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ORIGINAL ARTICLE

Task specialization and the Native-Foreign Wage Gap

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Abstract

This study documents that worker-level variation in tasks has played a key role in the widening of the German Native-Foreign Wage Gap. I find idiosyncratic differences account for up to 34 per cent of the wage gap. Importantly, natives specialize in high-paying interactive activities not only between, but also within occupations. In contrast, foreign workers specialize in low-paying manual activities. This enhanced degree of task specialization accounts for 11 per cent of the gap among high-wage earners and 25 per cent among low-wage earner, thus offering new insight into sources for imperfect substitution of native and foreign workers and consequently small migration-induced wage effects.

JEL CLASSIFICATION

J15, J21, J24, J31, J61

1 | INTRODUCTION

There are ongoing debates in the economic literature on the degree of substitutability between native and foreign workers. While some research suggests both groups are perfect substitutes (Aydemir & Borjas, 2007; Borjas et al., 2012; Llull, 2018a) others have found evidence implying imperfect substitutability instead (D'Amuri et al., 2010; Manacorda et al., 2012; Peri, 2012). This paper uses individual-level data on job tasks to document differential specialization patterns at the workplace that are consistent with imperfect substitutability, yet, are masked in conventional data.

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This idiosyncratic task specialization can help us better understand wage differences such as those illustrated for the German Native-Foreign Wage Gap in Figure 1. On the one hand, the unconditional wage gap has increased steadily from 7 to 13 per cent between 1992 and 2018. On the other hand, there are distributional implications as wage differences are more pronounced among low-wage earners. One possible explanation for these trends is that native and foreign workers have distinct roles in the production function and wage differences accordingly reflect underlying skill differences. Against these wage trends, Figure 2 reveals patterns on tasks performed at work that are inconsistent with this hypothesis. In the left panel we can see the increase in skill requirements in jobs, a well-known stylized fact documented since at least the 1970s.¹

This so-called “upskilling” is usually portrayed irrespective of nativity. The right panel indeed displays rising assimilation in job-related activities between natives and foreigners, suggesting

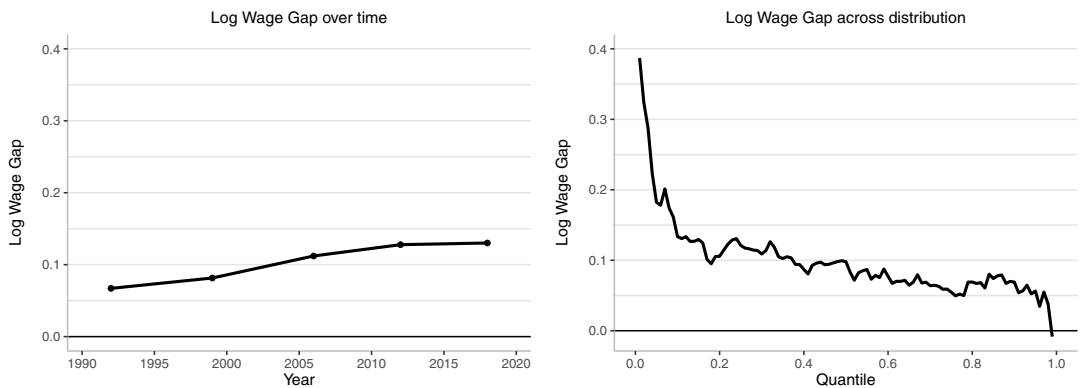


FIGURE 1 Native-Foreign Wage Gap in Germany, 1992–2018. Both panels display trends in the (unconditional) real hourly wage in Germany. Income data is deflated using the German CPI with base year 2015. Source: BIBB/BAuA/IAB, own calculations

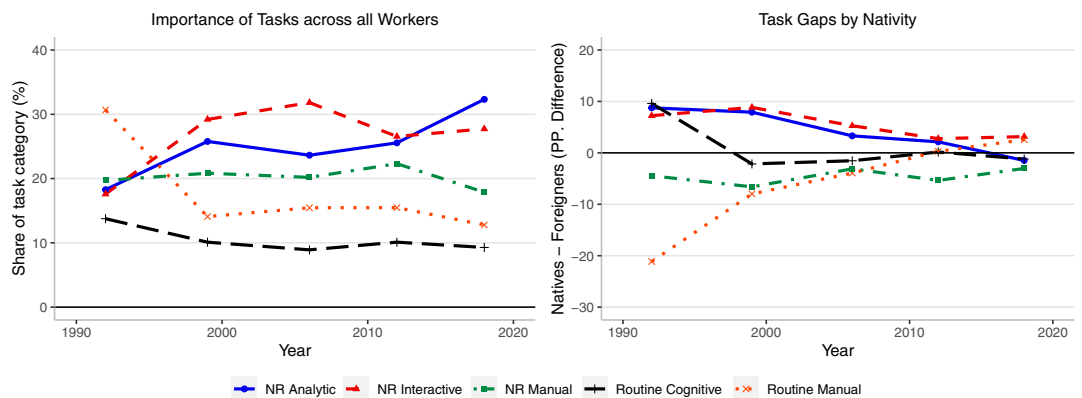


FIGURE 2 Task assignments in Germany, 1992–2018. “NR” stands for non-routine activities. NR Analytic and NR Interactive can be subsumed under *Abstract* tasks, involving lots of problem-solving skills. Routine Cognitive and Routine Manual can be subsumed under *Routine* tasks, characterized by various repetitive steps. NR *Manual* involves activities requiring hand-eye coordination, which are difficult to automate. Source: BIBB/BAuA/IAB, own calculations

rising skill requirements have allowed foreign workers to catch up. Strikingly, however, this convergence in job tasks coincided with the increase in the wage gap discussed above.²

This study offers three explanations in order to reconcile the divergent wage and task trends between native and foreign workers by using decomposition techniques and applying them to German survey data with self-reported information on job tasks. First, there are crucial differences in the allocation of narrowly defined tasks that are masked in broader task classifications. I show that variation in job-related activities at the individual-level is predictive of wage differences across the entire wage distribution and robust to inclusion of various education and experience measures. These findings thus object to the assumption of perfect substitutability of workers with similar education-experience profiles which is commonly made in the literature of estimating structural production functions (Borjas, 2003; D'Amuri et al., 2010; Llull, 2018a; Manacorda et al., 2012; Ottaviano & Peri, 2012). To my knowledge, no paper has explored individual-level variation in tasks in the context of migration before, thus adding new insight to this line of research.

Second, due to distributional variation, simple average measures are not adequate to capture differences in task assignments between natives and foreigners. I, therefore, decompose the Native-Foreign Wage Gap along the wage distribution, highlighting the role of tasks. The conventional Oaxaca-Blinder (OB) decomposition (Blinder, 1973; Oaxaca, 1973) is limited by its inability to evaluate the impact of single covariates for any distributional statistic but the sample mean. Yet, as suggested by Figure 1, the wage gap displays distributional implications and tasks may therefore have a differential impact along the wage distribution as well. For instance, performing more abstract tasks likely affects high-wage workers differently than low-wage workers as they are already specialized in underlying activities, thus being more equipped in executing them. Generalizing the conventional OB decomposition, I follow Firpo et al. (2009) and construct Recentered Influence Functions (RIF) to perform quantile regressions on the wage gap.

Applying this methodology reveals that variation in tasks at the worker-level is more pronounced among workers near the tails of the distribution and especially in regards to interactive and manual tasks. Previous research has identified these activities as key tasks to understand the Native-Foreign Wage Gap. Accordingly, native workers specialize in interactive activities while foreign workers specialize in manual activities (Peri & Sparber, 2009). My findings provide additional insight to these specialization patterns, showing that variation in interactive tasks is more important near the top of the wage distribution with contributions of up to 10 per cent between 1992 and 2018. In contrast, variation in manual tasks is relevant among low-wage earners, contributing up to 10 per cent to the wage gap.

Third, I study the degree of task specialization within occupations in more detail. If workers perform different tasks according to their comparative advantage, skill-biased technological change should amplify preexisting specialization patterns beyond occupational borders. Conditioning individual-level task measures on occupational affiliation via fixed effects (FE) thus allows to gauge the degree of specialization between natives and foreign workers. While existing research in the migration context focuses only on the occupational dimension, this is the first study to measure individual-level task specialization within occupations, suggesting contributions to the wage gap of up to 13 per cent.

The present study contributes to a growing literature exploring the relationship between skills, tasks, and wages. In particular, it provides new insight on specialization patterns in the migration context using task data. This research measures skill differences between native and foreign-born workers by utilizing occupation-level task data, thus emphasizing comparative advantages in the occupational choice as a key source for imperfect substitutability between native and foreign workers. The seminal study in this literature is Peri and Sparber (2009) who

use O*NET data and show that less-educated natives in US states with large inflows of less-educated immigrants respond by specializing in occupations intensive in interactive tasks. In a follow-up study, Peri and Sparber (2011) document that native college graduates in the United States tend to specialize in occupations intensive in communication-heavy activities while foreign graduates tend to specialize in occupations intensive in technical (i.e. relatively non-verbal) activities.

Combined, their findings lend credence to the distributional implications highlighted in the present study as variation in task is disproportionately important as a driver of wage differences for workers near the tails of the wage distribution. I expand on their research by exploring the importance of task specialization within occupations. These findings are particularly relevant for studies employing the Peri and Sparber (2009) framework in the German context (Cassidy, 2019; Haas et al., 2013; Sebastian & Ulceluse, 2019). Importantly, I argue that the inherent identification problem in migration research relying on conventional task data remains unsolved because above studies assume that workers within occupations perform the same set of activities.

Instead, my findings are consistent with only a handful of studies that have explored heterogeneous adoption of tasks at the individual level. Combining O*NET with cross-sectional survey data on individual-level task measures, Autor and Handel (2013) demonstrate that job tasks do vary substantially and are thus predictive of wage differences not only between but also within occupations. Cassidy (2017) and Rohrbach-Schmidt (2019) confirm individual task variation to be predictive of wage differences in Germany from, respectively, 1986–92 and in a 2012 cross-section. Moreover, de La Rica et al. (2020) find similar results for a short panel consisting of workers in 19 countries, adding cross-country evidence. These studies all focus on a rather short-term time horizon. I expand on their findings by (i) providing long-term evidence for 1992–2018³ and (ii) documenting that worker-level variation in tasks is predictive of wage differences between native and foreign workers with similar education-experience profile (rather than wage differences across the entire workforce). Collectively, individual-level task measures account for 20–37 per cent of the wage gap depending on specification and position in the wage distribution.

In a similar vein, the task specialization suggested in this paper is consistent with a growing literature employing job vacancy data to document rising heterogeneity in labor demand within occupations and job titles. Hershbein and Kahn (2018) find that a majority of upskilling since the Great Recession has taken place within occupations. Similarly, Deming and Kahn (2018) emphasize differences in social and cognitive skills to be predictive of wage differences beyond occupational borders. More specifically, related research argues that skill requirements did not only increase within occupations, but also within job titles. Modestino et al. (2019) provide evidence of stronger upskilling in regions with higher unemployment rates during the Great Recession, attributing these effects to greater recruitment intensity for abundantly available labor supply. Compiling a novel database by digitizing text from job ads, a series of papers by Atalay et al. (2018, 2020) not only confirm these trends in upskilling, but document a long-standing rise in changes of tasks within detailed job titles from 1950 to 2000. Hence, measures of skills that account for within-occupation disparities help to shed light on wage differences between workers.

In this regard, the present study is broadly related to the extensive research that has documented how occupations experienced substantial changes in job skill requirements due to technological change. Increasing automation has led to the re-allocation of workers previously employed in routine-heavy occupations, implying widespread employment polarization.⁴

Workers are, therefore, differentially affected by technological change depending on their human capital endowment, occupational affiliation, and tasks performed at work. If native and foreign workers differ in these attributes, they will likewise respond differentially to technological change beyond occupational boundaries.

Last, I add to the literature decomposing wage differences in the migration context⁵ and more generally in different contexts employing the regression-based RIF decomposition popularized by Firpo et al. (2009).⁶ To my knowledge, there is no study to date that decomposes the Native-Foreign Wage Gap using a task-approach. The closest comparison is Ingwersen and Thomsen (2019) who employ similar techniques. However, they use a German household panel since their focus is on differential effects among subgroups of foreigners with a core interest in cultural factors. In contrast, I use cross-sectional data on working conditions in order to emphasize workplace heterogeneity.

Taken together, the evidence in this paper points to substantial heterogeneity in the measurement of skills which traditional proxies pertaining to formal qualifications fail to address. This observation explains why, despite educational assimilation (Algan et al., 2010), the rise in the German Native-Foreign Wage Gap has been driven by workers near the tails of the wage distribution. As a consequence, previous studies emphasizing occupational segregation have underestimated the degree of task specialization between native and foreign workers. The findings of this study thus add new insight into the distinct roles of native and foreign workers in the production function, a feature that is at the root of small migration-induced wage effects.

2 | DATA

2.1 | Data source & key features

The data source is a series of German employment surveys, assembled by the Federal Institute for Vocational Education (BIBB), the Institute of Employment Research (IAB), and the Federal Institute of Occupational Safety and Health (BAuA), respectively. This data set establishes a repeated labor force cross-section on qualification and working conditions of workers in Germany, covering between 20,000–35,000 individuals in five waves: 1992, 1999, 2006, 2012, 2018.

Three key features make the data suitable for the present study. First, workers self-report their activities which allows an analysis on individual variation in task assignments *within* occupations.⁷ In contrast, the frequently used O*NET and *Dictionary of Occupational Titles* (DOT) databases in the United States, for instance, are based on occupational analysts (and partially job incumbents in the case of O*NET). Second, the employment surveys allow for an investigation of long-term trends. Comparable data sources providing self-reported information, such as the Princeton Data Improvement Initiative (PDII) and the survey of Skills, Technology, and Management Practices (STAMP) in the United States, usually only cover short time windows. Third, among surveys providing task information at the individual level, the data in this study offers the largest sample size (Rohrbach-Schmidt & Tiemann, 2013).

Despite these compelling features, there are a few notable disadvantages of the data. First, methodological changes limit the scope of its longitudinal usage. While the earlier BIBB/IAB surveys (1992–99) are based on the 1988 classification of occupations, the more recent ones conducted by BIBB/BAuA (2006–18) use the 1992 classification. To retain a consistent definition, I convert all occupations based on the 1988 classification, using the conversion tables provided by the German Federal Employment Agency (BA).⁸

Second, various occupations contain few observations on foreign workers. To enhance statistical precision, I aggregate the 3-digit occupations into closely related occupational groups following the methodology of the IAB (Ganzer et al., 2017, p. 60). To further limit the influence of extreme outliers I focus on occupations with at least six observations on foreign individuals overall and at least three in each of the sub-samples comprising surveys from the 1990s and 2000s, respectively. This restriction reduces the set of occupations from 118 to 86. An overview of the remaining occupational groups along with foreign share of employment can be found in Table A.1 in Supporting Information.

Third, wages are not consistently measured as a continuous variable. While the surveys from 2006 to 2018 do ask for monthly labor income, the first two surveys in 1992 and 1999 only provide income intervals. I follow Cassidy (2017) and impute the income information for those two samples by using the group midpoint as a proxy for monthly income. Income levels are subsequently converted into real terms using $CPI = 100$ as of 2015 based on the consumer price index from the Federal Statistical Office.⁹ Last, using information on weekly hours worked and assuming these are stable throughout the month, I calculate real hourly wages, the dependent variable in the empirical analysis.

2.2 | Sample selection

The baseline sample is restricted to West German civilian workers aged 18–65 who are not civil servants. Combined with restrictions placed on the set of occupations, this leaves a sample size of 59,098 workers (male and female) for whom individual-level information on tasks is available. Among those, 96.1 per cent are natives. Official data from the German employment agency, however, suggests that almost 12 per cent of workers subject to social security payments and working in West Germany had been foreign citizens in 2017, compared with some 8 per cent in 1999.¹⁰ Therefore, the data under-represent foreign workers by at least a half. A key reason for this discrepancy is requirements on proficiency of the German knowledge: only foreign workers with sufficient command of the German language are included in the surveys. This restriction thus introduces a bias stemming from self-selection of foreigners in favor of workers with relatively advanced German language proficiency. The two key limitations of the data are thus imprecise measurement of wages and under-representation of foreign workers. However, a comparison of the employment surveys with other common German data suggests the surveys are able to capture broad trends in the Native-Foreign Wage Gap. The Supporting Information accompanying this paper provides detailed validity checks on the survey data.¹¹ For brevity, I will only outline key takeaways here.

First, comparing the BIBB/BAuA/IAB surveys with administrative data, the former correctly characterizes (i) the rising wage gap for a majority of the past 30 years and (ii) a pronounced gap at the tails of the distribution. This is key as the goal of this paper is to study whether task specialization can explain these features. On a broader level, the survey data identifies compositional differences across occupations (Table A.1 in Supporting Information), notably those occupations employing a disproportionate number of foreign workers.

Second, in regards to under-representation of foreign workers, I argue the resulting bias actually works in my favor. In particular, the Supporting Information outlines a cohort-analysis on German immigrants and highlights changes in demographics and skill measures based on representative data from the German Socio-Economic Panel (SOEP). Despite convergence in educational outcomes over the past 30 years, command of the German language among immigrants deteriorated since the 1990s. This trend is presumably driven by a changing age

structure: On average, immigrants were around 20 years old in the early 1990s. More recent cohorts are 30 years or older, thus tend to spend less time in Germany than previous generations.

If the data used in this study were representative of the entire foreign workforce, it would include a disproportionate number of workers with little to no command of the German language. Presumably, these excluded workers are disproportionately employed in occupations requiring less interactive tasks. Specialization patterns across occupations are thus likely more pronounced in reality than what is implied by the data. I, therefore, view any contributions to the wage gap stemming from natives' comparative advantage in interactive-intensive occupations a lower bound in regards to the overall foreign population.

2.3 | Measuring task content

The key variables are individual skill requirements, measured by tasks performed on the job. To provide a consistent definition of tasks, I limit the study to comparable tasks that are frequently asked throughout the sample period 1992–2018 by following Rohrbach-Schmidt and Tiemann (2013) who compare different classifications of tasks. Similar to their strategy, I include only those tasks that were questioned in at least three out of five surveys. Despite potential concerns about these discontinuities in the data, related research has shown they have only negligible impact on empirical labor market analysis (Bachmann et al., 2019). Subsequently, I follow Autor et al. (2003) and Spitz-Oener (2006) by pooling activities into $J = 5$ task categories: (i) Non-routine (NR) Analytic tasks, (ii) NR Interactive tasks, (iii) Routine (R) Cognitive tasks, (iv) R Manual tasks, and (v) NR Manual tasks. Figure B.1 in Supporting Information illustrates the process of collecting related individual activities, followed by an aggregation into broader task groups. Subsequent classification of these groups into $J = 5$ categories constitutes the task content, measured either at the individual or occupational level.

Several studies use related, yet, broader definitions of tasks. For instance, Acemoglu and Autor (2011) subsume NR Analytic and NR Interactive into “Abstract.” Similarly, R Cognitive and R Manual tasks are subsumed into “Routine” with no change in NR Manual. Abstract tasks involve strong problem-solving skills, yet, communication-heavy activities are more relevant for the interactive category. In contrast, routine tasks are characterized by following explicit rules which can be codified and thus easily automated compared with NR tasks. Last, NR Manual requires hand-eye coordination which is difficult to automate. These activities are pronounced in basic services and are disproportionately found in the lower part of the income distribution.

Following Antoniczyk et al. (2009), I define task measures T_{ijt} for worker i at time $t \in \{1992, 1999, 2006, 2012, 2018\}$ as

$$T_{ijt} = \frac{\text{No. of activities performed by } i \text{ in task category } j \text{ at time } t}{\text{Total no. of activities by } i \text{ across all } j\text{'s at time } t}, \quad (1)$$

where $j = 1$ (NR Analytic), $j = 2$ (NR Interactive), $j = 3$ (R Cognitive), $j = 4$ (R Manual), and $j = 5$ (NR Manual). This definition implies (i) $T_{ijt} \in [0, 1] \forall j$ and (ii) $\sum_j T_{ijt} = 1$. Intuitively, it thus describes the relative importance of each task group j . For example, if worker i performs two NR Analytic, two NR Interactive, and one NR Manual task, then her NR Analytic, NR Interactive, and NR Manual task content, respectively, is 0.4, 0.4, and 0.2. Therefore, 80 per cent

of her overall activities comprise abstract tasks with equal contributions from NR Analytic and NR Interactive. The remaining 20 per cent involve NR Manual activities.

In the empirical analysis I will decompose the wage gap into contributions stemming from individual and occupation-level task variation. To separate these two channels more clearly and enhance interpretation I collect T_{ijt} for each of the workers employed in occupation o at t in order to calculate leave-one-out means. By restricting the analysis to occupations with at least six workers in the full sample, I alleviate concerns surrounding outlier effects in occupations with few observations.¹² Calculating occupation-level averages for each t , however, is not practical due to data limitations. Instead, I calculate occupational averages based on sub-samples $sub \in (o_{90}, o_{00})$ for the 1990s, o_{90} , and 2000s, o_{00} , respectively¹³:

$$T_{jot} = \frac{1}{N'_{ot}} \sum_i T_{ijt_{osub}}, \quad (2)$$

where T_{jot} simply reflects occupation-specific averages for each j and both sub and N'_{ot} is the number of workers in occupation o —excluding each worker's individual task content. Note that this measure has an interpretation analogous to Equation (1), defining the importance of each task group at the occupation-level instead. As described in Section 2.1, 3-digit occupations are grouped to enhance statistical precision. To account for size effects, I weigh the task content in Equation (2) by these narrow occupational categories.

2.4 | Descriptive statistics

2.4.1 | Sample

Table 1 provides an overview of summary statistics of the full sample. Next to displaying a mean wage gap of 4 pp., it suggests foreign workers are about 2 years younger, have 4 pp. less females, and are almost twice as likely to be residing in an urban area. In regards to education outcomes, they are disproportionately concentrated among high-skilled (college degree) and less-skilled workers (No Voca. Degree), an observation encountered frequently in the literature (Card, 2005). Moreover, they have on average almost 3 years less of occupational and, respectively, firm tenure, suppressing returns to seniority (Dustmann & Meghir, 2005).¹⁴

2.4.2 | Do natives and foreigners perform the same tasks?

Overall, there are important differences in observed outcomes typically associated with wage differences. The key hypothesis in this paper, however, is that these traditional measures fail to account for idiosyncratic differences resulting from task specialization. For that to be true, we first need to observe whether native and foreign workers indeed perform a different set of tasks at the workplace. Table 2 offers some suggestive evidence in favor of this point, displaying results of an OLS regression of task j on a set of controls, notably a dummy indicating nativity.

The key takeaway from this exercise is that foreign workers on average perform less abstract tasks, up to 3 pp. less than natives, while performing more manual tasks, up to 4 pp. compared

TABLE 1 Summary statistics

	Natives		Foreigners	
	Mean	SD	Mean	SD
Log wage	2.80	(0.53)	2.76	(0.61)
Age	41.10	(11.36)	38.93	(10.23)
Female	0.45	(0.50)	0.41	(0.49)
Urban area	0.16	(0.36)	0.29	(0.45)
College degree	0.20	(0.40)	0.26	(0.44)
Vocational degree	0.72	(0.45)	0.52	(0.50)
No vocational degree	0.08	(0.28)	0.22	(0.41)
Tenure (Occ.)	20.78	(12.09)	17.93	(10.89)
Tenure (firm)	11.35	(9.95)	8.79	(8.36)
Voca. school. abroad	0.02	(0.15)	0.32	(0.47)
Foreign language	0.08	(0.27)	0.77	(0.42)
Observations	56,792		2306	

Source: BIBB/BAuA/IAB.

with natives. Importantly, this observation remains valid even if I condition on occupational FE, thereby suggesting task specialization within occupations. This finding is important in the present context as it indicates native and foreign workers accumulate different skills on the job. In models not accounting for task specialization, these discrepancies would be subsumed under unobserved heterogeneity, potentially masking important productivity differences. Economic forces such as technological change, which tend to raise the importance of abstract tasks, may thus reinforce already existing specialization patterns at the workplace and give rise to wage differences.

2.4.3 | Trends in tasks

The relative importance of tasks from 1992 to 2018 is illustrated Figure 2, displaying aggregate trends and task gaps by nativity, respectively. Unsurprisingly, routine tasks experienced a substantial drop over time in aggregate terms from more than 40 per cent in 1992 to some 25 per cent in subsequent years. This reduction has been complemented by a rise in abstract tasks. Compared with 1992, the combined share of NR Analytic and NR Interactive increased from 38 to 59 per cent by 2018 with similar contributions from both task categories.

Table A.2 in Supporting Information summarizes the evolution of occupational task measures between the 1990s and 2000s sample and highlights how occupations have experienced these trends differentially. Notably, occupations considered to be routine-intensive such as accountants and assistants experienced a substantial increase in NR Interactive. This observation is consistent with evidence on the type of activities performed by bank tellers. Bessen (2015) documents how the introduction of automated teller machines induces a reallocation away from routine cash-handling activities toward customer relationship. These trends may have

TABLE 2 OLS task regressions

	NRA	NRI	RC	RM	NRM					
Dep. var.: Foreign dummy	-0.030*** (0.005)	-0.011** (0.004)	-0.026*** (0.005)	-0.011** (0.004)	-0.008** (0.003)	-0.004 (0.003)	0.021*** (0.006)	-0.004 (0.005)	0.042*** (0.006)	0.030*** (0.005)
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Occupation dummies (3-digit)	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Mean dep. var.	0.254	0.277	0.105	0.105	0.105	0.105	0.171	0.171	0.193	0.193
Observations	59,098	59,098	59,098	59,098	59,098	59,098	59,098	59,098	59,098	59,098
R ²	0.15	0.31	0.20	0.35	0.02	0.07	0.22	0.40	0.16	0.35

Note: Controls include demographic characteristics (age, sex, metropolitan area, ability to speak foreign language), education dummies (college degree, vocational schooling, no vocational degree, country in which degree has been earned), and firm- and occupation-specific variables (firm tenure, firm tenure squared, occupational tenure, occupational tenure squared) and dummies to capture time, region (state-level), and sectoral effects. Robust standard errors are reported in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Abbreviations: NRA, NR Analytic; NRI, NR Interactive; NRM, NR Manual; RC, Routine Cognitive; RM, Routine Manual.

favored native workers disproportionately, consistent with the idea of a comparative advantage in NR Interactive tasks.

The right panel in Figure 2, however, indicates an assimilation of the average task content between both groups. Foreign workers still perform relatively more manual tasks. Yet, abstract activities have become a more integral part of their job activities. In the 1990s, natives performed some 20 pp. more abstract tasks with equal contributions from NR Analytic and NR Interactive. This gap has closed by 2018, suggesting an assimilation along the task dimension. Somewhat puzzling, this development appears to be at odds with a rising Native-Foreign Wage Gap from 7 per cent in 1992 to 13 per cent by 2018 (Figure 1).

If foreign workers assimilate in terms of education outcomes (Algan et al., 2010) and increasingly perform the same tasks as natives—then why do we not observe a convergence in wages?

3 | OB DECOMPOSITION

3.1 | Empirical model

As a benchmark, I first employ the traditional OB decomposition (Blinder, 1973; Oaxaca, 1973) to highlight the relevance of tasks as a predictor of the mean wage gap at the occupational and individual level:

$$\bar{w}_N - \bar{w}_F = \underbrace{(\bar{X}_N - \bar{X}_F)\hat{\beta}_F}_{\text{Explained Part}} + \underbrace{\bar{X}_F(\hat{\beta}_N - \hat{\beta}_F)}_{\text{Unexplained Part}} + (c_N - c_F), \quad (3)$$

where the first term captures the explained part (“Endowment effect”) due to mean differences in covariates between native (N) and foreign (F) workers. The second term reflects the residual which cannot be explained by the model (“Wage Structure effect”), including group-specific constant terms c_g for groups $g = N, F$.¹⁵ The decomposition is then implemented by running OLS by groups g and plugging sample means and coefficients into Equation (3). In the specification below, the dependent variable is the log hourly real wage $\ln w_{it}$ of individual i at time t :

$$\ln w_{it} = \alpha + \beta \mathbf{T}_{it} + \gamma \mathbf{T}_{ot} + \gamma \mathbf{X}_{it} + \delta_t + \lambda_r + \eta_s + \epsilon_{it}, \quad (4)$$

where the key variables are individual and occupational task measures in the vectors $\mathbf{T}_{it} = (T_{i1t}, T_{i2t}, \dots, T_{ijt})$ and $\mathbf{T}_{ot} = (T_{o1t}, T_{o2t}, \dots, T_{oit})$, respectively, comprising NR Analytic, NR Interactive, R Manual and NR Manual task measures. Since $\sum_j T_{ijt} = 1$, one task group needs to be excluded, in this case R Cognitive.¹⁶ The benchmark specification includes occupation-level task measures \mathbf{T}_{jo} instead of \mathbf{T}_{it} to provide a reference to research utilizing occupational data. Subsequently, individual-level task measures are included to test whether worker-level information on tasks adds unique explanatory power. Augmenting Equation (4) by occupational dummies stresses the importance of idiosyncratic factors embodied in the task content by exploring task specialization *within* occupations.

The vector \mathbf{X}_{it} comprises control variables, including demographic characteristics (age, sex, metropolitan area, ability to speak foreign language), education dummies (college degree, vocational schooling, no vocational degree, country in which degree has been earned), and firm-

and occupation-specific variables (firm tenure, firm tenure squared, occupational tenure, occupational tenure squared, firm size indicator). Moreover, δ , λ , and η , respectively, denote 4 time, 10 region (state-level), and 33 sectoral dummies.

Two control variables are worth discussing in more detail. First, previous research points to foreign worker's inability to speak the native tongue as a common unobservable variable, reflecting a major reason for the limited substitutability between native and foreign workers (Dustmann & van Soest, 2002; Imai et al., 2018; Lewis, 2011). I am not able to directly control for this feature as only foreign workers with sufficient knowledge of the German language have been surveyed. Therefore, I resort to languages not commonly taught in school and associated with minorities as a proxy for language barriers.¹⁷ Second, it has been argued qualifications earned abroad have little to no returns in the German labor market due to lack of recognition and are thus a key determinant of wage differentials (Basilio et al., 2017). To account for the imperfect transferability of human capital, I create a dummy if a worker earned her qualifications in a foreign country. Both of these variables are closely related to the specialization patterns postulated in this study: Natives specialize in interactive tasks while foreigners specialize in manual tasks. Excluding them would otherwise confound effects attributed to occupational obstacles versus workplace heterogeneity resulting from task specialization.

3.2 | Results

Table 3 summarizes the key results from this baseline decomposition. The mean wage difference of 4.2 per cent can almost entirely be explained by mean differences in observable outcomes. Estimates in column (1) suggest that 36 per cent of the wage gap are attributed to occupational choice in the restricted model with no task measures (0.015/0.042). In comparison, columns (2) and (3), respectively, introduce occupation-level and individual-level task measures. Notably, the two task dimensions pick up different types of variation, thereby in line with previous findings (Autor & Handel, 2013; Cassidy, 2017; Rohrbach-Schmidt, 2019). Occupation-level measures suggest strong explanatory power in either abstract task measure, while the wage should in fact be smaller based on manual activities.

In contrast, explanatory power at the individual level is centered around variation in interactive and manual tasks, thus consistent with the comparative advantage hypothesized in this paper. Including both task measures (column 4) confirm this observation.

Column (5) proxies within-occupation task specialization by conditioning the wage gap on worker-level tasks and occupational FE. If variation in tasks merely reflects differences in occupational requirements, we would expect the coefficients on tasks to be insignificant. Nonetheless, conditional on occupational choice, variation in task measures remains significant and contributes 24 per cent to the mean gap (0.010/0.042). It could be argued, however, that the within-occupation variation is merely a statistical artefact. If occupations are grouped, the resulting residual variation may erroneously be assigned to task specialization.

To get a sense for the magnitude of this aggregation bias, column (6) summarizes results for a model with 219 3-digit occupations as opposed to 86 grouped occupations. This specification yields the same results, suggesting any potential measurement bias from classifying occupations is negligible. Moving forward, I will thus keep using 86 grouped occupations to maintain greater statistical precision.

TABLE 3 Tasks and the Native-Foreign Wage Gap—OB decomposition

Dependent variable: Log hourly real wage	(1)	(2)	(3)	(4)	(5)	(6)
Native-Foreign Wage Gap	0.042* (0.025)	0.042 (0.026)	0.042 (0.026)	0.042 (0.026)	0.042* (0.025)	0.042* (0.025)
Explained	0.040*** (0.011)	0.035*** (0.011)	0.028** (0.011)	0.032*** (0.011)	0.037*** (0.011)	0.037*** (0.012)
Unexplained	0.002 (0.024)	0.007 (0.025)	0.015 (0.025)	0.011 (0.025)	0.005 (0.024)	0.005 (0.024)
Occupation	0.015*** (0.004)				0.003 (0.004)	0.003 (0.004)
NR Analytic (Occup.)		0.026*** (0.004)		0.021*** (0.004)		
NR Interactive (Occup.)		0.013*** (0.002)		0.010*** (0.002)		
Routine Manual (Occup.)		-0.014*** (0.003)		-0.015*** (0.003)		
NR Manual (Occup.)		-0.007*** (0.002)		-0.009*** (0.002)		
NR Analytic (Indiv.)			0.003 (0.002)	0.002 (0.001)	0.002 (0.001)	0.002 (0.001)
NR Interactive (Indiv.)			0.003*** (0.001)	0.004*** (0.001)	0.004*** (0.001)	0.004*** (0.001)
Routine Manual (Indiv.)			0.002* (0.001)	0.001* (0.001)	0.001* (0.001)	0.001* (0.001)
NR Manual (Indiv.)			0.009*** (0.002)	0.006*** (0.001)	0.005*** (0.001)	0.005*** (0.001)

(Continues)

TABLE 3 (Continued)

Dependent variable: Log hourly real wage	(1)	(2)	(3)	(4)	(5)	(6)
Controls	✓	✓	✓	✓	✓	✓
Occupation dummies (grouped)	✓				✓	
Occupation dummies (3-digit)						✓
Task measure (occupational)		✓		✓		
Task measure (individual)			✓	✓	✓	✓
Observations	59,098	59,098	59,098	59,098	59,098	59,098

Note: The decomposition is based on regressions of log wages by nativity on, depending on specification, individual task measures (“Indiv.”) and/ or occupation-level task measures (“Occup.”). Controls include demographic characteristics (age, sex, metropolitan area, ability to speak foreign language), education dummies (college degree, vocational schooling, no vocational degree, country in which degree has been earned), and firm- and occupation-specific variables (firm tenure, firm tenure squared, occupational tenure, occupational tenure squared) and dummies to capture time, region (state-level), sectoral, and, in case of models (1), (5) and (6), occupation FE effects. Models (1) and (5) condition on a total of 86 grouped 3-digit occupational dummies.

This allows for more robust calculation of occupation-level task measures which are used in models (2) and (4). Model (6) uses 219 original 3-digit occupational dummies instead, allowing for a more granular classification. Robust standard errors are reported in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4 | RIF DECOMPOSITION

4.1 | Methodological background

A key limitation of the conventional OB decomposition is its inability to evaluate the impact of single covariates for any distributional statistic but the sample mean. However, the wage gap varies for workers at different parts of the wage distribution which motivates a more flexible approach to go beyond the mean. Moreover, it is reasonable to assume that individual characteristics have differential contributions to the wage gap along the distribution. For instance, performing more abstract tasks may affect high-wage workers differentially as they are typically specialized in those activities, thus being more equipped in executing them compared with low-wage earners.

One way to decompose distributional wage effects is to make use of an influence function (IF), a statistical tool to assess the influence of a single observation on a distributional statistic. A decomposition based on an IF allows wages to have unique responses at deciles resulting from a small disturbance in the data. Put differently, it enables the researcher to answer the following question: What is the effect on wages if the distribution of abstract tasks shifts to the right?

Firpo et al. (2009) show formally how to construct an IF as a measure of robustness and, importantly, demonstrate how this tool can be used to perform unconditional quantile regressions (UQR).¹⁸ Let $v(F_Y)$ denote a distributional statistic of interest for the cumulative wage distribution F_Y . Moreover, let $F_{Y(N)}$ denote the cumulative wage distribution observed for native workers (N) and $F_{Y(F)}$ the cumulative wage distribution observed for foreign workers (F). Consequently, the $IF(y;v;F_{Y(g)})$ measures the response in the distributional statistic $v(F_{Y(g)})$ resulting from a small perturbation of the data at point y for each $g = N, F$.

In general, an IF is centered around zero. To get unbiased estimates, a recentered RIF needs to be constructed, i.e. center the IF around the statistic of interest by simply adding that statistic: $RIF(y;v;F_{Y(g)}) = IF(y;v;F_{Y(g)}) + v(F_{Y(g)})$. Conditional on covariates X , we can, therefore, formulate the RIF in conditional expectation as $E(RIF(y;v;F_{Y(g)})|X) = X\beta_g$ where the coefficients β_g provide a linear approximation of a change in X on $v(F_{Y(g)})$ for each $g = N, F$. In the present context, the statistic of interest are log wages at decile p_τ , $\tau = 0.1, \dots, 0.9$. Collecting the β_g 's and using $RIF(y;v;F_{Y(g)})$ as dependent variable, the contributions of X can be decomposed as follows:

$$RIF_\tau^N - RIF_\tau^F = \underbrace{(\bar{X}_\tau^N - \bar{X}_\tau^F)\hat{\beta}_\tau^F}_{\text{Explained Part}} + \underbrace{\bar{X}_\tau^F(\hat{\beta}_\tau^N - \hat{\beta}_\tau^F)}_{\text{Unexplained Part}} + (c_\tau^N - c_\tau^F). \quad (5)$$

Note that Equation (5) is merely a generalization of the conventional OB method depicted in (4), applying the decomposition along the wage distribution and replacing mean wages for $g = N, F$ by their corresponding RIF on the LHS.

A RIF-decomposition has several key features that make it suitable for this study. First, it provides a linear approximation of non-linear functions, thus making the method flexible in the sense that it can be implemented for most commonly used distributional statistics. Second, the impact on the statistic of interest can be easily implemented using OLS regressions. Third, compared with other detailed decomposition methods, the empirical approach followed here is path independent, i.e. the order of covariates is irrelevant. Fourth, the estimated coefficients have an intuitive interpretation as they reflect the marginal effect of a change in a covariate evaluated at each desired statistic. Following Firpo et al. (2009), $RIF(y;v;F_{Y(g)})$ is specified as follows:

$$RIF_g(w_g, p_\tau) = \frac{\tau - I(w_g \leq p_\tau)}{f_{w_g}(p_\tau)} + p_\tau, \quad (6)$$

where the first term represents $IF(y; v; F_{Y(g)})$ and the second term represents the statistic of interest, namely the log wage at decile p_τ , $\tau = 0.1, \dots, 0.9$. The IF itself is a function of the marginal density of wage w_g associated with p_τ and an indicator, $I(w_g \leq p_\tau)$, suggesting if an observed wage for $g = N, F$ falls below decile p_τ .

In practice, a RIF decomposition can be implemented in two steps. First, using kernel methods, compute the wage density associated with $g = N, F$ and plug the estimated densities into Equation (6). Second, replace the dependent variable by its corresponding RIF from the first step and run simple quantile regressions:

$$E[RIF_g(\ln w_{it}, p_\tau | \mathbf{T}, \mathbf{X})] = \alpha + \beta_1 \mathbf{T}_{it} + \beta_2 \mathbf{T}_{ot} + \gamma \mathbf{X}_{it} + \delta_t + \lambda_r + \eta_s + \epsilon_{it}, \quad (7)$$

which generalizes the OB counterpart in Equation (4) with the same set of variables. By replacing $\ln w_{it}$ by the group-specific RIF, we can identify distinct distributional effects of changes in tasks on the wage gap. As common in linear regression-based frameworks, however, the estimates merely provide a local approximation around the decile of interest. On the other hand, a linear approach has the advantage that it is straightforward to invert the deciles by simply dividing an indicator function by corresponding densities as in Equation (6). Therefore, there is no need to evaluate the global impact, mitigating potential concerns about monotonicity (Firpo et al., 2009).

There are moreover additional concerns about the precision of the estimates resulting from the rather small sample. To address this data limitation, inference is conducted by bootstrapping standard errors with 100 replications. The illustrations of the RIF Decomposition below include 95% Confidence Intervals to highlight the degree of certainty of the point estimates.

4.2 | RIF decomposition: Baseline results

Before analysing the contributions of tasks, let us first inspect the model's ability to explain the Native-Foreign Wage Gap across the wage distribution. Along the 90–10 range, Figure 3 illustrates that the wage gap drops from 13 per cent at the 1st decile to 7 per cent at the 9th decile. Overall, the RIF Decomposition does a good job capturing the variation in the wage gap. There is large uncertainty around the estimates at the 9th decile, however, suggesting that around a third of the gap among high-wage earners can be explained by the model. Aside from the 9th, the null hypothesis of explaining the entire model cannot be rejected for all remaining deciles. Due to greater statistical precision, I will, therefore, consider the 8th decile to evaluate the impact of tasks on high-wage earners.

4.2.1 | “Between-occupation effects”

To gauge the relative importance of different task dimensions, I compare explanatory power of variation at the individual level relative to the occupation-level. Occupational variation

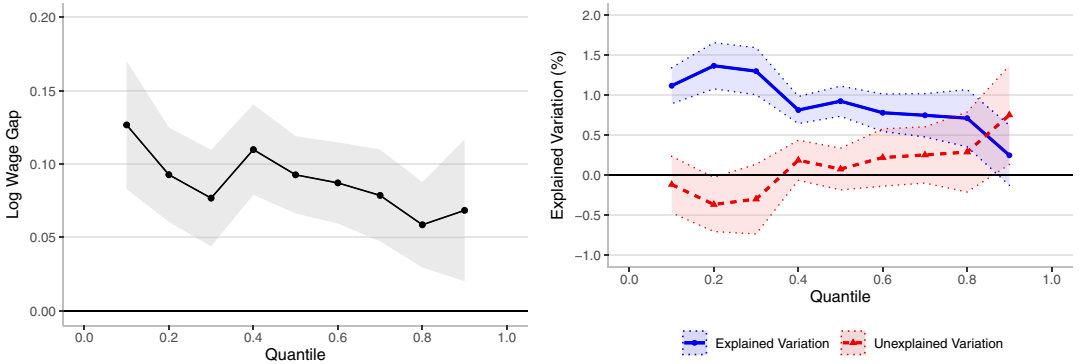


FIGURE 3 German Native-Foreign Wage Gap, 1992–2018. Point estimates are displayed with a 95% confidence interval

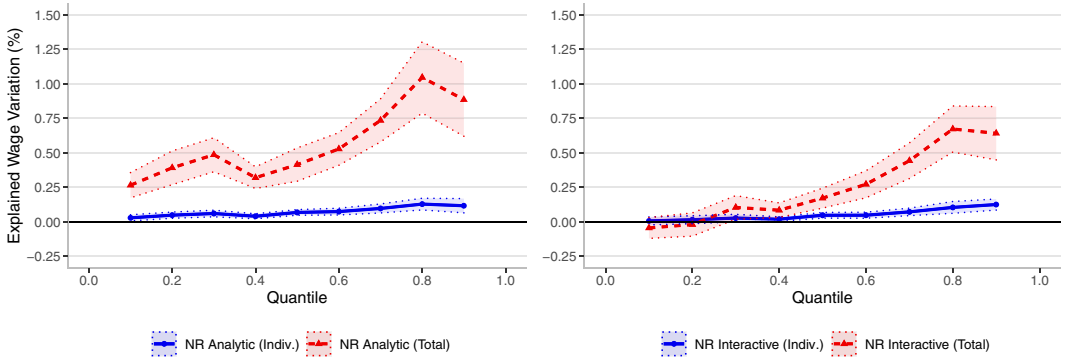
approximates comparative advantages in occupational choice, assumed by most of the existing literature (Haas et al., 2013; Peri & Sparber, 2009, 2011). In comparison, individual-level variation highlights the role of idiosyncratic differences that go beyond occupation-specific task assignments. Decomposing wage differences among these two dimensions, thus, allow a comparison of the relative importance of occupational segregation versus individual heterogeneity. Importantly, if idiosyncratic differences are a significant contributor to the wage gap, conventional occupation-level measures mask underlying heterogeneity in task specialization.

Let $\Delta T_{j,\tau} = \bar{T}_{j,\tau}^N - \bar{T}_{j,\tau}^F$ denote the difference in the overall task content in j at τ between foreign and native workers and let $\Delta X_{\tau}' = \bar{X}_{\tau}^{N'} - \bar{X}_{\tau}^{F'}$ denote the difference at τ between both groups in the remaining covariates. Recognizing that the unexplained variation in wages is overall small, implying that Equation (5) can be approximated by $RIF_{\tau}^N - RIF_{\tau}^F \approx (\bar{X}_{\tau}^N - \bar{X}_{\tau}^F) \hat{\beta}_{\tau}^F$, I expand on Equation (5) by decomposing the wage gap into its task-related components:

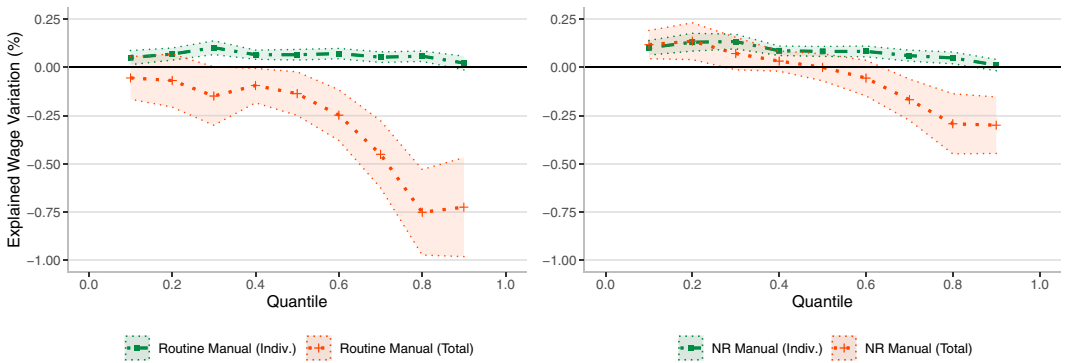
$$\begin{aligned}
 \underbrace{RIF_{\tau}^N - RIF_{\tau}^F}_{\text{Explained Wage Gap}} &= \sum_{j=1}^J \underbrace{\Delta T_{j,\tau} \hat{\beta}_{j,\tau}^N}_{\text{Total Task Variation}} + \underbrace{\Delta X_{\tau}' \hat{\beta}_{\tau}^N}_{\text{Controls}} \\
 &= \sum_{j=1}^J \left[\underbrace{\left(\bar{T}_{ij,\tau}^N - \bar{T}_{ij,\tau}^F \right) \hat{\beta}_{j(i),\tau}^F}_{\text{Individual-level Tasks}} + \underbrace{\left(\bar{T}_{jo,\tau}^N - \bar{T}_{jo,\tau}^F \right) \hat{\beta}_{j(o),\tau}^F}_{\text{Occupation-level Tasks}} \right] + \Delta X_{\tau}' \hat{\beta}_{\tau}^F \quad (8) \\
 &\equiv \sum_{j=1}^J \left[\Delta T_{j,\tau}^I \hat{\beta}_{j(i),\tau}^F + \Delta T_{j,\tau}^O \hat{\beta}_{j(o),\tau}^F \right] + \Delta X_{\tau}' \hat{\beta}_{\tau}^F,
 \end{aligned}$$

where the total contribution of tasks is disaggregated into variation at the individual level, $\Delta T_{j,\tau}^I$, and occupation-level, $\Delta T_{j,\tau}^O$, across all $J = 5$ task categories. Moreover, note that both task dimensions are evaluated at different coefficients. While $\Delta T_{j,\tau}^I$ is evaluated at coefficients resulting from variation at the individual level (i.e. $\hat{\beta}_{j(i),\tau}^F$), $\Delta T_{j,\tau}^O$ is evaluated at coefficients resulting from variation at the occupational level (i.e. $\hat{\beta}_{j(o),\tau}^F$).

Figure 4 illustrates this comparison for each j and τ . Evaluated at the 8th decile, it shows that $\Delta T_{j,\tau} = 67$ per cent of the wage gap among high-wage earners can be contributed to total variation in NR Interactive. Among that, $\Delta T_{j,\tau}^I = 10\%$ is due to idiosyncratic differences. Since $\Delta T_{j,\tau}^O = \Delta T_{j,\tau} - \Delta T_{j,\tau}^I$, the vertical distance between both lines indicates that 67 per cent – 10 per



(A) Abstract Tasks



(B) Manual Tasks

FIGURE 4 Baseline decomposition: Individual-level task variation relative to occupation-level variation, 1992–2018. The vertical difference between contributions from individual-level (“Indiv.,”) variation in tasks and total variation (“Total”) reflects contributions from occupation-level variation in tasks. Therefore, the smaller this vertical gap, the more important is idiosyncratic variation relative to occupational variation. Point estimates are displayed with a 95% confidence interval

cent = 57 per cent of the explained gap for high-wage earners is associated with occupational segregation in the interactive task content, i.e. occupation-level variation.

A consistent way to assess the relative importance of task dimensions is to compare the ratio of individual- to occupation-level variation (IOV) in j at τ :

$$IOV_j^\tau = \frac{\Delta T_{j,\tau}^I}{\Delta T_{j,\tau}^O} = \frac{\Delta T_{j,\tau}^I}{\left(\Delta T_{j,\tau} - \Delta T_{j,\tau}^I\right)} \quad (9)$$

implying that individual- and occupation-level variation in tasks are equally important if $IOV_j^\tau = 1$. Examining the role of abstract tasks among high-wage earners first, I find that $IOV_{NR}^{\tau=8} = 0.18 \left(\frac{0.10}{0.57}\right)$. Consequently, occupational segregation with respect to the interactive task domain is 5.5 times as important. To put this finding in context: Occupation-level variation in

tasks is even more pronounced in regards to NR Analytic. Exemplary, consider $IOV_{NRA}^{\tau=8} = 0.14$ ($\frac{0.13}{0.92}$), suggesting occupational segregation is around seven times more important with respect to the analytic task domain. Below the median, both task dimensions point to a diminished role of variation in abstract tasks to explain wage differences among low-wage earners. This is true even more so for individual-level variation compared with occupation-level task measures. In a nutshell, idiosyncratic differences among high-wage earners are relatively more pronounced in interactive activities, reinforcing the occupational specialization patterns among US professionals (Peri & Sparber, 2011).

Moving on, panel (b) displays the economic relevance of tasks in manual activities. Notably, individual-level variation is the sole contributor of variation in tasks among low-wage earners. Exemplary, $IOV_{NRM}^{\tau=1} \rightarrow \infty$ as occupation-level contributions are effectively zero. Similar results are found for both types of manual tasks around and below the median. Wage gaps are in fact suggested to be even smaller by at least 30 per cent based on variation in occupational task measures among high-wage earners. In contrast, both individual-level manual measures contribute a steady 5–13 per cent to the gap at all but the highest decile.

Taking Stock: The contribution of task specialization to the wage gap. To get a better sense about the overall importance of idiosyncratic differences in tasks, we can simply add up the individual-level contributions across all task groups for each decile. This simple exercise suggests that total contributions to the wage gap stemming from idiosyncratic variation in tasks ranges from 19 per cent at the 4th decile to 34 per cent at the 8th decile. Therefore, above results reflect long-term trends from 1992 to 2018 and suggest that, collectively, individual-level task measures contribute up to 34 per cent to the wage gap.

Notably, the Native-Foreign Wage Gap is driven by (i) variation in abstract task measures near the top of the distribution and (ii) variation in manual tasks among workers near the bottom and, to a lesser extent, middle parts of the distribution. Not only do we learn from this exercise that idiosyncratic differences in tasks represent important determinants of the wage gap. The findings moreover enhance our understanding about the role of manual tasks. Prior research, utilizing occupation-level variation (Peri & Sparber, 2009), has focused on specialization in those activities in the context of low-wage earners. However, individual-level evidence suggests specialization in manual tasks also contributes to wage gaps among mid-skilled and, to a lesser extent, even high-skilled workers.

From a methodological perspective, pronounced task specialization near the tails of the distribution reveals distributional implications a standard OB decomposition fails to address. Conventional decomposition methods thus understate the impact of tasks on the Native-Foreign Wage Gap, a novel finding that has not yet been documented in the literature.

4.2.2 | “Within-occupation effects”

The economic relevance of individual-level variation in tasks is consistent with rising heterogeneity in worker- and firm-specific factors. Using German establishment-level data, Card et al. (2013) argue that more than half of the wage gap between high- and less-educated workers in Germany is due to greater dispersion of average workplace premia. Applying this insight to the migration context, Dostie et al. (2020) show that different hiring patterns among firms contribute around 20 per cent to the Native-Foreign Wage Gap in Canada.

The task-based migration literature, on the other hand, has so far focused on occupational variation as a key driver for the wage gap. To shed more light on workplace heterogeneity, the

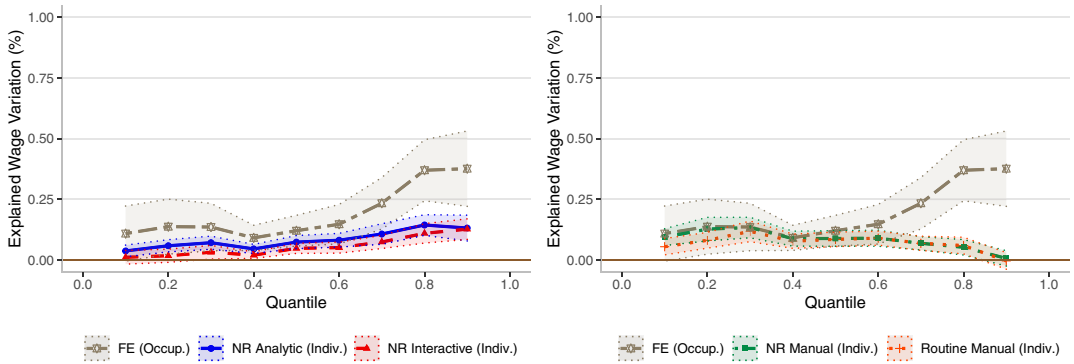


FIGURE 5 Decomposition with occupational FE: Within-occupation task specialization, 1992–2018. Point estimates are displayed with a 95% confidence interval

ensuing analysis explores the evolution of task specialization *within* occupations. Doing so, I augment Equation (7) by decomposing contributions of individual-level task measures to the Native-Foreign Wage Gap conditional on occupational FE, permitting an interpretation of Within-Occupation Task Specialization (Autor & Handel, 2013). Results of this exercise can be found in Figure 5.

Evaluated at the 8th decile, occupational characteristics contribute up to 37 per cent among high-wage earners with comparably modest contributions on the order of 10–15 per cent around and below the median. With respect to task measures, the findings are qualitatively similar to Between-Occupation effects presented in Section 4.2.1.¹⁹ Abstract tasks are more important in explaining the gap among high-wage earners as variation in interactive tasks, for instance, contributes up to 11 per cent for these workers. In comparison, variation in both manual tasks combined explains up to 25 per cent. Reaffirming previous results, these effects are more pronounced at or below the median.

Combined, these findings are consistent with the hypothesis that task specialization extends occupational borders and likewise takes place within occupations. In light of the selection bias in the data, however, caution is warranted in the interpretation of the key findings of this section. Workers excluded from the sample have little to no command of the German language. While this exclusion likely exacerbates specialization patterns between natives and foreign workers across occupations, the impact on task specialization within occupations is less clear.

5 | ROBUSTNESS

The baseline results above reflect long-term trends from 1992 to 2018. This period was characterized by rising Technological Change, Globalization, and large migration movements, just to name a few. While I view my findings as possible implications of these structural changes, the evidence on task specialization may nonetheless be the byproduct of spurious relationships. I, therefore, provide three robustness exercises to explicitly account for these developments. Note that all following specifications are based on the “within-occupation” model, i.e. individual-level task measures conditioned on occupational FE.

First, technological change has changed occupational structures profoundly, leading to differential employment growth over time (Boehm et al., 2019). I, therefore, modify the baseline

specification by accounting for relative employment size of each occupation at time t . Second, I account for the fact that size and composition of the foreign workforce have changed over time. Third, globalization has accelerated over the past 30 years, affecting open economies such as Germany in particular. I thus include measures for time-varying trade exposure to address this global trend.

5.1 | Technological change

A large literature has explored the labor market impact of technological change, documenting job and wage polarization in response to changes in demand for tasks.²⁰ These forces have led to a reallocation of workers across occupations with different requirements on tasks to be performed. While I view my baseline results as implications of this development, one might argue the evidence on task specialization is confounded by broader occupational changes. For instance, Figure 6 highlights that foreign workers are disproportionately employed in occupations that have been shrinking since the 1990s. If this is the case because they are drawn to particular occupations for reasons unrelated to the underlying task composition, my findings would be indeed confounded.

I thus augment wage Equation (7) by (i) the relative employment in occupation o at time t and (ii) the share of foreign workforce employed in o , thus accounting for the variation depicted in Figure 6. The panels in Figure D.1 in Appendix D.1 in Supporting Information suggest the key takeaways on task specialization remain robust, in particular with respect to most pronounced contributions near the tails of the wage distribution. Moreover, note that variation in occupational composition, in terms of share of foreign workers, is quite important in lower

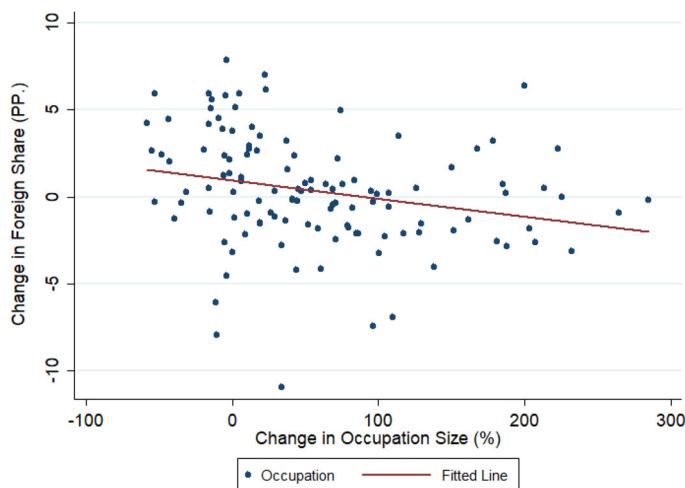


FIGURE 6 Change in occupation size versus change in share of foreign workers, 1992–2018. The graph compares changes in occupation sizes to compositional changes with respect to the foreign workforce. The average employment size for each occupation is calculated for the data from the 1990s and 2000s, respectively. Following the same procedure, I calculate the foreign share of the workforce for each time period. Along the vertical axis the graph then depicts the change in foreign employment share and plots it against changes in total occupational employment size across the horizontal axis. One outlier has been removed for visual clarity (watch-/clockmakers). *Source:* SIAB-R7517, own calculations

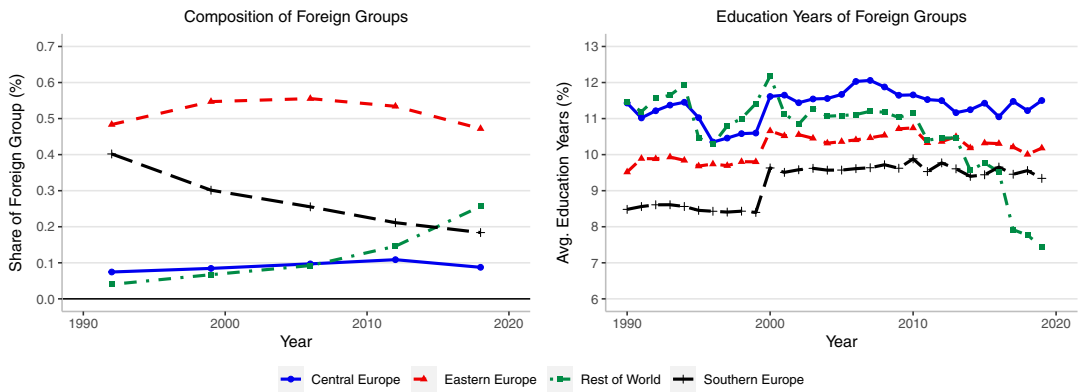


FIGURE 7 Immigrants & education outcomes: Cohort-comparison in Germany, 1992–2019. *Source:* SOEP v36, own calculations

parts of the distribution and accounts for up to 25 per cent of the wage gap (Figure D.2 in Supporting Information). Differential growth in employment size of occupations, on the other hand, is not important.

5.2 | Size & composition of foreign workforce

Germany has experienced a change in its immigrant composition over the last 30 years. Prior to the 1990s, most immigrants originated from Central and Southern Europe. Ever since the downfall of the Iron Curtain, however, there has been an increasing shift toward Immigration from Eastern Europe as illustrated in Figure 7. This evolution is important as schooling outcomes, such as average years of education, differ depending on region of origin and may thus confound the results on task specialization. There has been a substantial drop in schooling among immigrants from outside of Europe, the group displaying the strongest population growth in the 2000s. Notably, the sharp drop-off in schooling for “Rest of the World” coincides with the refugee crisis around 2015, suggesting this exercise also accounts for different reasons to migrate (i.e. economic migration vs refugee).

Figure D.4 in Appendix D.2.1 in Supporting Information displays the results of a robustness check in which I augment wage Equation (7) by accounting for compositional and skill differences of foreign workers over time. Overall, their inclusion does not affect the findings on task specialization. In particular, changes in the composition of the foreign workforce are irrelevant as all contributions are absorbed by skill differences (Figure D.4 in Supporting Information). Notably, the wage gap should actually be smaller among high-wage earners based on schooling years. This makes sense as this group presumably contains a disproportionate number of economic migrants from Europe whose schooling improved in recent decades.²¹

Moreover, to account for the overall growth in immigrant inflows in recent decades, I repeat above exercise and simply replace compositional changes by the national share of foreign workforce. The results of this exercise can be found in Figures D.6 in Appendix D.2.2 in Supporting Information with no major changes in interpretation.²²

5.3 | Globalization

The last robustness exercise addresses Germany's rising trade exposure, accompanied by trade liberalization in Europe and the rise of China, among others. Globalization has been shown to have similar effects as technological change by contributing to the polarization of labor markets and subsequent worker reallocation (Becker & Muendler, 2015). To lend further credence to my baseline results I collect data on imports and exports from the Federal Statistical Office of Germany and add those up to construct a measure for trade exposure.²³

I include this measure in wage Equation (7) along with interactions with industry dummies. This way I account for differential exposure to globalization at the sectoral level. Re-running the decomposition as before, the output of this specification is displayed in Figure D.8 in Appendix D.3 in Supporting Information. Clearly, evidence on task specialization remains statistically and economically significant, in line with all previous robustness checks.

6 | CONCLUSIONS

Using individual-level data from a series of German employment surveys, this paper studies the Native-Foreign Wage Gap and presents evidence of task specialization as a contributing factor to its widening in recent decades. I observe the number and type of activities workers, suggesting a key role is attributed to variation in tasks. Employing RIF Decompositions demonstrates distributional implications as task specialization is especially relevant for low- and high-wage earners. Combining all task measures, individual-level variation in tasks can explain up to 34 per cent of the wage gap near the top of the wage distribution. Much of this explanatory power can be attributed to differences with respect to interactive and manual task measures.

Natives are thus utilizing their interpersonal skills *within* occupations, adding important insight to a growing literature documenting comparative advantages in the choice of communication-intensive occupations. Highlighting the role of task specialization at the individual level offers a new perspective on the imperfect substitutability of native and foreign workers in the production function—a feature that is at the core of small migration-induced wage effects. While not explicitly explored in this paper, within-occupation task specialization between natives and foreigners is consistent with an outward shift of the production function, giving rise to production complementarities in spirit of Gunadi (2019) and Ma (2020). If true, research estimating structural models to recover wage elasticities may have understated migration-induced wage *gains*.²⁴ I leave this question for future research.

Relatedly, a large body in the literature has documented rising levels of automation as a result of technological change (Autor & Dorn, 2013; Senfleben & Wielandt, 2014) and offshoring resulting from globalization (Becker & Muendler, 2015). These forces have contributed to job polarization, inducing workers who previously performed routine-intensive tasks to reallocate to jobs with a different task mix. Economic theory posits workers reallocate based on comparative advantage, finding some support in empirical research (Boehm, 2020; Gottschalk et al., 2015). As abstract tasks generally pay higher returns than manual tasks, this reallocation of tasks has consequently created winners and losers. While I am silent on the underlying mechanisms, my findings are consistent with this literature, suggesting natives utilize their comparative advantage in (more rewarding) interactive tasks while foreigners utilize their comparative advantage in (less rewarding) manual tasks. I thus view the key takeaways of this paper as one implication of rising levels of technological change and globalization. Further

research may elaborate on the link between the documented specialization patterns and those structural changes more explicitly.

Last, the results of this study have important policy implications on the integration of immigrant workers. Worldwide, countries counter aging populations by competing for the best talents. The German Government has recognized this problem by implementing policies to improve the recognition of vocational qualifications earned abroad with the *Federal Recognition Act* of 2012²⁵ and the *Skilled Immigration Act* of 2020. Early evaluations of the *Federal Recognition Act* show promising improvements in terms of labor market entry.²⁶ Removing occupational barriers thus allows for greater sorting according to comparative advantage in the occupational choice. On top of that, the findings in the present study suggest these policies may further trickle down to enhanced specialization within occupations and thus ensure an even more efficient sorting process. On the flipside, this specialization appears to be associated with greater wage inequality between natives and foreigners as interactive tasks tend to be compensated better than manual ones. It is thus not entirely clear to what extent foreign workers benefit in terms of wage outcomes and whether these specialization patterns make outside options with weaker language barriers (e.g. English-speaking countries) more attractive. I leave this analysis on policy implications for future research.

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ENDNOTES

- ¹ See Acemoglu and Autor (2011), Atalay et al. (2018, 2020), Autor et al. (2003), Beaudry et al. (2016), Deming (2017), Hershbein and Kahn (2018), Modestino et al. (2019), and Spitz-Oener (2006) who, using different data and methods, document evidence that ties higher skill requirements to skill-biased technological change.
- ² Workers are distinguished by citizenship, that is, to be classified as “native,” one must have the German citizenship. While the sample focuses on people who live in West Germany at the time of the survey, the data does not consistently provide information on the birthplace. As a consequence, workers born in East Germany are likewise considered natives despite possible differences in quality of education and experience (Klein et al., 2019; Riphahn & Trübshwetter, 2013).
- ³ Covering a long-term horizon is essential in the context of this paper. As will be discussed in more detail in Section 2.4, the Native-Foreign Wage Gap increased steadily since 1992. Thus, tracing out contributions to the gap from different economic sources and different periods is necessary to get a better sense for underlying causes of this trend.
- ⁴ See Autor and Dorn (2013), Autor et al. (2003), Böckerman et al. (2019), Goos and Manning (2007), Goos et al. (2014), Michaels et al. (2014), Senfleben and Wielandt (2014), and Spitz-Oener (2006).
- ⁵ See Aldashev et al. (2008), Dostie et al. (2020), Lehmer and Ludsteck (2011), and Lessem and Sanders (2013).
- ⁶ For instance, see Cortes et al. (2021) and Rinawi and Backes-Gellner (2019) for two recent task-based studies on aggregate wage inequality in the German context.

- ⁷ The 1992 edition of the employment survey simply asks Yes/No questions on whether workers perform a task. Starting in 1998, they were asked if they perform tasks (i) often, (ii) sometimes, or (iii) never. In those cases, workers are coded to perform any given task only if they perform it “often.”
- ⁸ The conversion tables (in German language) can be found under the following link: <https://statistik.arbeitsagentur.de/Navigation/Statistik/Grundlagen/Klassifikationen/Klassifikation-der-Berufe/KldB2010/Arbeitshilfen/Umsteigeschluesel/Umsteigeschluesel-Nav.html> (Date accessed: 06/2/2021).
- ⁹ The data can be downloaded here: https://www.destatis.de/DE/Themen/Wirtschaft/Preise/Verbraucherpreisindex/_inhalt.html (Date accessed: 11/08/2021).
- ¹⁰ See the following link: <https://statistik.arbeitsagentur.de/Statistikdaten/Detail/201712/analyse/analyse-arbeitsmarkt-zeitreihen/analyse-arbeitsmarkt-zeitreihen-d-0-201712-pdf.pdf>, P. 30 (Date accessed: 6/2/2021).
- ¹¹ Please see: <https://eduardstorm.com/research/>
- ¹² More restrictive sample selection with at least 10 observations do not have major effects on the key results discussed later, yet, it does introduce more noise by reducing the sample size by about 10 per cent.
- ¹³ Performing a decomposition on a single occupation-level task measure for the entire sample enhances the statistical precision of the analysis. However, as pointed out in Atalay et al. (2020), fixing the task content at some point t in the past misses important job-specific trends resulting from Technological Change and Globalization. Ignoring these trends erroneously attributes a disproportionate amount of variation in tasks is attributed to idiosyncratic differences.
- ¹⁴ Moreover, note there are 2–8 per cent of workers classified as natives who either acquired vocational schooling abroad or grew up in a household speaking a foreign language. Some of these observations presumably reflect German citizens with a migration background because, for instance, their parents immigrated to Germany. While, in principle, these workers contaminate the analysis to some extent, the relatively small share suggests they do not affect the key results in a material way.
- ¹⁵ See Fortin et al. (2011) for a more thorough discussion on decomposition methods.
- ¹⁶ Omitting R Cognitive is not entirely arbitrary. In particular, choosing this task as the reference group is conform with the key hypothesis in this paper: Native workers specialize in interactive tasks, while foreign workers specialize in manual tasks in an environment characterized by polarization. Hence, as a rising number of routine tasks are being automated, workers need to be reallocated to perform more abstract and manual tasks instead.
- ¹⁷ Specifically, I control for fluency in the following languages: Spanish, Turkish, Italian, Greek, Portuguese, Russian, Polish, and Arabic.
- ¹⁸ In essence, an unconditional quantile merely describes the marginal distribution of the random variable of interest. Compared to more common conditional quantile regressions (CQR), the UQR framework is more general in nature and thus offers a more intuitive interpretation from a policy standpoint. In a traditional CQR setting the interest lies in the conditional expectation of the outcome variable for specific values of covariates. However, a more substantive analysis may be more interested in the effects of changes in the *unconditional* expectation of the outcome variable in response to a change in the unconditional distribution of covariates. For example, technological change has been responsible for widespread trends pertaining to job and wage polarization. From a policy perspective, it is thus of great interest how general phenomena such as rising skill requirements at the job affect the entire (working) population and how these trends translate into changes along the wage distribution. Hence, performing UQR permits more interpretable results, for example, marginalizing changes in task specialization over distributions of remaining covariates—as opposed to specific comparisons of different outcomes of tasks.
- ¹⁹ This observation suggests large-scale macroeconomic trends such as rising levels of Globalization and Technological Change do not confound the results in a substantial manner. Both clearly have an impact on occupational structures, for example, by accelerating polarization, thus possibly contaminating effects on “Between-Occupation” results. Yet, workers within those occupations faced the same kind of exposure. Similar results for “Within-Occupation” results thus suggests task specialization is a first-order contributor to the wage gap and does not merely accentuate Globalization or Technological Change. I account for those confounding factors more explicitly in Section 5.

- ²⁰ See, among others, Autor et al. (2003); Spitz-Oener (2006); Goos and Manning (2007); Autor and Dorn (2013); Goos et al. (2014); Michaels et al. (2014); Senfleben and Wielandt (2014); Böckerman et al. (2019).
- ²¹ In a similar vein, I split the data into a 1990s sample (years 1992–99) and a 2000s sample (years 2006–18) to explore time trends. This exercise reveals variation in tasks was more important from 1992 to 99. Variation in manual tasks was especially relevant for low-wage earners while variation in interactive tasks contributed to wage differences among high-wage earners by at least 10 per cent. Even though the quantitative relevance of all task measures has declined since 2006, variation in interactive and NR manual tasks remain the only significant contributors to wage differences. Each task measure contributes up to 8 per cent to the wage gap over the past 15 years. Hence, evidence for recent years remains consistent with task specialization between native and workers. More results of this exercise are available from the author upon request.
- ²² A notable omission from these robustness exercises, aiming at capturing cohort differences of the foreign workforce, is to account for time spent in Germany. While evidence on earnings assimilation of immigrant in Germany is ambiguous (Bauer et al., 2005; Constant & Massey, 2005), it is nonetheless reasonable to assume that other indicators such as language proficiency improve over time. I therefore also experimented with decompositions based on years since arrival to Germany to check whether compositional changes in that dimension confounded results on task specialization (not reported). Unfortunately, this information is only available in two surveys—1999 and 2018. While there is some evidence on task specialization, this exercise is characterized by lots of uncertainty. Results of this specification are available from the author upon request.
- ²³ The data can be downloaded here: <https://www.destatis.de/EN/Themes/Economy/Foreign-Trade> (Date accessed: 08/11/2021).
- ²⁴ See Borjas (2003), D'Amuri et al. (2010), Llull (2018a, 2018b), Manacorda et al. (2012), and Ottaviano and Peri (2012).
- ²⁵ The full Act in English language can be found under the following link: https://www.anerkennung-in-deutschland.de/media/bqfg_englisch.pdf (Date accessed: 01/18/2020).
- ²⁶ See Ekert et al. (2017) and the most recent report published by the Federal Ministry of Education and Science (BMBF, 2020).

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