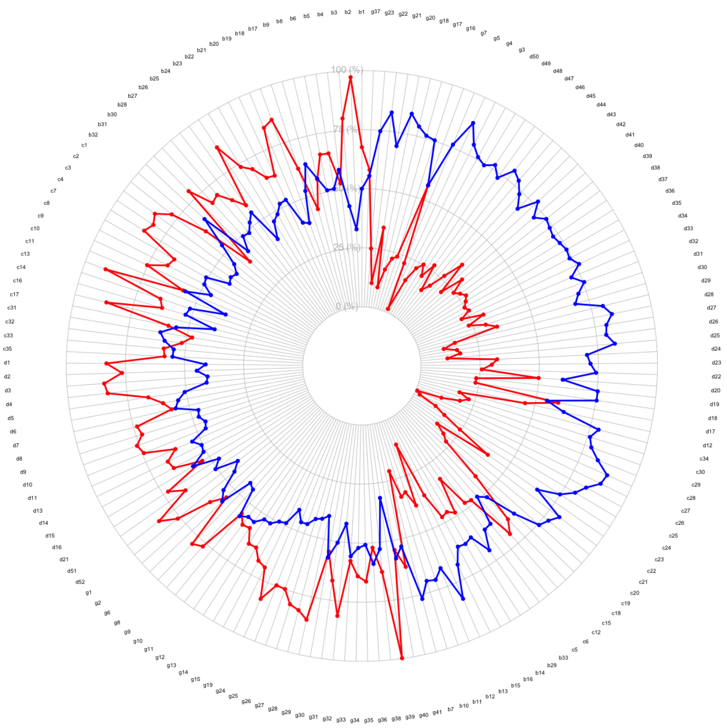


**Figure 2. The Radar Chart of Gendered Skill Intensity Scores.** The red line represents the skill intensity scores of females; the blue line demonstrates males' skill intensity scores. Each of the 161 skill types is represented with dots and labels.

## 5 Measuring the Gender Skill Gap: A New Indicator

The gender skill gaps at the individual level have generally been measured with decomposition methods based on Oaxaca-Blinder (Blinder, 1973; Fortin et al., 2015) when analysing their determinants. However, the present study does not intend to evaluate the determinants of the gender skill gaps, it intends to observe them. To the best of our knowledge, prior research does not provide an agreed pathway nor a specific approach to measure the gender skill gap at the industry level except for simple mean differences and female/male ratios. However, there are several measures that have been widely used in gender segregation studies including the Duncan index of dissimilarity (also known as Duncan segregation index) (Duncan and Duncan, 1955), sex ratio (Hakim, 1979), the IP index (Karmel and Maclachlan, 1988), and Gini coefficient (see Blackburn (2012) for a comparison). This study provides a new indicator inspired by the segregation indices: the gender skill gap indicator (GSGI).

The GSGI quantifies differences between the weighted skill intensity ratios of females and males for each industry-region-year triplet. The skill intensity ratio of females ($\sum_s I_{f,i,r,t} / \sum_s I_{i,r,t}$) is defined as the sum of skill intensity scores of females employed in industry $i$ located in region $r$ at time $t$ (the numerator) divided by the sum of skill intensity scores of the labour force (males plus females) employed in industry $i$ located in region $r$ at time $t$ (the denominator). Accordingly, the skill intensity ratio indicates the relative importance of each gender's skills to industry $i$ by also considering the general skill level of the industry. The skill intensity ratio of each gender is weighted by the gendered importance of industry $i$ in region $r$ at time $t$ which is measured by the gendered employment ratio ($Emp_{f,i,r,t}/Emp_{f,r,t}$): females employed in industry $i$ divided by the total female employment in region $r$. As underlined in the literature section, sectoral segregation of genders is widely observed and persistent. It has been shown that females are concentrated in fewer sectors, including food production, textile, and tourism, while males are more equally distributed. Therefore, we weight the skill intensity ratios of males and females in a particular industry-region-time triplet with the shares of their employment in the same region-time. By doing so, we account for the importance of the industry for the region while also accounting for the gender segregation in the industry[4]. Another advantage of using the gendered employment ratios as part of the indicator is making it margin-independent in the sense that a rising share of female employment compared to males would not bias the indicator.

The GSGI is obtained by subtracting the weighted skill intensity ratio of females from the weighted skill intensity ratio of males. The GSGI takes negative values if females have a higher weighted skill intensity ratio than males which we coin *female-biased skill gap*. Similarly, the GSGI takes positive values if males have a higher weighted skill intensity ratio than females, named as *male-biased skill gap*. Unlike some of the prior segregation indicators, such as the Duncan index of dissimilarity, we do not necessarily consider the absolute values of the GSGI not to have a gender-neutral measure. In other words, even though the indicator is symmetric[5] by definition, the exceeding gender is important given that females and males might have comparative advantages in different skills which have different roles in productive activities as pointed out by prior studies. Hence, considering only absolute values of the indicator (i.e. gender-neutral) would lead to the loss of information. Nevertheless, we consider both the gendered (equation 1) and gender-neutral versions (equation 2) of the GSGI in order to conduct a comparative and thorough empirical strategy.

$$GSGI_{i,r,t} = \left[ \left( \frac{\sum_s I_{m,i,r,t}}{\sum_s I_{i,r,t}} \right) \left( \frac{E_{m,i,r,t}}{E_{m,r,t}} \right) - \left( \frac{\sum_s I_{f,i,r,t}}{\sum_s I_{i,r,t}} \right) \left( \frac{E_{f,i,r,t}}{E_{f,r,t}} \right) \right] \tag{4}$$

$$Gender\ Neutral\ GSGI_{i,r,t} = |GSGI_{i,r,t}| \tag{5}$$

Figure 3 demonstrates the distribution of the GSGI over sectors with average GSGI values at the national level for the observation period 2013-2019. Positive values on the y-axis represent the male-biased skill gap and negative values represent the female-biased skill gap. The GSGI is winsorised at $-1.5$ and 1.5 for visualisation purposes. Evidently, there is high variation both across and within sectors. The first quartiles of the skill gaps in industry except construction (B-E), wholesale and retail trade; repair of motor vehicles and motorcycle (G), information and

[4]Recall that the most widely used indicator of gender segregation is the Duncan index which is composed of the gendered employment ratios: $1/2 \sum |(Emp_{m,i}/Emp_M) - (Emp_{f,i}/Emp_F)|$.

[5]The indicator is symmetric in the sense that the weighed skill intensity ratio of females subtracted from the weighed skill intensity ratio of males equals the weighed skill intensity ratio of males subtracted from the weighed skill intensity ratio of females in absolute value.

communication (J), and arts, entertainment and recreation; other service activities (R-U) are female-biased while 75th percentiles of them are male-biased. The gender skill gaps in construction (F) and transportation and storage (H) are fully male-biased. Accommodation and food service activities (I) and education; human health and social work activities (P/Q) exhibit female-biased skill gaps with over the 75th percentile. Unsurprisingly, these most female-biased sectors are related to occupations that are traditionally considered as *female jobs* (Blau and Kahn, 2000). Regarding within-sector variation, construction (F) and human health and social work activities (P/Q) display the highest dispersion as shown by larger interquartile ranges and whiskers while other sectors have relatively narrow skill gaps. The boxplot indicates the presence of outlier industries via black hollow circles. In other words, some industries are inherently more gendered than average. In this regard, Table 1 exemplifies the top five most gendered industries. The most male-biased industries are related to construction, repair, and transportation which require physical and technical skills. On the other hand, the most female-biased industries are related to education, healthcare, and beauty services which demand social and interacting skills.

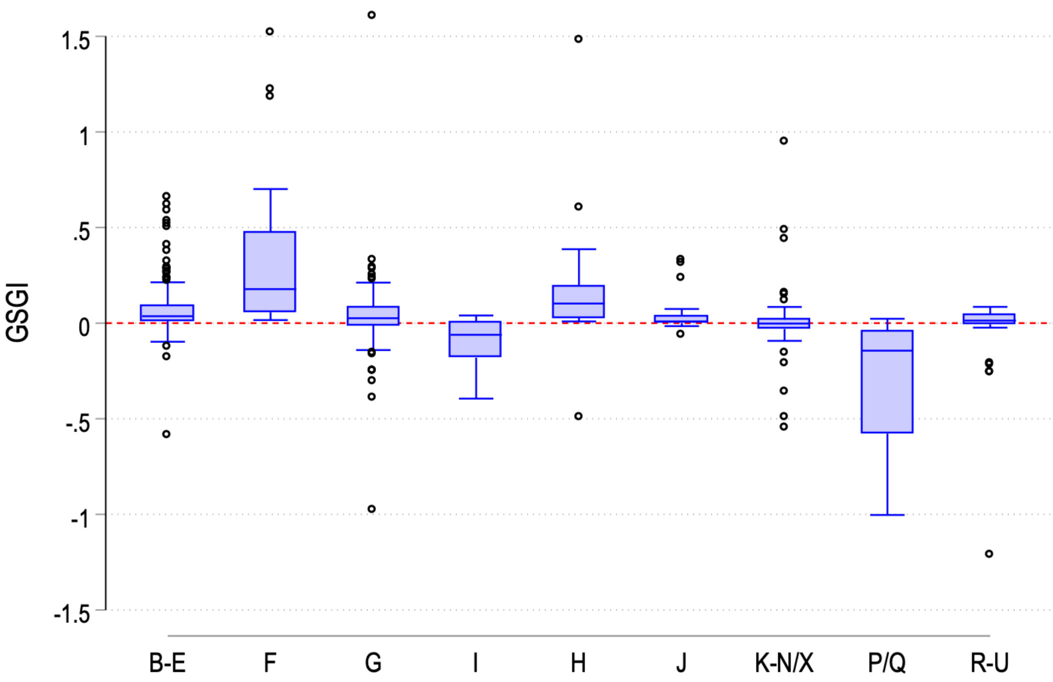



**Figure 3. The Distribution of the Gender Skill Gap (GSGI) over Sectors (2013-2019)** The y-axis indicates the gendered skill gap. Positive values represent the male-biased skill gap while negative values indicate the female-biased skill gap. The x-axis accommodates industries at the one-digit level defined as follows. (B-E) Industry, (F) Construction, (G) Wholesale and retail trade; repair of motor vehicles and motorcycles, (I) Accommodation and food service activities, (H) Transportation and storage, (J) Information and communication, (K-N/X) Financial, real estate, scientific and technical, administrative and support service activities, (P/Q) Education; human health and social work activities, (R-U) Arts, entertainment and recreation; other service activities.

We further explore gender skill gaps in the regional context. Given the high-granular nature of the indicator, we consider the average GSGI values at the region level for the period 2013-2019. Figures 4 and 5 display the spatial disparities in average, female-biased, and male-biased gender skill gaps. The maps exhibit substantial variation across the regions.

**Table 1. Top-Five Most Gendered Industries**

| | Ateco 4 |
|---|---|
| Male-Biased | |
| 4120 | Construction of residential and non-residential buildings |
| 4520 | Motor vehicle maintenance and repair |
| 4321 | Installation of electrical systems |
| 4941 | Road freight transport |
| 4322 | Installation of plumbing, heating and air conditioning systems |
| Female-Biased | |
| 8520 | Primary education |
| 8510 | Pre-school education |
| 8531 | General secondary education |
| 8610 | Hospital services |
| 9602 | Services of hairdressers and other beauty treatments |

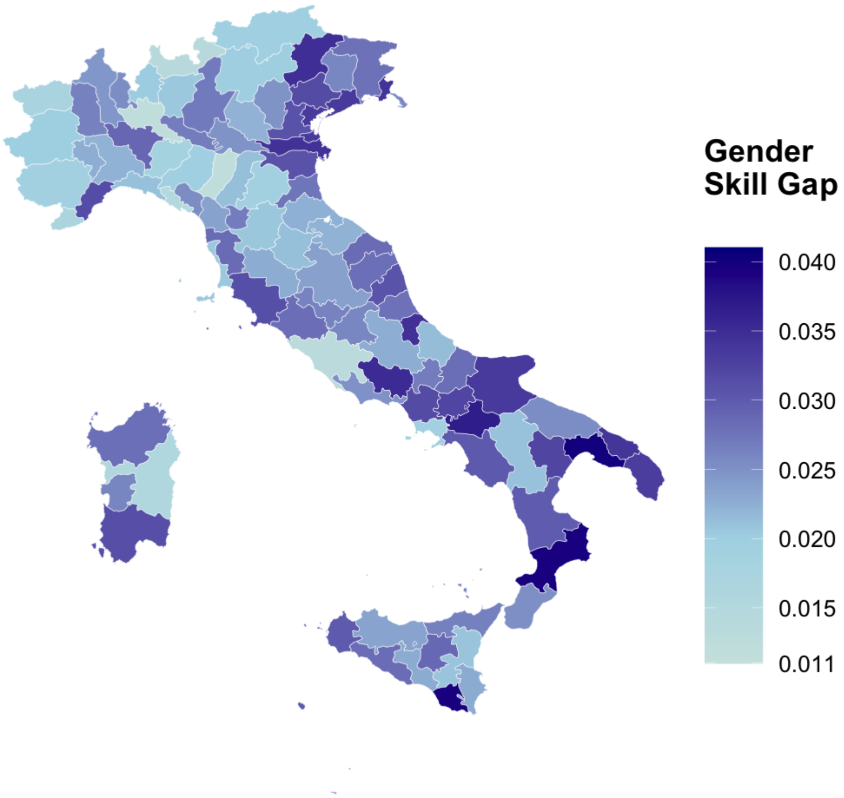



**Figure 4. Average Gender Skill Gap (GSGI) Across Italian Regions for the period 2013-2019.**

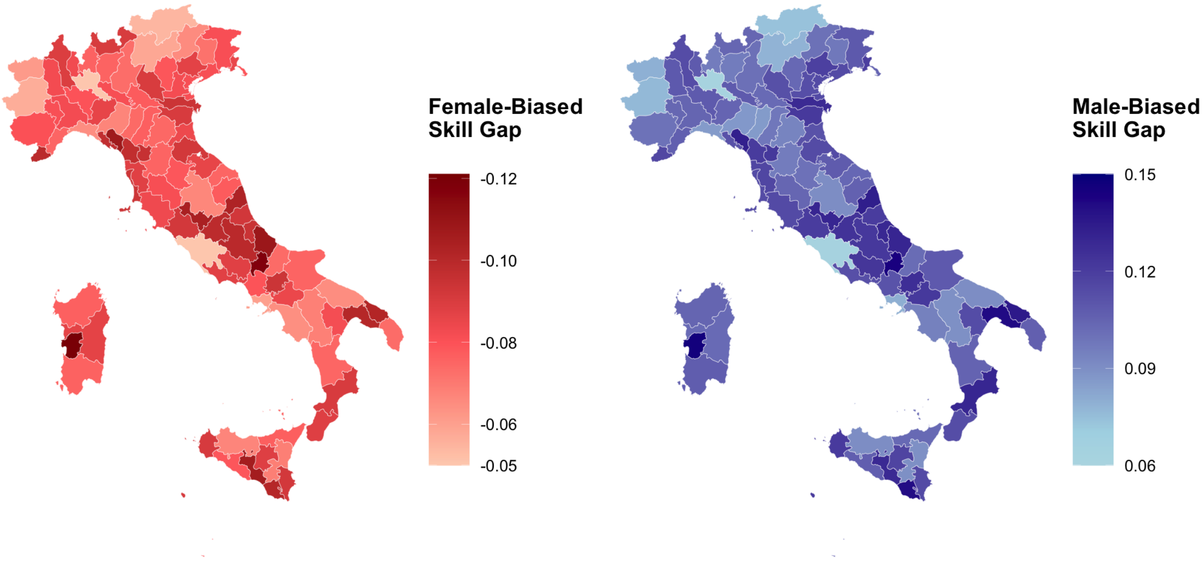



**Figure 5. Average Female-Biased and Male-Biased Skill Gaps Across Italian Regions for the period 2013-2019.**

## 6 Econometric Analysis

The descriptive results suggest a significant variation of gender skill gaps across industries and regions. In this section, we empirically assess the impact of the gender skill gaps on the industrial diversification of regions by employing entry and exit models. We define two binary dependent variables, *Entry* and *Exit*, to account for the diversification process as follows.

$$Entry_{i,p,t} = 1, \ \ if \ \ RCA_{i,p,t} > 1 \ \ and \ \ RCA_{i,p,t-3} \leq 1 \tag{6}$$

$$Exit_{i,p,t} = 1, \ \ if \ \ RCA_{i,p,t} \leq 1 \ \ and \ \ RCA_{i,p,t-3} > 1 \tag{7}$$

$$RCA_{i,p,t} = \frac{E_{i,p,t}/E_{i',p,t}}{E_{i,p',t}/E_{i',p',t}} \tag{8}$$

where $i$ is industry, $p$ is region, $t$ is year, and $E$ is employment. $RCA$ defines the revealed comparative advantage of each industry-region-year triplet in terms of the number of employed people. Accordingly, *Entry* accounts for a new industrial specialisation and takes value 1 if region $p$ develops a new comparative advantage ($RCA > 1$) in industry $i$ in year $t$ while it did not have a comparative advantage in year $t - 3$[6]; and *Entry* takes value 0 otherwise. *Exit* indicates losing an established comparative advantage and takes value 1 if region $p$ loses its comparative advantage ($RCA \leq 1$) in industry $i$ in year $t$ while it had a comparative advantage in year $t - 3$; *Exit* takes value 0 otherwise. Due to binary dependent variables, we estimate the following specification with the logistic model.

[6]The literature on industrial diversification that employs entry-exit models considers more than one year period to avoid potential noise in the data.

$$Y_{i,p,t} = [Entry_{i,p,t},\ Exit_{i,p,t}]$$

$$\begin{aligned} logit(Y_{i,p,t}) = {} & \beta_1 GSGI_{i,p,t-1} + \beta_2 \boldsymbol{IndustrySkills}_{i,p,t-1} + \\ & \beta_3 \boldsymbol{RegionControls}_{p,t-1} + \beta_4 \boldsymbol{IndustryControls}_{i,p,t-1} + \\ & \beta_5 \boldsymbol{GeoDistribution}_{i,p,t-1} + \rho_p + \iota_i + \gamma_t + \varepsilon_{i,p,t} \end{aligned}$$

where fixed effects for region $\rho_p$, industry $\iota_i$ , and time $\gamma_t$ are included. The main independent variable of interest is the gender skill gap indicator ($GSGI$) defined at the industry-region-year level as explained in Section 5. We consider four sets of control variables to account for the confounding factors. The first set is the standard socio-economic controls for regions: GDP per capita (log); population density (log), and the share of tertiary education in the population. The second set consists of skill relatedness and skill complexity variables that have been shown to be highly important in the diversification process (Neffke and Henning, 2013; Buyukyazici et al., 2023). Skill relatedness indicates the degree of skill and knowledge similarity of an industry to other industries' skills located in a particular region. If there is a high degree of skill relatedness between the new and existing industries then the new industry would have a relatively higher probability of being specialised in that region given that the region already possesses the necessary capabilities, knowledge, and skills that the new industry can combine and use. Skill complexity quantifies the sophisticatedness level of skills and knowledge of an industry. If an industry has a complex skill set with respect to other industries in the region, it is more likely to produce more valuable and unique goods and services and, thus more (less) likely to develop (lose) a comparative advantage. The formulas and computation of skill relatedness and complexity variables are explained in Section 4. The third set accounts for the general level of turnover at the industry-region level that might affect entry-exit probabilities. Business growth (percentage) is the net population growth of industries. Death rate (percentage) is the percentage of firms that went out of business. The last set considers the general distribution patterns of industries across regions. Industrial ubiquity –the number of regions that a particular industry already specialised in, i.e. $RCA > 1$– controls for the rarity of industries since rare industries are expected to form relatively fewer specialisations. Regional diversity –the number of specialised industries, i.e. $RCA > 1$, in a given region– accounts for the diversity of industry mixes of regions, given that more diversified regions might be more prone to attract new specialisations or, adversely, attract fewer specialisations since the number of potential specialisations decreases with each established specialisation. In addition, the effect of gender skill gaps may be moderated by the higher diversity of economic activities. The dependent variables are lagged by one year to moderate endogeneity concerns denoted as $t-1$ while $t$ is the first year of each three-year period. Summary statistics for the dependent and independent variables (Table A5) as well as their correlation matrix (Table A4) are reported in the Appendix.

Errors are likely to be correlated within regions and industries given the grouped structure of the data. Therefore, all estimates are presented with robust standard errors clustered at the industry-region level. Table 2 reports the results for entry (Columns 1-4) and exit (Columns 5-8)

**Table 2. Entry and Exit Models and Gender Skill Gap**

| | (1) Entry | (2) Entry | (3) Entry | (4) Entry | (5) Exit | (6) Exit | (7) Exit | (8) Exit |
|---|---|---|---|---|---|---|---|---|
| GSGI | 1.2344*** | 1.2056*** | | | 0.8708*** | 0.8826*** | | |
| | (0.0598) | (0.0552) | | | (0.0240) | (0.0246) | | |
| Neutral GSGI | | | 1.3548*** | | | | 0.6786*** | |
| | | | (0.0557) | | | | (0.0332) | |
| GSGI Std. | | | | 1.1120*** | | | | 0.9316*** |
| | | | | (0.0289) | | | | (0.0147) |
| Skill Rel. | | 1.0322*** | 1.0327*** | 1.0322*** | | 0.9795*** | 0.9791*** | 0.9795*** |
| | | (0.0031) | (0.0031) | (0.0031) | | (0.0030) | (0.0030) | (0.0030) |
| Skill Comp. | | 1.0046*** | 1.0041*** | 1.0046*** | | 0.9954*** | 0.9961*** | 0.9954*** |
| | | (0.0004) | (0.0004) | (0.0004) | | (0.0005) | (0.0005) | (0.0005) |
| GDP (log) | | 0.7441 | 0.7547 | 0.7443 | | 0.8480 | 0.8559 | 0.8478 |
| | | (0.3115) | (0.3160) | (0.3115) | | (0.3691) | (0.3730) | (0.3690) |
| Pop. Dens. (log) | | 1.0745 | 1.0485 | 1.0749 | | 0.5757 | 0.5783 | 0.5755 |
| | | (0.8055) | (0.7866) | (0.8058) | | (0.4522) | (0.4547) | (0.4521) |
| Education | | 0.9704 | 0.9714 | 0.9704 | | 0.9775 | 0.9772 | 0.9775 |
| | | (0.0153) | (0.0153) | (0.0153) | | (0.0164) | (0.0164) | (0.0164) |
| Death | | 1.0003* | 1.0003* | 1.0003* | | 0.9997* | 0.9997* | 0.9997* |
| | | (0.0001) | (0.0001) | (0.0001) | | (0.0001) | (0.0001) | (0.0001) |
| Bus. Growth | | 1.0138** | 1.0138** | 1.0138** | | 0.9924 | 0.9926 | 0.9924 |
| | | (0.0043) | (0.0043) | (0.0043) | | (0.0048) | (0.0048) | (0.0048) |
| Reg. Div. | | 0.9806*** | 0.9805*** | 0.9806*** | | 1.0239*** | 1.0238*** | 1.0239*** |
| | | (0.0025) | (0.0025) | (0.0025) | | (0.0027) | (0.0027) | (0.0027) |
| Ind. Ubi | | 0.9389*** | 0.9390*** | 0.9389*** | | 1.0676*** | 1.0667*** | 1.0676*** |
| | | (0.0041) | (0.0041) | (0.0041) | | (0.0054) | (0.0054) | (0.0054) |
| *N* | 155583 | 155583 | 155583 | 155583 | 65649 | 65649 | 65649 | 65649 |
| chi2 | 31086 | 31716 | 31719 | 31716 | 12945 | 13230 | 13166 | 13230 |
| bic | 74227 | 73327 | 73263 | 73327 | 57160 | 56757 | 56639 | 56757 |
| aic | 67995 | 67005 | 66942 | 67005 | 51441 | 50956 | 50838 | 50956 |

Heteroskedasticity-robust standard errors clustered at the region-industry level are displayed in parentheses. Fixed effects for industry, region, and time are included in every model specification. $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$.

models using odd ratios. The gendered GSGI (*GSGI*), gender-neutral GSGI (*Neutral GSGI*), and standardised (to have a mean 0 and standard deviation 1) GSGI (*Std GSGI*) are the main coefficients of interest. Interestingly, the results show that higher gender skill gaps significantly increase the probability of entry and decrease the probability of exit, regardless of the indicator type. Column 1 shows that the odds of developing a new comparative advantage of an industry in a region increases by 23% when the gender skill gap (*GSGI*) in that industry increases by one unit. This effect stays pretty stable at 20.6% when adding the full set of controls in Column 2. The principal variable of interest is the gender-neutral skill gap in Column 3 which increases the odds of entry by 35%, substantially higher than the gendered skill gap. Column 4 reports the effect size of the gender skill gap: one standard deviation increase in the gender skill gap enhances the odds of entry by 11%. Regarding the exit models, the odds of losing an established comparative advantage decrease by 13% when the gender skill gap increases by one unit as indicated in Column

5. Similar to the entry models, this effect is stable at 12.7% when adding the full set of controls (Column 6). The gender-neutral skill gap posits the highest exit odds by 32%. Column 8 reports that one standard deviation increase in the gender skill gap decreases the odds of exit by 7%.

The impact of the gender skill gap on the industrial diversification of regions seems pretty robust to a large set of control variables alongside three-way fixed effects, regardless of the indicator type. However, the positive relation with entry and negative relation with exit probability is somewhat unexpected which we will discuss extensively later on. Another interesting point is that the impact of the gender-neutral skill gap on both entry and exit models is almost double compared to the gendered skill gap. These results imply that the effects of the female-biased skill gap (i.e. females have higher weighted skill intensity ratios than males) and the male-biased skill gap (i.e. males have higher weighted skill intensity ratios than females) on the industrial diversification process might significantly differ. As underlined in previous sections, females and males are likely to have comparative advantages in different skills which are intertwined with occupational and sectoral segregation. Hence, the impact of the gendered skill gap on industrial diversification might differ depending on the direction of the skill gap. Indeed, simple linear fit plots (Figure 6) show that our sample follows two different linear trends before and after zero, demonstrating the divergence of the female-biased and male-biased skill gaps. Correspondingly, using a conventional linear model, as in Table 2 and Figure 6, without considering the gendered nature of the skill gap leads to an important amount of information loss. Despite the gendered-skill gap indicator having a non-neutral nature, using it in conventional logistic regression results in qualitatively similar output to the gender-neutral skill gap (see also Figure A1). Motivated by this reasoning, a model that is able to quantify the divergent effects of female-biased and male-biased skill gaps is needed. A potential good fit for the problem at hand is piecewise regression.

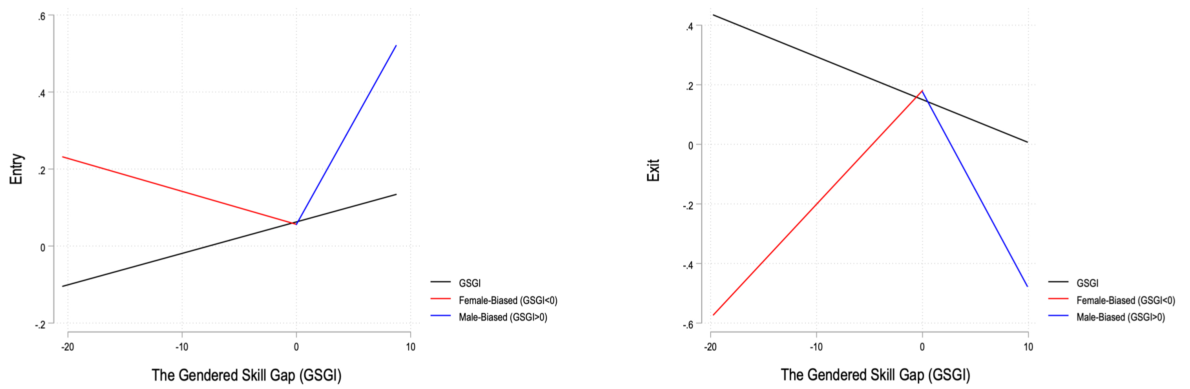



**Figure 6. The Simple Association between the Gendered Skill Gap and Entry and Exit**

## 6.1 Exploring the Gendered Skill Gap: Piecewise Logistic Regression

Piecewise regression, also known as segmented or broken-line regression, comes in handy when data include changes in gradient which makes fitting one continuous linear line less optimal. In other words, piecewise regression can be used when the relationship between dependent and independent variables is represented by at least two linear lines connected at some change points, i.e. break-points or knots. Accordingly, zero is a natural break-point[7] in our model at which females and males have

[7]The validity of zero as a break-point has been checked with the R package *segmented* (Muggeo, 2008).

no observable skill differences. Given the binary dependent variables defined above, we estimate the following specification with the logistic piecewise model.

$$\begin{aligned}
logit(Y_{i,p,t}) = {} & \beta_1 GSGI_{i,p,t-1} + \beta_2 (GSGI_{i,p,t-1} - GSGI^b)d + \beta_2 \boldsymbol{IndustrySkills}_{i,p,t-1} + \\
& \beta_3 \boldsymbol{RegionControls}_{p,t-1} + \beta_4 \boldsymbol{IndustryControls}_{i,p,t-1} + \\
& \beta_5 \boldsymbol{GeoDistribution}_{i,p,t-1} + \rho_p + \iota_i + \gamma_t + \varepsilon_{i,p,t}
\end{aligned}$$

$$\begin{aligned}
& d = 1 \ if \ GSGI_{i,p,t-1} > 0 \\
& d = 0 \ if \ GSGI_{i,p,t-1} \leq 0
\end{aligned}$$

where $GSGI^b$ is the value of the break-point which is zero in our model. d is a dummy variable that indicates observations below and above the break-point. Table 3 displays the results.

Column 1 presents the impacts of the female-biased (*Female-Biased GSGI*) and male-biased (*Male-Biased GSGI*) skill gaps on entry without controls. One unit increase in the female-biased gender gap in industry $i$ located in region $p$ decreases the odds of industry $i$ developing a new comparative advantage in region $p$ by 18%, which is robust to a large set of control variables in Column 2 with a decrease in the coefficient to 15%. On the contrary, one unit increase in the male-biased skill gap increases the odds of entry by 59% as indicated in Column 1 which is robust to the controls in Column 2 with a decrease to 55%. When it comes to exit, Columns 4 and 5 show that one unit increase in the female-biased skill gap is associated with a 33% increase in the odds of exit. The male-biased skill gap decreases the odds of exit by 40% when it increases one unit. Columns 3 and 6 demonstrate the effect sizes of the gender-biased skill gaps and control variables. Accordingly, one standard deviation increase in the female-biased skill gaps is associated with by 6.6% decrease in the entry odds and by 10% increase in the exit odds. Regarding the male-biased skill gap, one standard deviation increase is associated with by 17% increase in the entry odds and by 15.7% decrease in the exit odds.

The gendered results provided in this section suggest that the industrial diversification process of regions is hampered if females have higher weighted skill intensity ratios than males, confirming the hypothesis *H1a: Female-biased skill gaps negatively affect the industrial diversification process of regions.* Reversely, males having higher weighted skill intensity ratios than females seem to support the diversification process, confirming the hypothesis *H2b: Male-biased skill gaps positively affect the industrial diversification process of regions.* In addition, the male-biased skill gap is more potent for both industrial entry and exit processes that might be stemmed from the larger skill gap on technical-physical skill cluster compared to social-cognitive skill cluster (see Figure 2). All in all, the estimates for the gendered skill gap using piecewise regression highlight the importance of gender-specific measures as there is a non-ignorable heterogeneity between genders which cannot be detected with gender-neutral approaches.

**Table 3. Entry and Exit Models: The Gendered Skill Gap with Piecewise Logistic Model**

| | (1) Entry | (2) Entry | (3) Entry | (4) Exit | (5) Exit | (6) Exit |
|---|---|---|---|---|---|---|
| Female-Biased GSGI | $0.8215^{***}$ | $0.8502^{***}$ | $0.9341^{***}$ | $1.3326^{***}$ | $1.2663^{***}$ | $1.1042^{***}$ |
| | (0.0394) | (0.0401) | (0.0185) | (0.0857) | (0.0777) | (0.0285) |
| Male-Biased GSGI | $1.5894^{***}$ | $1.5548^{***}$ | $1.1706^{***}$ | $0.6013^{***}$ | $0.6196^{***}$ | $0.8430^{***}$ |
| | (0.1035) | (0.1016) | (0.0273) | (0.0448) | (0.0457) | (0.0222) |
| Dummy FB. | $0.0058^{***}$ | $0.0024^{***}$ | $0.0025^{***}$ | $0.1453^{*}$ | 0.4520 | 0.4207 |
| | (0.0037) | (0.0021) | (0.0022) | (0.1249) | (0.4814) | (0.4481) |
| Dummy MB. | $0.0073^{***}$ | $0.0028^{***}$ | $0.0030^{***}$ | $0.1256^{*}$ | 0.4106 | 0.3821 |
| | (0.0047) | (0.0025) | (0.0027) | (0.1080) | (0.4373) | (0.4069) |
| Skill Rel. | | $1.0329^{***}$ | $1.5724^{***}$ | | $0.9788^{***}$ | $0.7411^{***}$ |
| | | (0.0031) | (0.0651) | | (0.0030) | (0.0314) |
| Skill Comp. | | $1.0035^{***}$ | $1.1191^{***}$ | | $0.9963^{***}$ | $0.8895^{***}$ |
| | | (0.0004) | (0.0155) | | (0.0005) | (0.0130) |
| GDP (log) | | $0.3070^{*}$ | $0.7229^{*}$ | | 1.6612 | 1.1497 |
| | | (0.1759) | (0.1138) | | (1.0347) | (0.1968) |
| Pop. Dens. (log) | | 0.2781 | 0.3680 | | 1.6188 | 1.4567 |
| | | (0.2839) | (0.2934) | | (1.7577) | (1.2353) |
| Education | | 0.9755 | 0.9479 | | 0.9738 | 0.9445 |
| | | (0.0155) | (0.0325) | | (0.0165) | (0.0345) |
| Death | | $1.0003^{*}$ | $1.0705^{*}$ | | $0.9997^{*}$ | $0.9278^{*}$ |
| | | (0.0001) | (0.0361) | | (0.0001) | (0.0311) |
| Bus. Growth | | $1.0135^{**}$ | $1.0466^{**}$ | | 0.9930 | 0.9766 |
| | | (0.0043) | (0.0150) | | (0.0048) | (0.0161) |
| Reg. Div. | | $0.9801^{***}$ | $0.6555^{***}$ | | $1.0242^{***}$ | $1.6515^{***}$ |
| | | (0.0025) | (0.0352) | | (0.0027) | (0.0929) |
| Ind. Ubi. | | $0.9391^{***}$ | $0.3616^{***}$ | | $1.0669^{***}$ | $2.8536^{***}$ |
| | | (0.0042) | (0.0259) | | (0.0054) | (0.2329) |
| $N$ | 155583 | 155583 | 155583 | 65649 | 65649 | 65649 |
| chi2 | 31443 | 31771 | 31771 | 12915 | 13164 | 13164 |
| bic | 73668 | 73218 | 73218 | 56955 | 56633 | 56633 |
| aic | 67406 | 66867 | 66867 | 51209 | 50805 | 50805 |

Heteroskedasticity-robust standard errors clustered at the region-industry level are displayed in parentheses. Fixed effects for industry, region, and time are included in every model specification. $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$.

# 7 Sensitivity Analyses

## 7.1 Raw Gender Skill Gap

As the first sensitivity analysis, we consider the gender skill gap based on average skill intensity scores over 161 different skill types which we call the raw gender skill gap (RGSG). We do so to show that the results obtained from the empirical analyses are not driven by a particular type of indicator but are also visible in the raw skills data. In this regard, RGSG is defined as the difference between the average skill level of males and females employed in industry $i$ located in region $p$ at time $r$ as defined below.

$$RGSG_{i,r,t} = \left[ \left( \frac{1}{n} \sum_{s} I_{m,i,r,t} \right) - \left( \frac{1}{n} \sum_{s} I_{f,i,r,t} \right) \right] \tag{9}$$

where $n$ is the total number of skills which is 161 in our case. We reestimate the baseline specifications in Table 2 with RGSG to compare the results that are presented in Table 4. Similarly, Columns 1 and 5 report the impact of RGSG on entry and exit respectively without any controls. Columns 2 and 6 add the full set of controls to the same specifications. Columns 3 and 7 show the impact of gender-neutral RGSG which is the absolute value of RGSG. Finally, Columns 4 and 8 are estimated with a standardised RGSG variable, thus, they indicate the effect size of RGSG. Overall, the impact of RGSG on entry and exit is similar to those estimated with GSGI. Higher

**Table 4. Entry and Exit Models: Raw Gender Skill Gaps**

| | (1) Entry | (2) Entry | (3) Entry | (4) Entry | (5) Exit | (6) Exit | (7) Exit | (8) Exit |
|---|---|---|---|---|---|---|---|---|
| RGSG | 1.0069*** | 1.0058*** | | | 0.9943*** | 0.9958** | | |
| | (0.0016) | (0.0015) | | | (0.0014) | (0.0014) | | |
| Neutral RGSG | | | 1.0144*** | | | | 0.9934*** | |
| | | | (0.0016) | | | | (0.0017) | |
| RGSG Std. | | | | 1.0536*** | | | | 0.9627** |
| | | | | (0.0145) | | | | (0.0122) |
| Skill Rel. | | 1.0323*** | 1.0325*** | 1.0323*** | | 0.9794*** | 0.9793*** | 0.9794*** |
| | | (0.0030) | (0.0030) | (0.0030) | | (0.0030) | (0.0030) | (0.0030) |
| Skill Comp. | | 1.0045*** | 1.0038*** | 1.0045*** | | 0.9954*** | 0.9956*** | 0.9954*** |
| | | (0.0004) | (0.0004) | (0.0004) | | (0.0005) | (0.0005) | (0.0005) |
| GDP (log) | | 0.7502 | 0.7491 | 0.7508 | | 0.8509 | 0.8484 | 0.8505 |
| | | (0.3138) | (0.3133) | (0.3140) | | (0.3704) | (0.3693) | (0.3702) |
| Pop. Dens. (log) | | 1.0545 | 1.0434 | 1.0557 | | 0.5715 | 0.5778 | 0.5710 |
| | | (0.7899) | (0.7816) | (0.7909) | | (0.4489) | (0.4539) | (0.4485) |
| Education | | 0.9707 | 0.9711 | 0.9707 | | 0.9780 | 0.9777 | 0.9780 |
| | | (0.0153) | (0.0153) | (0.0153) | | (0.0164) | (0.0164) | (0.0164) |
| Death | | 1.0003* | 1.0003* | 1.0003* | | 0.9997* | 0.9997* | 0.9997* |
| | | (0.0001) | (0.0001) | (0.0001) | | (0.0001) | (0.0001) | (0.0001) |
| Bus. Growth | | 1.0138** | 1.0139** | 1.0138** | | 0.9923 | 0.9923 | 0.9923 |
| | | (0.0043) | (0.0043) | (0.0043) | | (0.0048) | (0.0048) | (0.0048) |
| Reg. Div. | | 0.9806*** | 0.9806*** | 0.9806*** | | 1.0239*** | 1.0239*** | 1.0239*** |
| | | (0.0025) | (0.0025) | (0.0025) | | (0.0027) | (0.0027) | (0.0027) |
| Ind. Ubi. | | 0.9389*** | 0.9390*** | 0.9389*** | | 1.0676*** | 1.0674*** | 1.0676*** |
| | | (0.0041) | (0.0041) | (0.0041) | | (0.0054) | (0.0054) | (0.0054) |
| $N$ | 155583 | 155583 | 155583 | 155583 | 65649 | 65649 | 65649 | 65649 |
| chi2 | 31121 | 31732 | 31713 | 31731 | 12949 | 13229 | 13226 | 13229 |
| bic | 74236 | 73338 | 73268 | 73338 | 57171 | 56771 | 56764 | 56771 |
| aic | 68005 | 67017 | 66946 | 67017 | 51452 | 50971 | 50963 | 50971 |

Heteroskedasticity-robust standard errors (clustered at the region-industry level) are displayed in parentheses. Fixed effects for industry, region, and time are included in every model specification. $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$.

gender skill gaps are positively related to entry and negatively related to exit. One standard deviation increase in RGSG increases the probability of developing a new comparative advantage by 5% while it decreases the probability of losing an established comparative advantage by 4%.

### 7.2 Essential Skills based on Relative Skill Advantage

The empirical strategy of the present study considers the full set of skills available and combinable in the skill data we use. The main reason behind this design is not to impose any value judgements on the importance of particular skills given that our analysis is at the industry level and a specific industry might employ diverse occupations requiring diverse skills. Nevertheless, one concern can be that using all types of skills to construct the gender skill gap might introduce some noise to the results. Given that the occupational segregation of genders is a well-documented and persistent fact, one might argue that using all types of skills to construct the gender skill gap scores captures the occupational distribution of genders rather than the skill gap in the industry. A potential solution to this possibility is to consider the most important skills for each industry and construct the gender skill gaps based on these skill types. Following this motivation, we define the most important, i.e. essential, skills for each industry and rebuild GSGI based on those skills as a sensitivity check.

As the first step, 20 essential skills for each industry are identified by using the RSA formula (Equation 1). Non-binary RSA values are calculated by using industry-skill matrices. Then 20 skill types for each industry are selected by ranking the RSA values. In other words, skills in which each industry has the highest comparative advantage are defined as essential skills that are needed to conduct production activities in that industry. In the second step, GSGI is reconstructed for each industry-region-year triplet using the skill intensity scores of industry-specific essential skills as defined below.

$$GSGI_{i,r,t}^{RSA} = \left[ \left( \frac{\sum_{h \in H} I_{m,i,r,t}}{\sum_{h \in H} I_{i,r,t}} \right) \left( \frac{E_{m,i,r,t}}{E_{m,r,t}} \right) - \left( \frac{\sum_{h \in H} I_{f,i,r,t}}{\sum_{h \in H} I_{i,r,t}} \right) \left( \frac{E_{f,i,r,t}}{E_{f,r,t}} \right) \right] \tag{10}$$

where $h \in H_i$ represents an essential skill and $H_i$ denotes the essential skills set per industry. Essential skills are subsets of all skill types ($H_i \in S$) documented in Table A1. As the last step, we reestimate the baseline logistic and piecewise logistic models with the skill gap indicator based on essential skills ($GSGI^{RSA}$). Table 5 displays the results. Column 1 represents results for $GSGI^{RSA}$ and entry, while Column 2 does so by using the standardised version of $GSGI^{RSA}$ to report the effect size. Column 3 shows the impacts of female-biased and male-biased $GSGI^{RSA}$ on entry while Column 4 reports their effect sizes. Columns 5, 6, 7, and 8 display the estimates for the exit with the main coefficients of interests $GSGI^{RSA}$, standardised $GSGI^{RSA}$, gender-biased $GSGI^{RSA}$, and standardised gender-biased $GSGI^{RSA}$ respectively. The results confirm the previous results qualitatively and quantitatively while the effect sizes are stronger for $GSGI^{RSA}$. This is to say that the impact of the gender skill gap is stronger on the diversification process when considering the essential skills for industries. One standard deviation increase in $GSGI^{RSA}$ is related to a 14% increase in the probability of entry and a 12% decrease in the probability of exit while they are respectively 11% and 7% for $GSGI$ in Table 2. Regarding female-biased $GSGI^{RSA}$, one standard deviation decreases the entry probability by 7% and increases the exit probability by 10%. One standard deviation increase in male-biased $GSGI^{RSA}$ is associated 19% increase in the entry probability and is related to a 19% decrease in the exit probability.

**Table 5. Entry and Exit Models: The Most Important Skills**

| | (1) Entry | (2) Entry | (3) Entry | (4) Entry | (5) Exit | (6) Exit | (7) Exit | (8) Exit |
|---|---|---|---|---|---|---|---|---|
| $GSGI^{RSA}$ | 1.1901$^{***}$ | | | | 1.1901$^{***}$ | | | |
| | (0.0546) | | | | (0.0546) | | | |
| $GSGI^{RSA}$ Std. | | 1.1150$^{***}$ | | | | 0.9125$^{***}$ | | |
| | | (0.0319) | | | | (0.0154) | | |
| Female-Biased $GSGI^{RSA}$ | | | 0.8466$^{***}$ | 0.9289$^{***}$ | | | 1.2470$^{***}$ | 1.1027$^{***}$ |
| | | | (0.0397) | (0.0193) | | | (0.0716) | (0.0280) |
| Male-Biased $GSGI^{RSA}$ | | | 1.5221$^{***}$ | 1.1902$^{***}$ | | | 0.5949$^{***}$ | 0.8064$^{***}$ |
| | | | (0.1060) | (0.0344) | | | (0.0419) | (0.0235) |
| Dummy FB. | | | 0.0025$^{***}$ | 0.0025$^{***}$ | | | 0.4245 | 0.4245 |
| | | | (0.0022) | (0.0022) | | | (0.4514) | (0.4514) |
| Dummy MB. | | | 0.0030$^{***}$ | 0.0030$^{***}$ | | | 0.3781 | 0.3781 |
| | | | (0.0027) | (0.0027) | | | (0.4020) | (0.4020) |
| Skill Rel. | 1.0327$^{***}$ | 1.0327$^{***}$ | 1.0329$^{***}$ | 1.0329$^{***}$ | 1.0327$^{***}$ | 0.9793$^{***}$ | 0.9787$^{***}$ | 0.9787$^{***}$ |
| | (0.0031) | (0.0031) | (0.0031) | (0.0031) | (0.0031) | (0.0030) | (0.0030) | (0.0030) |
| Skill Comp. | 1.0046$^{***}$ | 1.0046$^{***}$ | 1.0035$^{***}$ | 1.0035$^{***}$ | 1.0046$^{***}$ | 0.9954$^{***}$ | 0.9965$^{***}$ | 0.9965$^{***}$ |
| | (0.0004) | (0.0004) | (0.0004) | (0.0004) | (0.0004) | (0.0005) | (0.0005) | (0.0005) |
| GDP (log) | 0.1265$^{***}$ | 0.1266$^{***}$ | 0.3041$^{*}$ | 0.3041$^{*}$ | 0.1265$^{***}$ | 1.4668 | 1.6694 | 1.6694 |
| | (0.0713) | (0.0714) | (0.1742) | (0.1742) | (0.0713) | (0.9011) | (1.0410) | (1.0410) |
| Pop. Dens. (log) | 0.0003$^{***}$ | 0.0003$^{***}$ | 0.2821 | 0.2821 | 0.0003$^{***}$ | 0.6673 | 1.6322 | 1.6322 |
| | (0.0001) | (0.0001) | (0.2879) | (0.2879) | (0.0001) | (0.5893) | (1.7725) | (1.7725) |
| Education | 0.9961 | 0.9961 | 0.9756 | 0.9756 | 0.9961 | 0.9769 | 0.9735 | 0.9735 |
| | (0.0156) | (0.0156) | (0.0155) | (0.0155) | (0.0156) | (0.0164) | (0.0166) | (0.0166) |
| Death | 1.0003 | 1.0003 | 1.0003$^{*}$ | 1.0003$^{*}$ | 1.0003 | 0.9997$^{*}$ | 0.9997$^{*}$ | 0.9997$^{*}$ |
| | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) |
| Bus. Growth | 1.0129$^{**}$ | 1.0129$^{**}$ | 1.0136$^{**}$ | 1.0136$^{**}$ | 1.0129$^{**}$ | 0.9927 | 0.9931 | 0.9931 |
| | (0.0043) | (0.0043) | (0.0043) | (0.0043) | (0.0043) | (0.0048) | (0.0048) | (0.0048) |
| Reg. Div. | 0.9788$^{***}$ | 0.9788$^{***}$ | 0.9800$^{***}$ | 0.9800$^{***}$ | 0.9788$^{***}$ | 1.0241$^{***}$ | 1.0242$^{***}$ | 1.0242$^{***}$ |
| | (0.0025) | (0.0025) | (0.0025) | (0.0025) | (0.0025) | (0.0027) | (0.0027) | (0.0027) |
| Ind. Ubi. | 0.9447$^{***}$ | 0.9447$^{***}$ | 0.9390$^{***}$ | 0.9390$^{***}$ | 0.9447$^{***}$ | 1.0686$^{***}$ | 1.0669$^{***}$ | 1.0669$^{***}$ |
| | (0.0041) | (0.0041) | (0.0042) | (0.0042) | (0.0041) | (0.0054) | (0.0054) | (0.0054) |
| $N$ | 155583 | 155583 | 155583 | 155583 | 155583 | 65649 | 65649 | 65649 |
| chi2 | 31691 | 31691 | 31765 | 31765 | 31691 | 13235 | 13152 | 13152 |
| bic | 73387 | 73387 | 73207 | 73207 | 73387 | 56744 | 56588 | 56588. |
| aic | 67066 | 67065 | 66855 | 66855 | 67066 | 50944 | 50760 | 50760 |

Heteroskedasticity-robust standard errors clustered at the region-industry level are displayed in parentheses. Fixed effects for industry, region, and time are included in every model specification. $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$.

## 8 Discussion: What are the potential underlying channels?

Interestingly, the econometric analyses conducted in the previous sections suggest a positive relationship between the gender skill gaps and the industrial diversification process of regions. This finding is robust to several skill gap indicators, different model specifications, and further sensitivity analyses. The exploration of the gendered skill gap has revealed contrasting impacts of the female-biased and male-biased skill gaps. One potential channel through which the observed patterns may appear can be the within-industry wage gap between genders induced by gender skill differences. When there is a gender skill gap in an industry, the gender with higher skill intensity is expected to earn more than the gender with lower skill intensity, all else is equal, if there is no discrimination in the market. The higher the skill gap, the higher the wage gap. In this scenario, firms operating in an industry with a large gender skill gap have the opportunity to hire more labour at a low cost. Since comparative advantage is defined as the over-presence of an industry in a region in terms of the number of employed people, the availability of low-cost labour increases the probability of hiring more labour thereby facilitating the establishment of a comparative advantage. However, this process might only work one way in favour of males. Prior research has shown that wages are lower in occupations dominated by women and this fact cannot be explained by human capital differences, skill specialisation, domestic work or unobserved factors (Perales, 2010). On the other hand, females have little bargaining power when they have lower skills, thus earning less even within the same occupation (Christl and Köppl–Turyna, 2020; Peto and Reizer, 2021). In this regard, Figure A2 demonstrates the average wage share of females and males[8] across the industries in our sample. The figure shows that the female wage share is below 0.5 of the total wage in 462 out of 532 (87%) industries. Conversely, the male wage share is above 0.5 in 462 industries.

On the other hand, females can better negotiate their wages for some positions in which females are better qualified in terms of the necessary skills since female labour force participation is generally lower than men (Barza et al., 2020), making the labour market more competitive. In this case, high female wages can prevent firms from employing more labour and increasing labour costs, leading to an unfavourable effect on creating a comparative advantage. In addition, prior research has shown that females are concentrated in some sectors while men are more equally distributed. Hence, the gender skill gap may disproportionately affect industries with a lower female share in their employment relative to other industries.

Another mechanism that might contribute to the observed patterns of the gendered skill gaps in the industrial diversification process of regions might be conscious and unconscious gender bias and discrimination in the workplace and market (ILO ACT/EMP, 2015). If the industry where females have higher skills is characterised by gender bias in leadership and decision-making roles, it might struggle to harness and promote the talents of skilled women (Koenig et al., 2011; Stamarski and Son Hing, 2015; Galsanjigmed and Sekiguchi, 2023). For example, if women are not encouraged to pursue leadership roles or are denied access to networks and opportunities, the industry may not capitalise on their skills. This underutilisation of talent, resources and expertise can hinder the industry's ability to innovate and adapt to changing market conditions, ultimately limiting its potential to develop a comparative advantage. Reversely, long-standing gender norms and market preferences can favour industries where men have traditionally been more prevalent in the sense

[8] Average female wage in industry $i$ divided by average female wage plus average male wage in the industry $i$.

that stronger professional networks and advocacy efforts. Such preferences can translate into higher demand and growth prospects by leading to better access to funding, government support, and partnerships, positively impacting the industry's comparative advantage. If gender bias is present, the industry with higher-skilled females may face challenges in securing investment and resources compared to male-dominated sectors. This disparity in access to capital can impede the industry's ability to innovate and expand, diminishing its comparative advantage.

It is important to emphasise that the potential underlying factors mentioned above are not exhaustive and mutually exclusive, but are rather descriptive. There might be many other observable and unobservable factors and mechanisms that interact with each other. Hence, future studies may focus on unpacking the determinants of the asymmetric effects of the gender skill gaps.

# 9 Conclusion

The industrial diversification process of regions has long been analysed by scholars (Neffke et al., 2011; Xiao et al., 2018; Buyukyazici et al., 2023). The literature largely agrees on the path-dependent nature of diversification which is dependent on pre-existing regional capabilities. However, a more micro approach to regional capabilities is needed to observe their nature and evaluate their effect. In this regard, the present paper sheds light on an important aspect of regional capabilities: gender skill differences. By building a gender skill gap indicator at the industry and region level, this study documents that female-biased and male-biased skill gaps differently affect the industrial diversification of regions. Interestingly, the female-biased skill gap is negatively related to industrial entry and positively related to industrial exit while the male-biased skill gap is positively associated with entry and negatively associated to exit, unfolding the complex and multifaceted relationship between the gender skill gaps and industrial diversification of regions.

The methodology and results we document in this paper contribute to the future research agenda. Firstly, the results presented underline the need for a more explicit and micro approach to analyse regional capabilities and how they underpin the path-dependent process of diversification. Secondly, we briefly discussed that gender dynamics –including biases in wage and employment distribution, labour force participation, leadership and decision-making process, market perceptions, and access to resources– can play a crucial role in determining how the distribution of skills between genders affects the industries' comparative advantages within a region. In future works, these mechanisms should be empirically considered with adequate data sources to achieve a more complete picture of the gender dimension of industrial diversification. Thirdly, prior research showed that diversification patterns might contribute to regional inequalities (Pinheiro et al., 2022). In this paper, we prove that regional inequalities, in the form of skill gaps, might be a source of diversification, i.e. comparative advantage. In this regard, future studies should focus on the intertwined nature of regional inequalities and diversification that might work both ways.

The present study is not free of limitations. First, workplace skills survey data are not available for the majority of countries, posing a crucial constraint to the reproducibility of the method and gender skill gap indicator developed in this study as well as preventing multi-country analyses. Two potential data sources can be used in case of the lack of skills survey data: online job market data and the completed years of education of genders. Online job market data obtained from online platforms can be reconstructed to create job or industry-wise skill set scores to build a gender skill gap indicator. On the other hand, the completed years of education of genders is a more readily available data source while it is apparently a very rough proxy of skills data[9]. Second, it is essential to underline that this study takes the gender skill gaps as given and aims at measuring and observing their effects on the diversification process. Future studies may investigate the determinants of the gender skill gaps within the sectoral and regional contexts to further analyse how they interact with the industrial diversification process of regions.

It's important to note that while the results documented in this study highlight the diverging impacts of the gender skill gaps, they do not diminish the importance of promoting higher female skills and gender equality in the workforce. Achieving gender equity and challenging gender stereotypes is essential for creating fair and competitive industrial landscapes. In fact, addressing these challenges can help create a more inclusive and diversified economy, leading to greater overall prosperity and progress for regions. Efforts to remove barriers to women's participation in all industries and sectors, promoting diversity and inclusion, can ultimately lead to more robust industrial diversification and economic growth. Addressing and closing the gender skill gap is essential for promoting equitable employment opportunities and fostering economic development in regions.

[9] The gender skill gap indicator and econometric analyses in this study are also reproduced with the completed years of education of genders instead of skills data to test the persistence of the observed patterns. The results are qualitatively and quantitatively similar to those obtained with the skills data. The tables are available upon request.

# Appendix

**Table A1. ICP Categories**

| | |
|---|---|
| **1.Knowledge** | (B1) Administration and Management, (B2) Office Work, (B3) Economics and Accounting, (B4) Sales and Marketing, (B5) Services to Customers, (B6) Human Resources Management, (B7) Production and Processing, (B8) Food Production, (B9) IT and Electronics, (B10) Engineering and Technology, (B11) Technical Design, (B12) Building and Construction, (B13) Mechanical, (B14) Mathematics, (B15) Physics, (B16) Chemistry, (B17) Biology, (B18) Psychology, (B19) Sociology and Anthropology, (B20) Geography, (B21) Medicine and Dentistry, (B22) Therapy and Counseling, (B23) Education and Training, (B24) Italian Language, (B25) Foreign Language, (B26) Fine Arts, (B27) History and Archaeology, (B28) Philosophy and Theology, (B29) Civil Protection and Public Safety, (B30) Legislation and Institutions, (B31) Telecommunications, (B32) Communication and Media, (B33) Transportation |
| **2.Skills** | |
| 2.1 Basic Skills | (C1) Reading Comprehension, (C2) Active Listening, (C3) Writing, (C4) Speaking, (C5) Mathematics, (C6) Science, (C7) Critical Thinking, (C8) Active Learning, (C9) Learning Strategies, (C10) Monitoring |
| 2.2 Social Skills | (C11) Social Perceptiveness, (C12) Coordination, (C13) Persuasion, (C14) Negotiation, (C15) Instructing, (C16) Service Orientation |
| 2.3 Complex Problem | (C17) Complex Problem Solving |
| 2.4 Technical Skills | (C18) Operations Analysis, (C19) Technology Design, (C20) Equipment Selection, (C21) Installation, (C22) Programming, (C23) Quality Control Analysis, (C24) Operation Monitoring, (C25) Operation and Control, (C26) Equipment Maintenance, (C27) Troubleshooting, (C28) Repairing |
| 2.5 Systems Skills | (C29) Systems Analysis, (C30) Systems Evaluation, (C31) Judgement and Decision Making |
| 2.6 Resource Management Skills | (C32) Time Management, (C33) Management of Financial Resources, (C34) Management of Material Resources, (C35) Management of Personnel Resources |
| **3.Attitudes** | |
| 3.1 Cognitive | (D1) Oral Comprehension, (D2) Written Comprehension, (D3) Oral Expression, (D4) Written Expression, (D5) Fluency of Ideas, (D6) Originality, (D7) Problem Sensitivity, (D8) Deductive Reasoning, (D9) Inductive Reasoning, (D10) Information Ordering, (D11) Category Flexibility, (D12) Math Reasoning, (D13) Number Facility, (D14) Memorisation, (D15) Speed of Closure, (D16) Flexibility of Closure, (D17) Perceptual Speed, (D18) Spatial Orientation, (D19) Visualisation, (D20)Selective Attention, (D21) Time Sharing |
| 3.2 Psychomotor | (D22) Arms-Hand Steadiness, (D23) Manual Dexterity, (D24) Finger Dexterity, (D25) Control Precision, (D26) Multilimb Coordination, (D27) Response Orientation, (D28) Rate Control, (D29) Reaction Time, (D30) Wrist-Finger Speed, (D31) Speed of Limb Movement |
| 3.3 Psychical | (D32) Static Strength, (D33) Explosive Strength, (D34) Dynamic Strength, (D35) Trunk Strength, (D36) Stamina, (D37) Extent Flexibility, (D38) Dynamic Flexibility, (D39) Gross Body Coordination, (D40) Gross Balance Body Equilibrium |
| 3.4 Sensory | (D41) Near Vision, (D42) Far Vision, (D43) Visual Colour Discrimination, (D44) Night Vision, (D45) Peripheral Vision, (D46) Depth Perception, (D47) Glare Sensitivity, (D48) Hearing Sensitivity, (D49) Auditory Attention, (D50) Sound Localisation, (D51) Speech Recognition, (D52) Speech Clarity |
| **4.Work Activities** | |
| 4.1 Information Input | (G1) Getting Information, (G2) Identifying Objects, Actions, and Events, (G3) Monitor Processes, Materials or Surroundings, (G4) Inspecting Equipment, Structures or Material, (G5) Estimate the Quantifiable Characteristics of Products, Events, or Information |
| 4.2 Mental Process | (G6) Judging the Qualities of Things, Services or People, (G7) Evaluating Information to Determine Compliance with Standards, (G8) Processing Information, (G9) Analysing Data or Information, (G10) Making Decisions and Solving Problems, (G11) Thinking Creatively, (G12) Updating and Using Relevant Knowledge, (G13) Developing Objectives and Strategies, (G14) Scheduling Work and Activities, (G15) Organising, Planning, and Prioritising Work |
| 4.3 Work Output | (G16) Performing General Physical Activities, (G17) Handling and Moving Objects, (G18) Controlling Machines and Processes, (G19) Interacting With Computers, (G20) Operating Vehicles, Mechanised Devices, or Equipment, (G21) Drafting, Laying Out, and Specifying Technical Devices, Parts, and Equipment, (G22) Repairing and Maintaining Mechanical Equipment, (G23) Repairing and Maintaining Electronic Equipment, (G24) Documenting/Recording Information |
| 4.4 Interacting with Others | (G25) Interpreting the Meaning of the Information for Others, (G26) Communicating with Supervisors, Peers, or Subordinates, (G27) Communicating with Persons Outside Organisation, (G28) Establishing and Maintaining Interpersonal Relationships, (G29) Assisting and Caring for Others, (G30) Selling or Influencing Others, (G31) Resolving Conflicts and Negotiating with Others, (G32) Performing for or Working in Directly with the Public, (G33) Coordinating the Work and Activities of Others, (G34) Developing and Building Teams, (G35) Training and Teaching Others, (G36) Guiding, Directing, and Motivating Subordinates, (G37) Train and Nurture Other People, (G38) Provide Consultation and Advice to Others, (G39) Performing Administrative Activities, (G40) Staffing Organisational Units, (G41) Monitoring and Controlling Resources |

Author's own elaboration on ICP 2013[10] and O*NET data descriptors[11].

**Table A2. Detected Communities**

| | |
|---|---|
| Cluster 1: Social-Cognitive | Critical Thinking, Active Learning, Active Listening, Administration and Management, Analysing Data or Information, Assisting and Caring for Others, Category Flexibility, Communicating with Persons Outside Organisation, Communicating with Supervisors, Peers, or Subordinates, Communication and Media, Complex Problem Solving, Coordinating the Work and Activities of Others, Deductive Reasoning, Developing Objectives and Strategies, Developing and Building Teams, Documenting/Recording Information Economics and Accounting, Education and Training, Establishing and Maintaining Interpersonal Relationships, Fine Arts, Flexibility of Closure, Fluency of Ideas, Food Production, Foreign Language, Geography, Getting Information, Guiding, Directing, and Motivating Subordinates, History and Archaeology, Human Resources Management, IT and Electronics, Identifying Objects, Actions, and Events, Inductive Reasoning, Information Ordering, Instructing, Interacting with Computers, Interpreting the Meaning of the Information for Others, Italian Language, Judging the Qualities of Things, Services or People, Judgement and Decision Making, Learning Strategies, Legislation and Institutions, Making Decisions and Solving Problems, Management of Financial Resources, Management of Personnel Resources, Medicine and Dentistry, Memorisation, Monitoring, Monitoring and Controlling Resources, Negotiation, Number Facility, Office Work, Oral Comprehension, Oral Expression, Organising, Planning, and Prioritising Work, Originality, Performing Administrative Activities, Performing for or Working in Directly with the Public, Persuasion, Philosophy and Theology, Problem Sensitivity, Processing Information, Provide Consultation and Advice to Others, Psychology, Reading Comprehension, Resolving Conflicts and Negotiating with Others, Sales and Marketing, Scheduling Work and Activities, Selling or Influencing Others, Service Orientation, Services to Customers, Social Perceptiveness, Sociology and Anthropology, Speaking, Speech Clarity, Speech Recognition, Speed of Closure, Staffing Organisational Units, Telecommunications, Therapy and Counseling, Thinking Creatively, Time Management, Time Sharing, Training and Teaching Others, Updating and Using Relevant Knowledge, Writing, Written Comprehension, Written expression |
| Cluster 2: Technical-Physical | Mathematics, Science, Biology, Building and Construction, Arms-Hand Steadiness, Auditory Attention, Chemistry, Civil Protection and Public Safety, Control Precision, Controlling Machines and Processes, Coordination, Depth Perception, Drafting, Laying Out, and Specifying Technical Devices Parts and Equipment, Dynamic Flexibility, Dynamic Strength, Engineering and Technology, Equipment Maintenance, Equipment Selection, Estimate the Quantifiable Characteristics of Products, Events or Information, Evaluating Information to Determine Compliance with Standards, Explosive Strength, Extent Flexibility, Far Vision, Finger Dexterity, Glare Sensitivity, Gross Balance Body Equilibrium, Gross Body Coordination, Handling and Moving Objects, Hearing Sensitivity, Inspecting Equipment, Structures or Material, Installation, Management of Material Resources, Manual Dexterity, Math Reasoning, Mathematics, Mechanics, Monitor Processes, Materials or Surroundings, Multilimb Coordination, Near Vision, Night Vision, Operating Vehicles, Mechanised Devices, or Equipment, Operation Monitoring, Operation and Control, Operations Analysis, Perceptual Speed, Performing General Physical Activities, Peripheral Vision, Physics, Production and Processing, Programming, Quality Control Analysis, Rate Control, Reaction Time, Repairing, Repairing and Maintaining Electronic Equipment, Repairing and Maintaining Mechanical Equipment, Response Orientation, Selective Attention, Sound Localisation, Spatial Orientation, Speed of Limb Movement, Stamina, Static Strength, Systems Analysis, Systems Evaluation, Technical Design, Technology Design, Train and Nurture Other People, Transportation, Troubleshooting, Trunk Strength, Visual Colour Discrimination, Visualisation, Wrist-Finger Speed |

### Table A3. Descriptive Statistics for Skill Variables

| Industry | Full Skills | Min | Max | Social-Cognitive | Min | Max | Technical-Physical | Min | Max |
|---|---|---|---|---|---|---|---|---|---|
| Female | | | | | | | | | |
| B–E | -0.0514 | -0.892 | 2.120 | -0.0195 | -1.153 | 2.388 | -0.0888 | -0.824 | 3.204 |
| | (0.322) | | | (0.577) | | | (0.386) | | |
| F | 0.0912 | -0.854 | 1.456 | 0.310 | -1.213 | 2.349 | -0.166 | -0.805 | 2.818 |
| | (0.348) | | | (0.496) | | | (0.514) | | |
| G | -0.267 | -0.892 | 1.329 | -0.132 | -1.128 | 2.348 | -0.426 | -0.824 | 1.430 |
| | (0.329) | | | (0.539) | | | (0.205) | | |
| I | -0.216 | -0.899 | 0.688 | -0.252 | -1.126 | 1.434 | -0.174 | -0.657 | 0.562 |
| | (0.239) | | | (0.408) | | | (0.170) | | |
| H | -0.126 | -0.854 | 1.251 | 0.0309 | -1.105 | 2.348 | -0.309 | -0.805 | 2.223 |
| | (0.294) | | | (0.475) | | | (0.382) | | |
| J | 0.184 | -0.751 | 1.175 | 0.557 | -1.003 | 2.348 | -0.254 | -0.824 | 1.491 |
| | (0.342) | | | (0.519) | | | (0.348) | | |
| K–N/X | 0.106 | -0.855 | 1.755 | 0.427 | -1.213 | 2.348 | -0.271 | -0.824 | 2.364 |
| | (0.397) | | | (0.593) | | | (0.406) | | |
| P/Q | 0.209 | -0.899 | 1.515 | 0.485 | -1.258 | 2.487 | -0.115 | -0.702 | 1.854 |
| | (0.334) | | | (0.506) | | | (0.291) | | |
| R–U | -0.0171 | -0.854 | 2.105 | 0.0860 | -1.213 | 2.348 | -0.138 | -0.802 | 3.659 |
| | (0.385) | | | (0.581) | | | (0.415) | | |
| Male | | | | | | | | | |
| B–E | 0.0369 | -0.892 | 2.120 | -0.203 | -1.213 | 2.388 | 0.319 | -0.824 | 3.659 |
| | (0.329) | | | (0.505) | | | (0.415) | | |
| F | 0.0813 | -0.556 | 2.120 | -0.399 | -1.213 | 1.917 | 0.646 | -0.635 | 3.659 |
| | (0.273) | | | (0.470) | | | (0.298) | | |
| G | -0.178 | -0.855 | 1.335 | -0.111 | -1.213 | 2.191 | -0.257 | -0.824 | 2.635 |
| | (0.295) | | | (0.482) | | | (0.315) | | |
| I | -0.105 | -0.899 | 0.688 | -0.182 | -1.258 | 1.434 | -0.0147 | -0.635 | 1.539 |
| | (0.247) | | | (0.391) | | | (0.269) | | |
| H | -0.0301 | -0.711 | 1.480 | -0.321 | -1.123 | 1.516 | 0.312 | -0.732 | 2.823 |
| | (0.386) | | | (0.477) | | | (0.562) | | |
| J | 0.314 | -0.774 | 1.329 | 0.534 | -1.104 | 2.191 | 0.0557 | -0.824 | 1.413 |
| | (0.245) | | | (0.411) | | | (0.371) | | |
| K–N/X | 0.169 | -0.854 | 1.755 | 0.384 | -1.213 | 2.348 | -0.0830 | -0.824 | 2.823 |
| | (0.380) | | | (0.640) | | | (0.491) | | |
| P/Q | 0.301 | 0.819 | 1.762 | 0.504 | -1.213 | 2.577 | 0.0628 | -0.805 | 1.854 |
| | (0.414) | | | (0.610) | | | (0.439) | | |
| R-U | 0.110 | -0.854 | 1.861 | 0.0378 | -1.213 | 2.348 | 0.194 | -0.805 | 3.625 |
| | (0.360) | | | (0.517) | | | (0.500) | | |

(B-E) Industry, (F) Construction, (G) Wholesale and retail trade; repair of motor vehicles and motorcycles, (I) Accommodation and food service activities, (H) Transportation and storage, (J) Information and communication, (K-N/X) Financial, real estate, scientific and technical, administrative and support service activities, (P/Q) Education; human health and social work activities, (R-U) Arts, entertainment and recreation; other service activities.

**Table A4. Correlation Matrix**

| | GSGI | FB G. | MB G. | RSGI | GSGI$^{RSA}$ | FB G$^{RSA}$ | MB G$^{RSA}$ | S.Rel | S.Comp | GDP | Pop. Dens. | Educ. | Death | Bus.Gr. | Reg. Div. | Ind. Ubi. |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| GSGI | 1.0000 | | | | | | | | | | | | | | | |
| FB GSGI | 0.7785 | 1.0000 | | | | | | | | | | | | | | |
| MB GSGI | 0.6736 | 0.0605 | 1.0000 | | | | | | | | | | | | | |
| RSGI | 0.4456 | 0.2604 | 0.4020 | 1.0000 | | | | | | | | | | | | |
| GSGI$^{RSA}$ | 0.9675 | 0.7419 | 0.6651 | 0.3926 | 1.0000 | | | | | | | | | | | |
| FB GSGI$^{RSA}$ | 0.7706 | 0.9906 | 0.0591 | 0.2456 | 0.7485 | 1.0000 | | | | | | | | | | |
| MB GSGI$^{RSA}$ | 0.6322 | 0.0572 | 0.9380 | 0.3284 | 0.7048 | 0.0571 | 1.0000 | | | | | | | | | |
| Skill Rel. | -0.0151 | -0.0006 | -0.0232 | 0.0488 | -0.0079 | -0.0011 | -0.0107 | 1.0000 | | | | | | | | |
| Skill Comp. | 0.0134 | -0.1694 | 0.2208 | 0.1513 | 0.0253 | -0.1672 | 0.2170 | 0.2633 | 1.0000 | | | | | | | |
| GDP (log) | -0.0051 | 0.0147 | -0.0254 | 0.0277 | 0.0023 | 0.0148 | -0.0124 | 0.6688 | 0.1418 | 1.0000 | | | | | | |
| Pop. Dens. | -0.0014 | 0.0084 | -0.0121 | 0.0262 | 0.0004 | 0.0087 | -0.0087 | 0.4310 | 0.1048 | 0.2569 | 1.0000 | | | | | |
| Education | -0.0016 | -0.0002 | -0.0023 | -0.0022 | -0.0007 | -0.0001 | -0.0009 | 0.1181 | 0.0235 | 0.0807 | 0.1472 | 1.0000 | | | | |
| Death | 0.0429 | 0.0510 | 0.0081 | 0.0479 | 0.0440 | 0.0506 | 0.0121 | 0.4330 | 0.1484 | 0.1862 | 0.4822 | 0.1312 | 1.0000 | | | |
| Bus. Growth | -0.0995 | -0.0867 | -0.0561 | -0.0412 | -0.1026 | -0.0867 | -0.0617 | 0.0446 | 0.0361 | -0.0166 | 0.0773 | 0.1105 | 0.0270 | 1.0000 | | |
| Reg. Div. | -0.0007 | 0.0078 | -0.0103 | 0.0344 | 0.0018 | 0.0075 | -0.0054 | 0.4847 | 0.0985 | 0.1066 | 0.3897 | 0.0435 | 0.3922 | 0.0647 | 1.0000 | |
| Ind. Ubi. | 0.0714 | -0.0833 | 0.2115 | 0.0827 | 0.0852 | -0.0809 | 0.2147 | 0.0580 | 0.2221 | 0.0000 | -0.0000 | 0.0008 | 0.1209 | -0.0483 | 0.0000 | 1.0000 |

**Table A5. Summary Statistics for Independent Variables**

| Variable | Obs | Mean | Std. dev. | Min | Max |
|---|---|---|---|---|---|
| Entry | 157,602 | 0.063 | 0.242 | 0 | 1 |
| Exit | 65,814 | 0.149 | 0.356 | 0 | 1 |
| GSGI | 223,416 | 0.026 | 0.568 | -20.45 | 23.19 |
| FB GSGI | 223,416 | -0.083 | 0.420 | -20.45 | 0 |
| MB GSGI | 223,416 | 0.109 | 0.357 | 0 | 23.19 |
| RSGI | 223,416 | 2.499 | 8.978 | -42.77 | 42.77 |
| GSGI$^{RSA}$ | 223,416 | 0.036 | 0.624 | -20.45 | 23.19 |
| FB GSGI$^{RSA}$ | 223,416 | -0.086 | 0.443 | -20.454 | 0 |
| MB GSGI$^{RSA}$ | 223,416 | 0.122 | 0.414 | 0 | 23.188 |
| Skill Rel. | 223,416 | 33.80 | 13.96 | 0 | 100 |
| Skill Comp. | 223,416 | 19.99 | 31.84 | 0 | 100 |
| GDP (log) | 223,416 | 10.09 | 0.275 | 9.54 | 10.88 |
| Pop. Dens. (log) | 223,416 | 5.23 | 0.78 | 3.67 | 7.90 |
| Education | 223,416 | 20.13 | 2.15 | 15.53 | 27.36 |
| Death | 223,416 | 169.90 | 231.81 | 2 | 2760 |
| Bus. Growth | 223,416 | -1.722 | 3.391 | -19.51 | 26.16 |
| Reg. Div. | 223,416 | 0 | 20.96 | -74.17 | 64.83 |
| Ind. Ubi. | 223,416 | 0 | 16.18 | -30.52 | 43.48 |

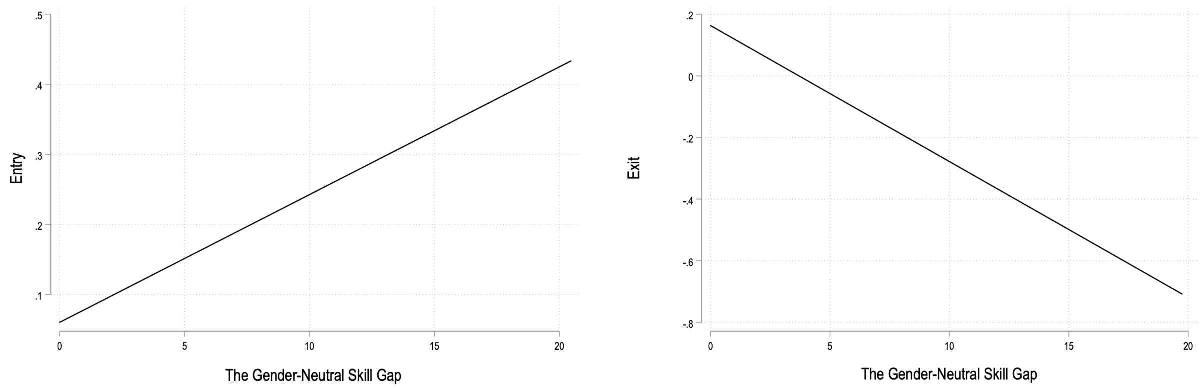
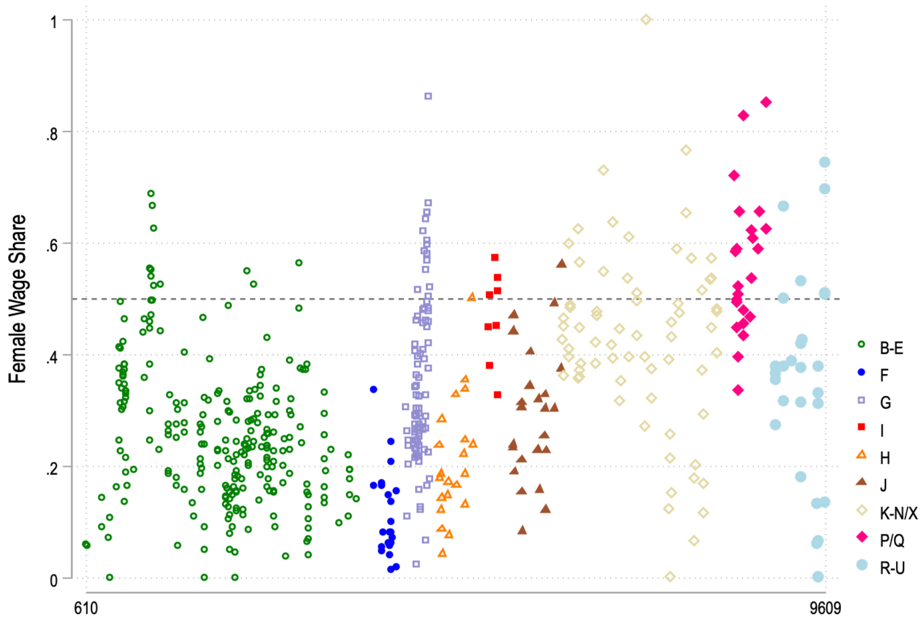
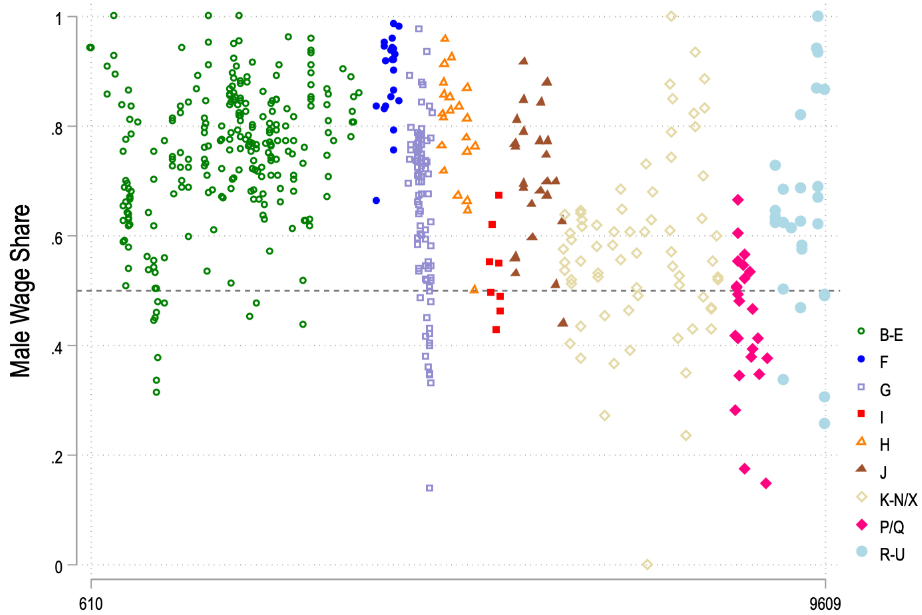



**Figure A1. The Simple Association between the Gender-Neutral Skill Gap and Entry and Exit**




(a)




(b)

**Figure A2. Female and Male Wage Shares.** (B-E) Industry, (F) Construction, (G) Wholesale and retail trade; repair of motor vehicles and motorcycles, (I) Accommodation and food service activities, (H) Transportation and storage, (J) Information and communication, (K-N/X) Financial, real estate, scientific and technical, administrative and support service activities, (P/Q) Education; human health and social work activities, (R-U) Arts, entertainment and recreation; other service activities.

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