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Skills, Tasks, and Wages in Labor Markets

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by

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ABSTRACT

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A key interest in labor economics is to understand quality differences between workers and why technology helped some types of labor, while hurting others. Conventional methods rely on formal qualifications such as education or experience to measure skill differences between workers. These are crude measures, however, as they assume that workers with comparable formal qualifications perform similar activities at work and thus earn similar wages. To provide remedy, this dissertation extends the task approach to labor markets, popularized by Autor, Levy & Murnane (2003), by utilizing information on tasks performed at work. This strand of the literature utilizes information on job-related activities to enhance our understanding of the concept of 'skill' and how it translates into wage differences.

The first chapter uses novel survey data from Germany which provide self-reported information on job-related activities by individuals, thus task requirements at the worker level. Commonly used data such as the Occuptional Information Network (O*Net) database in the US are based on occupational analysts and therefore provide external assessment on the job-specific task requirements at the occupation-level. Comparing this task data with Expert-based data provided by the German Federal Employment Agency, similar in spirit to the O*Net database, my findings document substantial heterogeneity in task assignments at the individual level. This variation in job-related activities is predictive of wage differences between and within occupations and robust to a series of alternative model specifications. Importantly, various statistical tests favor individual-level information on tasks over occupational measures due to greater explanatory power on wages. The superior statistical performance of Survey data is

related to intra-occupational efficiency gains workers earn as a result of task specialization within occupations. Suggestive evidence indicates this enhanced degree of task specialization may become even more important if greater weight is given to the time allocation of job-related activities. Overall, the results suggest incomplete information on the part of Expert data and recommend worker-level information in studies on job tasks.

The second chapter applies the detailed information on individual tasks to explore the wage gap between native and foreign workers. In this study, I decompose wage differences along the wage distribution, adopting a statistical tool called 'Recentered Influence Function' (RIF). This way I estimate unique wage responses resulting from a change in job activities by nativity and at different points of the distribution. According to this distributional analysis, variation in interactive tasks has been a key contributor to the rising native-foreign wage gap, suggesting that native and foreign workers perform distinct activities at work. Importantly, variation in task assignments is most pronounced among high-wage earners, explaining up to 25% of wage differences, and can also be found among workers with similar formal qualifications. Previous research has documented how natives utilize their comparative advantage in interactive tasks by choosing occupations intensive in communication-heavy activities. However, my research is the first to demonstrate that this specialization pattern can likewise be found *within* occupations and as this trend has become more meaningful in recent years it reinforced already existing wage disparities. These idiosyncratic differences can explain small migration-induced wage effects despite assimilation in formal qualifications. My research thus has important implications for the integration of immigrant workers and offers a novel source of imperfect substitutability between native and foreign workers, which is at the core of small migration-induced wage effects usually found in the literature.

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Chapter 1

ON THE MEASUREMENT OF TASKS: DOES EXPERT DATA GET IT RIGHT?

1.1 Introduction

A growing body of research has gone beyond the canonical model which describes a production function as the collection of inputs. Instead, over the past decade, a rising number of studies have explored which services these factors provide (Acemoglu & Autor 2011). The idea behind this research is to observe the different *tasks* production inputs have to offer. A key emphasis is to better understand quality differences in the labor aggregate of the production function and why technology helped some types of labor, while hurting others. Traditionally, Economists have used formal qualifications such as completed schooling or potential years of work experience to measure differences in *skill*. However, skills are merely a representation of the human capital endowment workers can draw on to perform tasks. It is these tasks that produce output and that workers are being compensated for. Traditional models implicitly assume skills and task to be equivalent. Yet, workers differ in their human capital endowment and different skills make them differently equipped to perform one task over another.[1] The "task-approach" to labor markets (Autor 2013) thus allows a more nuanced evaluation on the role of skills in the production process.

Most studies employing task data use information at the occupation-level, externally assessed by labor market experts. However, this approach is based on strong assumptions,

[1]This idea reflects the classic unbundling problem: Workers choose to perform tasks that offer the highest return on their overall skills, yet, this does not imply that each element of their skill set will be equally valuable. As a consequence, workers with similar education-experience profile may perform a different combination of tasks, reflecting differences in the valuation of single skill elements.

namely that i) there is a common set of tasks within occupations and ii) labor market experts have a complete understanding of occupation-specific task requirements. In a recent study, Autor & Handel (2013) use the Princeton Data Improvement Initiative (PDII), a survey collecting information on cognitive, interpersonal, and manual job activities of US workers at the workplace. This allows them to compare the implications of individual-level information on tasks with the most commonly used data source on tasks, the Occupational Information Network (O*Net). If the assumptions underlying occupation-level data were valid, we would expect little explanatory power added by individual-level information. Their findings suggest, however, that worker-level information on tasks is predictive of wage differences not only between occupations, but also within.[2] Their analysis therefore casts doubt on the strong assumptions embedded in occupation-level data derived from external assessment.

The PDII data, however, is limited in its scope. On the one hand, its information on tasks is sparse and broad in nature, such as the frequency of problem-solving tasks requiring at least 30 minutes for Abstract tasks or the absence of face-to-face interactions with several entities as a proxy for routine tasks. On the other hand, it has a limited sample size of around 2,500 observations.[3] Therefore, while their results are overall robust and intuitive, the flaws of the data call their key findings into question. In light of the growing popularity of the task-approach to labor markets, this paper extends their analysis and contributes to the literature in two important ways.

First, employing a sizable cross-section of more than 32,000 workers in Germany since 2012, I use Survey data which offers richer and more detailed information on job-related activities and conduct more formal testing of the underlying assumptions of Expert-based data.[4] To facilitate this analysis, I compare task data derived from employment surveys

[2]Related evidence on dispersion of tasks within occupations can be found in Atalay, Phongthiengtham, Sotelo & Tannenbaum (2018a,b, 2019), Deming & Noray (2019), and Modestino, Shoag & Ballance (2019).

[3]For a consistent sample, comprising at least two observations per occupation, Autor & Handel (2013) only have 1,333 observations at their disposal.

[4]A recent study by Cassidy (2017) uses the same employment surveys, showing that individual-level variation in tasks is indeed predictive of wage differences. However, his paper uses old surveys from 1986 and 1992, thus not being able to address implications on the task content resulting from technological change. However, in light of evidence emphasizing the growing importance of social skills at the workplace, for instance, this analysis is somewhat outdated (Deming 2017).

with recently made available Expert-based data in Germany (Dengler, Matthes & Paulus 2014).[5] In line with Autor & Handel (2013), my findings reject the assumption of common tasks within occupations. In fact, a comparison of various goodness-of-fitness measures across a set of specifications strongly suggests variation in individual-level tasks to be more important in the process of wage determination. The baseline specification reveals an incremental R-squared of 9.5% of tasks at the worker-level in specifications in which both task dimensions are included. In comparison the incremental R-squared of tasks derived from Expert-based data amounts to 6.6%.

Second, I conceptualize the benefits of using worker-level information on tasks based on a wage equation accounting for intra-occupational efficiency gains. This wage premium reflects an enhanced degree of specialization within occupations if workers are more efficient at performing occupation-specific core tasks. The empirical analysis supports the notion that these intra-occupational efficiency gains are an important component of wage differences, implying additional incremental wage gains of at least 22%. This channel is especially pronounced for occupations intensive in abstract tasks, which require problem-solving skills. Moreover, suggestive evidence indicates that task specialization within occupations is reinforced by greater variation in time spent on job-related activities. In models in which workers are allowed to spend a differential amount of time on activities (measured by a 3 point Likert scale) incremental wage gains are at least 42%. Hence, the explanatory power of tasks on wages may not only be driven by variation in skill, but also by variation in time spent on a task.

1.2 Conceptual Background on Tasks and Wages

Let me first sketch a brief conceptual framework to develop some thoughts on the role of tasks in the process of wage determination and to motivate the subsequent empirical analysis. The task approach allows the researcher to shed light on how workers use skills embodied in their human capital to carry out tasks that are demanded by their

[5]This data is derived from the Berufenet Database, a free online portal for occupations provided by the German Federal Employment Agency, thus comparable to the O*Net database in the US.

employer to produce output. As workers differ in their human capital endowment, they will be differentially compensated depending on their ability to perform tasks specific to a particular job.

Following Autor & Handel (2013), let worker i be employed in occupation o in which she receives a wage w in return for performing J tasks. Abstracting from inherent ability and idiosyncratic shocks to output, a worker combines these tasks to produce output according to

$$Y_{io} = exp\left(\sum_{J} \lambda_{jo} T_{ij}\right) \tag{1.1}$$

where the output price in each occupation is normalized to unity.[6] Assuming she is being paid her marginal product we can write her log wage as

$$ln\ w_i = \sum_{J} \lambda_{jo} T_{ij} \tag{1.2}$$

where T_{ij} denotes task j performed by i and $\lambda_{jo} \geq 0$ represents returns earned for performing task j in o, i.e. tasks returns are occupation-specific. To conceptualize quality differences in labor, let's expedite on the idea that employers seek to hire workers with similar skills. Workers need to be able to perform tasks necessary to produce occupation-specific output, but may have different levels of expertise in carrying out those activities. Let $\boldsymbol{T_i} = \left(T_{i1}, T_{i2}, ..., T_{iJ}\right)$ summarize her skill endowment across J tasks and $\boldsymbol{\Lambda_o} = \left(\lambda_{1o}, \lambda_{2o}, ..., \lambda_{Jo}\right)$ summarize the occupation-specific task returns. By adding and subtracting the average task endowment of the N_o workers already employed in occupation o, i.e. $\pm \frac{1}{N_o} \sum_{i=i'} \boldsymbol{T_{i'}} \boldsymbol{\Lambda_o}$, we can allow workers to be differentially specialized within an occupation:

$$ln\ w_{io} = \frac{1}{N_o} \sum_{i=i'} \boldsymbol{T_{i'}} \boldsymbol{\Lambda_o} + \left(\boldsymbol{T_i} - \frac{1}{N_o} \sum_{i=i'} \boldsymbol{T_{i'}}\right) \boldsymbol{\Lambda_o} \tag{1.3}$$

[6] As pointed out in Autor & Handel (2013) this assumption is not restrictive as a logarithmic change in the price of output can be re-expressed in form of multiplicative change in the exponential in the exponential term of eq. (1.1). For instance, we can think of productivity shifters embodied in the tasks workers perform, possibly reflecting market demand factors and affecting the output price that way.

Following this representation, worker i's wage is not only a function of her own task endowment $\boldsymbol{T_i}$, but also its relative comparison to her peers. Notably, the first term can be interpreted as an occupational entry barrier explicitly derived from the stock of task endowment of workers $i^{'}$ already employed in occupation o. Moreover, the elements collected in $\boldsymbol{T_i}$ can be interpreted in terms of efficiency units, i.e. the more units T_{ij} of task j individual i performs, the more efficient she is (e.g. think of output produced per hour). Hence, the second term captures her degree of specialization in tasks demanded in o. These tasks are valued by occupation-specific returns embodied in $\boldsymbol{\Lambda_o}$, implying that a particular skill will not be equally valuable across occupations.

Of course, this does not solve the classic unbundling problem: Workers choose an occupation that offers the highest return on their overall skills, yet, this does not imply that each element of their skill set will be equally valuable across occupations (Heckman & Scheinkman 1987, Lazear 2009). Nonetheless, this simple conceptual framework has testable implications related to task specialization. If worker i is more efficient in performing task j relative to the overall population and if j is of great importance for o, then (i) she is more likely to pass the occupational entry barrier implied by the current skill structure and (ii) she will be relatively specialized in task j, even compared to her colleagues. According to eq. (1.3), these intra-occupational efficiency gains should subsequently translate into wage gains.

In a nutshell, not only do we expect individual-level tasks to be predictive because of the unique skills they embody, but also because workers with a skill endowment suited to perform occupation-specific core tasks are able to specialize to a degree beyond her peers. This enhanced task specialization *within* occupation is the unique contribution of worker-level data on the measurement of tasks. The more meaningful this channel, the greater the benefit of using Survey-based data on individual task assignments over occupation-level data derived from external assessment.

1.3 Data

1.3.1 Data Sources

The primary data source is a series of German employment surveys, assembled by the Federal Institute for Vocational Education (BIBB) and the Federal Institute of Occupational Safety and Health (BAuA), respectively, in 2012 and 2018.[7] This data set establishes a repeated labor force cross-section on qualification and working conditions of workers in Germany, covering 20,000 in each wave. The secondary data source is derived from the Berufenet Database, a free online portal for occupations provided by the German Federal Employment Agency (BA). This database is a popular research tool for people seeking career guidance and exploring job placements. Occupations must offer legally regulated vocational training to be included in the database and provide a rich set of occupation-specific information, including task requirements. Using data compiled by previous research (Dengler, Matthes & Paulus 2014) (henceforth DMP), I gather information on the relative importance of occupation-level tasks. This database is conceptually similar to the frequently used O*Net data in the US. As a consequence, this method of measuring tasks limits the scope of any analysis at the occupation-level and relies on the external assessment about the importance of occupation-specific tasks.

Three key features make the BIBB/BAuA employment surveys suitable for the present study. First, workers self-report job-related activities. While the primary interest of Expert-based data is on the occupational dimension, the unit of interest in Survey data is the workplace. Hence, Survey data naturally introduces more variation in task measures. This detailed information permits an analysis on individual variation in task assignments and therefore relaxes the implicit assumption of a common set of tasks performed within occupations in studies utilizing occupation-level data. Second, compared to other surveys providing task information at the individual level, the BIBB/BAuA surveys offer a sizable sample.[8] Third, each of the employment surveys provides information on monthly labor income. This allows a study on the effects of individual variation in task assignments on

[7]See Hall, Siefer & Tiemann (2014) and Hall, Hünefeld & Rohrbach-Schmidt (2020) for data manuals for each of the surveys used in this study.

[8]See Rohrbach-Schmidt & Tiemann (2013) for a comprehensive comparison among task data sets.

wages. Expert-based data, on the other hand, has to be combined with other data sources to infer wage implications. I convert nominal income levels into real terms using CPI=100 as of 2015 and calculate the hourly wage rate using information on weekly hours worked and assuming that each individual works 8 hours per day.[9]

1.3.2 Measuring Task Content

1.3.2.1 Survey Selection

The key variables are individual skills, approximated by tasks performed on the job. Prior to 2012 and 2018, there had been five more employment surveys released, offering information on job activities. BIBB/ BAuA collaboratley released another survey in 2006. Prior to that, from 1979 - 1999, the BIBB released four more surveys in cooperation with the Institute of Employment Research (IAB). Despite the possibility to include more data, I restrict the analysis to the most recent surveys from 2012 and 2018 for two reasons. First, DMP use information on occupational requirements from years 2011-2013 for their classification. Hence, using the most recent surveys aligns well with the time horizon in the Expert-based data they made available. Second, unlike earlier versions of the questionnaire, the surveys released in 2012 and 2018 are conceptually alike, i.e. tasks questioned in 2012 have likewise been included in 2018. The definition and framing of tasks is therefore consistent in this data set and avoids measurement error resulting from pooling activities over time, an approach that has been criticized in prior research (Rohrbach-Schmidt & Tiemann 2013).

1.3.2.2 Occupational Dimension

To increase statistical precision, I use average values of worker-level information from 2012 and 2018. The 3-digit occupations are subsequently aggregated into 2-digit occupational groups based on the official BA Classification of Occupations, issue 2010 (KldB

[9]The CPI data is taken from the Federal Reserve Bank of St. Louis (FRED) and can be downloaded under the following link: https://fred.stlouisfed.org/series/DEUCPIALLAINMEI (Date accessed: 01/18/2020).

2010). This classification scheme has a high degree of compatibility with the International Standard Classification of Occupations 2008 (ISCO-08), thus making it comparable with international classifications. Analyzing occupational groups at these two dimensions provides a reference about the degree of similarity in task requirements across related occupations of distinct dimension. Baseline specifications, however, are based on a 2-digit definition to enhance statistical precision when computing occupational averages.

1.3.2.3 Task Classification & Characteristics of underlying Activities

In terms of the classficiation of job-related activites, I follow Spitz-Oener (2006) and pool activities described in the surveys into five narrow task categories: (i) Non-Routine (NR) Analytic tasks, (ii) NR Interactive tasks, (iii) Routine Cognitive tasks, (iv) Routine Manual tasks, and (v) NR Manual tasks. This task classification is based on Autor, Levy & Murnane (2003), the landmark study in this literature, and has been used frequently ever since.[10] Table (1.1) provides an overview of activities included in the task categories. Following DMP, it moreover offers a comparison of task requirements based on the Berufenet Database (column 3) and comparable requirements based on the BIBB/BAuA surveys (4), along with descriptions about underlying activities (5).

Previous studies have criticized this narrow classification and its underlying activities, displayed in Table (1.1). Key objections are with regard to the sensitivity of the task measures subject to the number of tasks performed (Rohrbach-Schmidt & Tiemann 2013) and the unclear distinction between Routine Cognitive and NR Analytic task measures. Some activities, for instance in regards to clerical work, require cognitive skills involving routine and NR tasks. This overlap in narrow task groups makes any task classification somewhat inconsistent. To account for this ambiguity, I follow Acemoglu & Autor (2011) in subsuming analytic and interactive tasks under "Abstract". Similarly, routine cognitive and routine manual tasks are subsumed under "Routine". Non-Routine manual tasks, on the other hand, are not categorized further.

[10] See, e.g., Black & Spitz-Oener (2010), Gathmann & Schönberg (2010), Haas, Lucht & Schanne (2013), and Cassidy (2017).

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 to NR tasks.[11] Lastly, NR tasks require hand-eye coordination which is difficult to automate. These activities are pronounced in basic services and are disproportionately found in lower parts of the income distribution. For the sake of brevity I will refer to this task group simply as "Manual", as opposed to routine manual tasks which are easier to automate.

(1)	(2)	(3)	(4)	(5)
Task Category (Broad)	**Task Category (Narrow)**	**Requirements (Berufenet)**	**Requirements (BIBB/BAuA)**	**Task Content**
Abstract	Non-Routine Analytic	Management, Planning & Supervision, Fields of Competencies, Economy, Leadership, Network Certifications, Monitoring, Music, Singing, Ballet, Musical Instruments, Optics, Applying Laws Design, Design (Art), Analysis, Control, Therapy, Programming	Research, Analyse Plan, Construct Design, Create, Evaluate Apply & Interpret Rules Work out Rules/ Regulations, Employ or Manage Staff	Gathering Information, Investigating, Researching Organizing, Making Plans, Decision Making Constructing, Devloping, Evaluating Applying Law, Notirizing Working with Computers, Programming Managing Personnel, Leading, Employing
	Non-Routine Interactive	Commerce, Counselling, Service, Support, Training, Marketing, Advertisting	Consult, Inform Negotiate, Represent Interests Teach, Train Sell, Purchase, Acquire Customers, Advertise, Entertain, Present	Consulting, Advising, Negotiating , Lobbying Teaching, Training, Educating Purchasing, Procuring, Selling Marketing, PR, Presenting
Routine	Routine Cognitive	Technology, Metrics, Administration, Graphics, Network Technology, Network Protocols Operating Systems, Certificates, Languages, Knowledge of Goods & Products, Competencies, Sensor Technology, Electronics, Mechanics, Mechanotrics, Hydraulics, Processing, Revision, Test, Inspection, Measurement, Monitoring, Procedures, Diagnostics	Correct Texts/ Data Measure Length/ Height/ Temperature Apply Languages Calculate, Accounting Application User Programs Administration (IT)	Use of Email, Internet Measuring, Evaluating Frequent Use of Foreign Languages Frequent Calculating/ Applying Math and Statistics Frequent Use of Software database, Computer Programs Administration of database, Networks, IT-Systems
	Routine Manual	Cultivation, Farming, Construction, Manufacture, Production, Harvesting	Pack, Ship Operate Machines Process	Planting, Storing, Transporting, Stocking, Posting Operating, Controling, Equipping Producing, Manufacturing Goods
Non-Routine	Non-Routine Manual	Dancing, Refurbishing, Service, Therapy (Manual Focus), Special/ Custom/ Bespoke Productions, Handicraft Businesses (Bakery, Carpentry, etc.)	Clean Guard Caretake Repair, Renovate Host	Cleaning, Recycling Guarding Caretaking, Healing Repairing, Renovating, Restoring, Refurbishing Preparing Food, Serving

Table 1.1: Task Categories and their Contents

1.3.2.4 Classification of Survey Responses

Unfortunately, the BIBB/BAuA surveys do not provide detailed information on time devoted to each activity, thus not making it possible to distinguish whether a task is important because of a worker's underlying skill level or because of the time devoted to a task. To my knowledge, the only data able to address these questions is the Berea Panel

[11] Because of these characteristics, a series of papers has identified routine tasks as a primary reason for increasing employment polarization over the last decades (Autor, Levy & Murnane 2003, Spitz-Oener 2006, Goos & Manning 2007, Autor & Dorn 2013, Goos, Manning & Salomons 2014, Senftleben & Wielandt 2014). In particular, people with medium education (e.g. high school degree, some college) have been detrimentally affected by this trend as they perform clerical work, quality control, bookkeeping (routine cognitive) or manual tasks that follow a set of strict rules and, in the latter case, demand more physical activities.

Study (BPS), a longitudinal data set in which two cohorts of students of the Berea College reported the percentage of time spent on tasks (Stinebrickner et al. 2018, 2019). Compared to the BIBB/BAuA surveys, though, this data set lacks sample size ($N = 528$).

Task Category (Broad)	Task Category (Narrow)	Requirements (BIBB/BAuA)	Task Time Allocation	All	College	Voca.	No Voca.
Abstract	NR Analytic	Research, Analyse	Often	0.60	0.80	0.54	0.35
			Sometimes	0.25	0.18	0.28	0.27
			Never	0.15	0.03	0.17	0.38
		Plan, Construct	Often	0.44	0.55	0.41	0.29
			Sometimes	0.29	0.29	0.29	0.27
			Never	0.27	0.16	0.30	0.44
		Design, Create, Evaluate	Often	0.13	0.25	0.09	0.07
			Sometimes	0.23	0.30	0.21	0.15
			Never	0.64	0.45	0.70	0.78
	NR Interactive	Consult, Inform	Often	0.64	0.78	0.59	0.43
			Sometimes	0.25	0.19	0.27	0.30
			Never	0.11	0.03	0.13	0.27
		Negotiate, Represent Interests	Often	0.48	0.64	0.40	0.30
			Sometimes	0.40	0.33	0.45	0.44
			Never	0.11	0.04	0.15	0.27
		Teach, Train	Often	0.24	0.36	0.20	0.11
			Sometimes	0.35	0.36	0.36	0.24
			Never	0.40	0.28	0.44	0.65
		Sell, Purchase, Acquire Customers	Often	0.20	0.14	0.23	0.21
			Sometimes	0.26	0.31	0.24	0.17
			Never	0.54	0.55	0.53	0.62
		Advertise, Entertain, Present	Often	0.11	0.15	0.10	0.08
			Sometimes	0.30	0.42	0.27	0.20
			Never	0.58	0.43	0.63	0.72
Routine	Routine Cognitive	Correct Texts/ Data	Often	0.70	0.88	0.63	0.51
			Sometimes	0.18	0.10	0.22	0.21
			Never	0.12	0.02	0.16	0.28
		Measure Length, Height, Temperature	Often	0.43	0.39	0.45	0.39
			Sometimes	0.26	0.32	0.24	0.23
			Never	0.31	0.29	0.31	0.38
	Routine Manual	Pack, Ship	Often	0.22	0.08	0.27	0.33
			Sometimes	0.27	0.24	0.28	0.23
			Never	0.51	0.68	0.44	0.45
		Operate Machines	Often	0.22	0.11	0.26	0.22
			Sometimes	0.17	0.15	0.17	0.19
			Never	0.62	0.74	0.57	0.59
		Process	Often	0.13	0.06	0.16	0.18
			Sometimes	0.07	0.06	0.07	0.07
			Never	0.80	0.87	0.77	0.75
Manual	NR Manual	Clean	Often	0.23	0.06	0.28	0.38
			Sometimes	0.24	0.20	0.26	0.25
			Never	0.53	0.74	0.46	0.37
		Guard	Often	0.20	0.15	0.22	0.19
			Sometimes	0.15	0.15	0.16	0.14
			Never	0.65	0.70	0.62	0.66
		Caretake	Often	0.18	0.15	0.18	0.13
			Sometimes	0.08	0.10	0.07	0.07
			Never	0.75	0.75	0.75	0.80
		Repair, Renovate	Often	0.14	0.05	0.17	0.14
			Sometimes	0.25	0.21	0.26	0.26
			Never	0.62	0.74	0.57	0.61
		Host	Often	0.09	0.04	0.11	0.14
			Sometimes	0.11	0.12	0.11	0.09
			Never	0.80	0.84	0.79	0.77
			N	32,002	8,922	21,635	1,445

Task Category (Broad)	Task Category (Narrow)	Requirements (BIBB/BAuA)	Skill Level Required	Percent	College	Voca.	No Voca.
Abstract	NR Analytic	Apply, Interpret Rules	No Knowledge	0.32	0.17	0.36	0.55
			Basic Knowledge	0.44	0.50	0.42	0.34
			Advanced Knowledge	0.25	0.33	0.22	0.12
		Requirements (BIBB/BAuA)	**Occurrence**	**Percent**	**College**	**Voca.**	**No Voca.**
		Work out Rules, Regulations	Yes	0.07	0.14	0.05	0.05
			No	0.93	0.86	0.95	0.95
		Employ, Manage Staff	Yes	0.30	0.35	0.28	0.19
			No	0.70	0.65	0.72	0.81
Routine	Routine Cognitive	Apply Languages	No Knowledge	0.41	0.19	0.45	0.56
			Basic Knowledge	0.40	0.42	0.41	0.32
			Advanced Knowledge	0.19	0.40	0.14	0.12
		Calculate, Accounting	No Knowledge	0.25	0.18	0.25	0.46
			Basic Knowledge	0.49	0.47	0.50	0.42
			Advanced Knowledge	0.27	0.35	0.25	0.12
		Application User Programs	No Knowledge	0.05	0.01	0.06	0.12
			Basic Knowledge	0.49	0.42	0.51	0.56
			Advanced Knowledge	0.47	0.56	0.43	0.32
		Requirements (BIBB/BAuA)	**Occurrence**	**Percent**	**College**	**Voca.**	**No Voca.**
		Administration (IT)	Yes	0.02	0.05	0.01	0.01
			No	0.98	0.95	0.99	0.99

Table 1.2: Task and Time Allocation by Education Groups
(College, Vocational Degree, No Vocational Degree)

Similar to the PDII, the Survey data used in the present study nonetheless offers some insight on the time dimension of tasks. Specifically, workers are asked whether they perform an activity "never", "sometimes", or "often". Based on their responses, I create a dummy variable equal to 1 if individual i performs activity a belonging to task group j "often":

$$d_{iaj} = \begin{cases} 1, & \text{if } a = \text{“often”} \\ 0, & \text{if } a = \text{“sometimes”} \lor a = \text{“never”} \end{cases} \tag{1.4}$$

Hence, I focus on workers who spend a considerable amount of time on a particular task. Of course, however, performing a task "often" may be perceived differentially from one worker to another. Table (1.2) illustrates the answers of workers, providing a sense for the time allocation devoted to each task. Unsurprisingly, college graduates are over-represented in performing abstract tasks "often" and under-represented in performing manual tasks "often". The opposite is true for workers with no vocational degree, while those who have earned some vocational degree lie in between those specialization patterns. In a few instances, workers answer whether they require no knowledge, basic knowledge, or advanced knowledge of a particular activity. In these cases, the dummy variable equals 1 if they require advanced knowledge. For two activities, managing personnel and programming, there is no additional information on time allocation or required skill level.[12]

1.3.2.5 Task Construction

In the construction of the individual task content T_{ij}, the key variable of this study, I follow DMP, who themselves apply a common method introduced by Antonczyk, Fitzenberger & Leuschner (2009). Let A_j denote the number of activities included in task group

[12]The selection of activities slightly differs from previous studies. Typically, only activities which workers perform "never", "sometimes", or "often" are considered. I extend the range of activities to include relevant levels of skill, primarily to make the relative importance of tasks between the Expert-based and Survey data more comparable. From Table (1.1) it can be inferred that Routine Cognitive and NR Analytic would be under-represented without this extension. Moreover, information aimed at the required skill level of an activity has changed substantially across surveys and generally been asked infrequently. Therefore, inconsistent appearance of questions is another reason these activities have not been included in prior research. Restricting the analysis to surveys conducted in 2012 and 2018 avoids this measurement error, though, maintaining consistency in the type of activities asked over time.

j and let A denote the total number of activities across all j. The individual task content T_{ij} is then defined as:

$$T_{ij} = \frac{\text{No. of activities a performed by i in task category j}}{\text{Total no. of activitites a by i across } \textit{all} \text{ j's}} = \frac{\sum_{a=1}^{A_j} d_{iaj}}{A} \tag{1.5}$$

where $j = 1$ (NR Analytic), $j = 2$ (NR Interactive), $j = 3$ (Routine Cognitive), $j = 4$ (Routine Manual), and $j = 5$ (NR Manual) reflect the narrow task categories defined above. Hence, for each i we compare the number of activities a belonging to j relative to all activities A. This definition implies that the number of task-specific activities is proportional to all activities and adds up to 1 over all tasks, i.e. $\sum_J T_{ij} = 1$. Intuitively, it thus describes the relative importance of each task category. Pertaining to the empirical implementation, the task endowment $\boldsymbol{T_i}$ is based on a series of dummy variables which, using eq. (1.5), are subsequently converted into a continuous measure $T_{ij} \in [0,1]\ \forall j$. For example, if employee i, Jane, indicates that she performs two analytic, two interactive, and one routine cognitive activity, then her analytic, interactive, and routine cognitive task content, respectively, is 0.4, 0.4, and 0.2. Therefore, 80% of Jane's overall activities comprise abstract tasks with equal contributions from NR Analytic and NR Interactive. The remaining 20% involve routine cognitive activities.[13] Note that two workers employed in the same occupation may have a different task content if they perform a different combination of activities.

By collecting individual responses for each of the N_o workers employed in o, we can compute occupational averages $\forall j$, the common task dimension used in the literature:

$$T_{jo}^{S} = \frac{1}{N_o} \sum_i T_{ij} \tag{1.6a}$$

$$T_{jo}^{Exp} = T_{jo} \text{ if data source = BERUFENET} \tag{1.6b}$$

[13]Intuitively, this task definition is related to the skill-weight approach in Lazear (2009). In this study, returns to skills are determined by weights firms attach to core skills. Constructing these weights implies that a high weight attached to a particular skill means a low weight on the other skills. This trade-off is motivated by constraining all workers to enter the same occupations, i.e. making worker's skills distinguishable. Hence, workers will choose a firm which places a high weight on skills they are well-endowed with. This idea likewise applies to the construction of the task content in the present study with a focus on the occupational dimension instead.

where T_{jo}^{S} merely represents occupation-specific averages across individual responses and T_{jo}^{Exp} is taken from the data set made available by DMP, comprising occupation-level task measures assessed by labor market experts. Both measures proxy the stock of task endowment of workers employed in occupation o (first term in eq. (1.3)) and have an interpretation analogous to T_{ij}, defining the importance of each task category at the occupation-level instead.

The intuition behind these task measures will turn out to be useful when testing the implications of the conceptual framework in section 1.2 in regards to intra-occupational efficiency gains resulting from task specialization within occuaptions. Let $\boldsymbol{T_o^S} = \left(T_{1o}^S, T_{2o}^S, ..., T_{Jo}^S\right)$ summarize the occupation-specific averages of tasks $\forall j$ based on Survey data. Analogously, let $\boldsymbol{T_o^{Exp}} = \left(T_{1o}^{Exp}, T_{2o}^{Exp}, ..., T_{Jo}^{Exp}\right)$ summarize the occupation-specific averages of tasks based on Expert data. We can then define the within-occupation degree of task specialization by computing the deviation between individual task content from the occupational average:

$$\boldsymbol{\widetilde{T}_{io}^{S}} = \boldsymbol{T_i} - \boldsymbol{T_o^{S}} \tag{1.7a}$$

$$\boldsymbol{\widetilde{T}_{io}^{Exp}} = \boldsymbol{T_i} - \boldsymbol{T_o^{Exp}} \tag{1.7b}$$

where $\boldsymbol{\widetilde{T}_{io}^{S}} = \left(\widetilde{T}_{i1o}^S, \widetilde{T}_{i2o}^S, ..., \widetilde{T}_{iJo}^S\right)$ summarizes worker i's degree of specialization across J tasks based on occupation-level tasks derived from Survey data. Similarly, $\boldsymbol{\widetilde{T}_{io}^{Exp}} = \left(\widetilde{T}_{i1o}^{Exp}, \widetilde{T}_{i2o}^{Exp}, ..., \widetilde{T}_{iJo}^{Exp}\right)$ summarizes worker i's degree of specialization across J activities based on occupation-level tasks derived from Expert data. Continuing on above example, recall that Jane's individual task content in abstract activities is equal to 0.8. If the occuapation-level average is equal to 0.7, her degree of specialization amounts to 0.1. Therefore, she is more specialized in abstract tasks than her peers by 10 pp. According to wage equation (1.3), we would expect her to earn intra-occupational efficiency gains due to an enhanced degree of task specialization *within* her occupation.

1.3.3 Sample Selection

To be included in the sample, workers need to meet two criteria. First, their individual tasks must be observed. Second, their occupation can be matched with the Berufenet Database. Applying these restrictions leaves a total sample comprising 32,003 workers. Table (1.3) provides descriptive statistics on the sample. In particular, it compares the relative importance of tasks based on the BIBB/BAuA surveys (column 2) and the Berufenet Database (3). Note that values based on the employment surveys reflect averages over all workers. Abstract task measures represent around half of activities of workers while two fifths of all tasks are of routine nature. In terms of broad task groups, the average distribution between job-related activities is almost identical among both data sources. While similar patterns do carry over to a more narrow task classification, a few discrepancies stand out. Notably, interactive tasks are somewhat over-represented in the employment surveys at the detriment of NR Analytic and vice versa for analytic tasks in the Expert-based data. Overall, though, both data sources tell a similar story and avoid substantial over- or under-representation of any task group, especially when tasks are defined broadly.

(1)		(2)		(3)	
Socio-Economic		**Tasks (BIBB/BAuA)**		**Tasks (Berufenet)**	
Log Wage	3.10	NR Analytic	0.24	NR Analytic	0.31
Female (% of total workforce)	0.52	NR Interactive	0.23	NR Interactive	0.16
Age	46.41	Routine Cognitive	0.29	Routine Cognitive	0.28
College Degree	0.28	Routine Manual	0.10	Routine Manual	0.08
Vocational Degree	0.67	NR Manual	0.13	NR Manual	0.17
Dropouts	0.06				
Hours worked (Weekly)	35.73	Abstract	0.48	Abstract	0.47
Tenure (Firm, in Years)	14.09	Routine	0.39	Routine	0.36
Tenure (Occup., in Years)	25.69	Manual	0.13	Manual	0.17
N = 32,026					

Table 1.3: Descriptive Statistics

For the empirical analysis below, the baseline sample comprises broad task groups (Abstract, Routine, Manual) based on 2-digit occupations. The broad task classification alleviates measurement error in the task content outlined in section 1.3.2.3. Meanwhile, adopting a broader occupational classification enhances statistical precision when computing occupational averages. Of course, these broad definitions come at the cost of potentially generalizing job-related activities or related occupation, but which have different task requirement. To test for the robustness of the baseline classifications, I adopt more narrow definitions of tasks and occupations in section 1.5.2.

1.4 Empirical Methodology

The conceptual framework laid out in section 1.2 suggests an important role for individual-level variation of tasks in the process of wage determination. To explore task elements embodied in different data sources more formally, the empirical analysis emphasizes two key questions: First, are worker-level tasks predictive of wage differences in ways that occupation-level data is not? In particular, if they are not correlated with unobserved features of occupation beyond occupation-level tasks, this would be consistent with the task content being a key component of occupations, reinforcing the need to measure tasks precisely. Second, which task dimension is economically more meaningful? Greater emphasis on occupation-level measures of tasks may place greater entry barriers to occupations. On the other hand, greater importance of individual characteristics gives workers more opportunities to exert comparative advantages beyond occupational borders. Hence, workers may likewise specialize within occupations according to their task endowment, allowing them to earn higher wages per eq. (1.3).

1.4.1 Baseline Wage Regressions

To assess the predictive elements embodied in the task content, I run a series of wage regressions comprising task measures of distinct dimension. The key regression takes the following form:

$$ln\ w_i = \alpha + \boldsymbol{\beta T_i} + \boldsymbol{\gamma X_i} + \delta_r + \eta_s + \epsilon_i \tag{1.8}$$

where w_i is the hourly real wage for individual i. Note that the mix of tasks is not occupation-specific, workers can thus differentially specialize according to their skill endowment $\boldsymbol{T_i} = \left(T_{i1}, T_{i2}, ..., T_{iJ}\right)$. The vector $\boldsymbol{X_i}$ comprises control variables, including demographic characteristics (sex, age, age squared, metropolitan area), education dummies (college degree, vocational schooling, no vocational degree), and firm- and occupation-specific variables (firm tenure, firm tenure squared, occupational tenure, occupational tenure squared, firm size indicator). Moreover, δ_r and η_s, respectively, denote region and sectoral dummies.[14]

Importantly, the vector of coefficients $\boldsymbol{\beta}$ should not be interpreted as average task returns, at least not in a causal sense. This is because workers choose an occupation in which they can carry out activities they are particularly efficient at. Since workers are non-randomly assigned into occupations, perhaps due to comparative advantage, this self-selection introduces a bias. One would ideally use longitudinal data to conduct FE regressions, yet, the cross-sectional nature of most data sets prevents this approach from being used widely. The regressions conducted in this study should thus be considered exploratory as they merely reflect correlations between tasks and wages. Despite these identification issues, Stinebrickner, Stinebrickner & Sullivan (2019) find task returns from OLS and FE regressions to be remarkably similar based on US panel data. Hence, OLS regressions may serve as credible suggestive evidence.

A comparison of eq. (1.8) with models comprising occupation-level tasks based on Survey data, $\boldsymbol{T_o^S}$, and Expert-based data, $\boldsymbol{T_o^{Exp}}$, is informative on the validity of the latter to capture task-related occupational characteristics as self-selection into occupations should be embodied in both measures. Augmenting eq. (1.8) by occupational dummies θ_o stresses the importance of idiosyncratic factors embodied in the task content by exploring task specialization *within* occupations.[15] Estimating models containing both task dimensions, on the other hand, will shed light on the unique variation in wages that can be attributed to worker-level differences in tasks. Other than task measures, all regressions are identical and are weighted by survey weights. In order to asses the relative importance of task measures across specifications formally, I report (i) R-squared, (ii) Adjusted R-squared,

[14] To be specific, the dummies encompass 16 states (Western & Eastern Germany) and 34 sectoral groups (industrial, craft, commerce, services, others). Note that there are no time dummies as the data from the 2012 and 2018 surveys has been pooled for the purpose of greater statistical precision.

[15] Depending on the definition of occupations, the model comprises 36 (137) 2-digit (3-digit) occupational groups.

(iii) F-test for joint significance of task measures, (iv) Incremental R-squared for task measures, and (v) Akaike (AIC) and Bayesian (BIC) Information Criterion. While the first four measures offer insight on the goodness of fit across specifications, the AIC and BIC shed light on model selection by virtue of out-of-sample prediction errors.

Lastly, two more aspects worth mentioning. First, manual tasks are omitted as, by construction, the task measures add up to 100. Second, for similar reasons, one education group has to be omitted, in this case workers who have not completed any vocational schooling. Therefore, the reference group consists of workers with no vocational degree who perform predominantly manual tasks. Since these workers are typically found in lower parts of the wage distribution, we should expect positive and sizable task returns.

1.4.2 Degree of Specialization within Occupations

A key implication of the conceptual framework linking tasks to wages is that enhanced task specialization within occupations should translate into a wage premium. The underlying idea is that these workers are more efficient at performing occupation-specific core tasks relative to their peers. To expedite on this hypothesis, we can empirically test eq. (1.3) by running the following wage regression:

$$ln\ w_{io} = \alpha + \boldsymbol{\lambda} \boldsymbol{T_o^S} + \boldsymbol{\Omega} \boldsymbol{\widetilde{T}_{io}^S} \times \boldsymbol{T_o^S} + \boldsymbol{\gamma} \boldsymbol{X_i} + \delta_r + \eta_s + \epsilon_{io} \tag{1.9}$$

where $\boldsymbol{\widetilde{T}_{io}^S}$ represents worker i's degree of specialization across J tasks in occupation o as defined in eq. (1.7a). Of key interest are the interaction terms, which offer insight on worker's degree of task specialization. Positive coefficients in the vector $\boldsymbol{\Omega}$ would be consistent with intra-occupational efficiency gains. The larger these gains, the more lucrative is task specialization within occupations. Replacing Survey-based tasks at the occupation-level, $\boldsymbol{T_o^S}$, with Expert data, $\boldsymbol{T_o^{Exp}}$, offers a robustness exercise to check whether the latter points to the same direction. Of course, such an analysis would not feasible relying only on Expert data, however.

1.5 Results

1.5.1 Baseline: Individual vs Occupation-level Task Measures

The baseline estimates can be found in Table (1.4). Columns (1) - (3) correspond to eq. (1.8), displaying specifications including occupation-level tasks from Survey data, individual-level tasks, and occupation-level tasks from Expert data, respectively. All three models show significant and positive estimates as expected, illustrating the returns to performing abstract and routine tasks compared to manual. For instance, relative to manual tasks, column (2) indicates that performing 1 pp. more abstract tasks individually raises the log wage by 0.58 points.[16] To assess whether individual-level tasks have statistically significant explanatory power beyond the occupational level, columns (4) and (5) combine task measures of both dimensions. Notably, not only does worker-level variation remain robust to inclusion of either occupational measures, it is also economically more meaningful than Expert-based measures.

Moreover, it absorbs substantial variation from both occupation-level tasks as measures for abstract and routine tasks shrink by up to a half compared to specifications excluding individual-level measures. These findings suggest that idiosyncratic factors embodied in the task content are an important component in the process of wage determination. Accounting for occupational affiliation via FE supports this narrative, consistent with task specialization within occupations. The robustness of the point estimates suggests that worker-level information on tasks is not correlated with unobserved features of occupations beyond the task content (6), making it an informative measure of occupational characteristics.

The general deduction that tasks are predictive of wage differences is in line with the results reported in Autor & Handel (2013). The F-tests on joint significance of task measures reinforce this finding and indicate that each measure, regardless of specification and task dimension, makes independent and statistically significant contributions

[16] The mean abstract task content is 0.48, compared to 0.13 in the manual task content. The average worker thus performs more abstract tasks to begin with. In fact, a quarter of workers performs no manual tasks at all. Tilting the task content even more in favor of abstract tasks therefore leads to the sizable wage gains presented above.

in explaining variation in wages. At the same time, the evidence points to a prominent role for the worker-level dimension, especially pertaining to abstract tasks. Not only are estimates on individual-level tasks significant, but both measures of R-squared also suggest they consistently have a greater explanatory power than either occupation-level variables (columns 1-3). The information criteria displayed at the bottom reaffirm this view. Both, AIC and BIC, suggest a model comprising individual-level task measures has a superior relative likelihood than including either occupation-level measure as it implies the smallest out-of-sample prediction error.

Dependent Variable: Log Hourly Real Wage	(1)	(2)	(3)	(4)	(5)	(6)
Abstract (Occ.)	0.92***			0.48***		
	(0.07)			(0.07)		
Routine (Occ.)	0.48***			0.24***		
	(0.08)			(0.08)		
Abstract (Ind.)		0.58***		0.47***	0.48***	0.48***
		(0.04)		(0.04)	(0.04)	(0.04)
Routine (Ind.)		0.38***		0.29***	0.30***	0.29***
		(0.04)		(0.04)	(0.04)	(0.04)
Abstract (Exp.)			0.44***		0.25***	
			(0.03)		(0.03)	
Routine (Exp.)			0.26***		0.17***	
			(0.03)		(0.03)	
Survey tasks (Occupational)	✓			✓		
Survey tasks (Individual)		✓		✓	✓	✓
Expert tasks (Occupational)			✓		✓	
Occupation Dummies						✓
F (Task Measures, Occ.)	92.55		118.17	22.27	37.29	
F-pval (Task Measures, Occ.)	(0.00)		(0.00)	(0.00)	(0.00)	
F (Task Measures, Ind.)		146.41		83.82	89.53	90.47
F-pval (Task Measures, Ind.)		(0.00)		(0.00)	(0.00)	(0.00)
R-squared	0.190	0.197	0.189	0.199	0.200	0.209
Adj. R-squared	0.188	0.195	0.188	0.198	0.198	0.206
AIC	60363.56	60090.77	60383.93	59995.34	59967.28	59679.36
BIC	60874.35	60593.19	60886.35	60514.50	60494.81	60483.22
Observations	32003	32003	32003	32003	32003	32003

Robust standard errors in parentheses

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

* Note: The first two rows display coefficients based on occupational averages derived from individual responses in the employment surveys ("(Occ.)"). Point estimates corresponding to those individual responses are displayed in the third and fourth row ("(Ind.)"). Lastly, the last two rows display coefficients based on occupational averages derived from the Expert database ("(Exp.)"). All specifications include controls for gender, age, age squared, a dummy for living in an urban area, education dummies, occupational tenure, firm tenure, squared tenure for each dimension of experience, and a categorical variable reflecting firm size. The omitted task category is "Manual".

Table 1.4: Task Measures as Wage Predictors: Survey vs Expert Data
(Baseline: Broad Task Categories, 2-digit Occupations)

To quantify the relative importance of worker-level task measures more directly, Table (1.5) displays the incremental R-squared of task measures. The results are based on computing the squared semipartial correlation between log wages and the task measure of interest and are relative to the R-squared of a specification with a full set of variables for each of the models (1) - (6). For instance, column (2) implies a reduction in R-squared by 13.7% once individual abstract tasks are removed from the model. Similarly, 9.6% and 12.1%, respectively, of R-squared are lost once occupation-level measures from Survey or Expert data are removed (columns 1 & 3). Columns (4) and (5) combine individual and occupation-level measures, reaffirming that individual-level tasks are more informative. The bottom two rows summarize these findings, highlighting that worker-level tasks have a larger incremental R-squared compared to occupation-level measures by about 50%.

Table (1.6) tells a similar story, displaying the unique variation in wages associated with task measures, once more in relative terms. These values are based on computing the squared partial correlation between log wages and the task measure of interest. Individual task measures consistently explain a substantial share of the residual variance in log wages that other covariates are not able to explain. For instance, the common approach in the literature is based on model (3), comprising occupation-level information derived from Expert data. This model explains 15.8% of variation that traditional wage regressions are not able to explain. But how much of the variance in wages does this standard task-approach miss out on by not accounting for worker-level variation? According to column (5), idiosyncratic factors account for 8.0% of the variation not explained by occupation-level measures nor any other covariates. The lion's share of these contributions is due to differences in abstract activities. Model (6), conditioning individual task measures on occupational FE, supports this conjecture. Within occupations, almost 18% of the unexplained variance in a traditional wage regression can be attributed to variation in tasks.

Model:	(1)	(2)	(3)	(4)	(5)	(6)
Abstract (Occ.)	9.6%			2.0%		
Routine (Occ.)	6.3%			1.4%		
Abstract (Ind.)		13.7%		5.5%	6.2%	12.9%
Routine (Ind.)		8.1%		2.5%	3.3%	7.6%
Abstract (Exp.)			12.1%		4.1%	
Routine (Exp.)			6.4%		2.6%	
Total (Occ.)	15.8%		18.5%	3.4%	6.6%	
Total (Ind.)		21.8%		8.1%	9.5%	20.6%

* Note: The displayed values represent the percentage drop-off in R-squared after removing task measures and are relative to the R-squared of the full model. Results are based on computing the squared semipartial correlation between log wages and the task measure of interest. Models (1)-(3) correspond to specifications including occupation-level tasks from Survey data ("(Occ.)"), individual-level tasks ("(Ind.)"), and occupation-level tasks from Expert data ("(Exp.)"), respectively. Models (4) and (5) combine individual-level tasks with occupation-level tasks from Survey and Expert data, respectively. Lastly, model (6) includes individual-level tasks and occupational FE. The two bottom rows summarize the importance of different dimensions of task measures by adding up the decrease in R-squared after removing individual- and occupation-level tasks, respectively, from the model. All specifications include controls for gender, age, age squared, a dummy for living in an urban area, education dummies, occupational tenure, firm tenure, squared tenure for each dimension of experience, and indicator for firm size.

Table 1.5: Incremental R-squared
(Baseline: Broad Task Categories, 2-digit Occupations)

Model:	(1)	(2)	(3)	(4)	(5)	(6)
Abstract (Occ.)	8.4%			1.7%		
Routine (Occ.)	5.3%			1.2%		
Abstract (Ind.)		11.8%		4.7%	5.2%	11.1%
Routine (Ind.)		7.0%		2.1%	2.8%	6.6%
Abstract (Exp.)			10.4%		3.4%	
Routine (Exp.)			5.4%		2.1%	
Total (Occ.)	13.6%		15.8%	2.9%	5.6%	
Total (Ind.)		18.8%		6.8%	8.0%	17.7%

* Note: The displayed values represent the unique variation in log wages associated with the task measure of interest, expressed relative to the R-squared of the full model. Results are based on computing the squared partial correlation between log wages and the task measure of interest. The model description for specifications (1)-(6) along with controls included is the same as in Table (1.5) described above. The two bottom rows summarize the variance in low wages associated with task measures of interest, which has not been explained by all other covariates (including other task dimensions).

Table 1.6: Unique Variation Explained by Task Measures
(Baseline: Broad Task Categories, 2-digit Occupations)

1.5.2 Robustness: Individual vs Occupation-level Task Measures

1.5.2.1 Narrow Task Classification

The descriptive statistics displayed in Table (1.3) show minor discrepancies in the relative importance of analytic and interactive tasks. While these differences do not matter in a broad classification scheme, they are relevant in empirical settings in which a narrow task classification is imperative. The migration literature, for instance, has emphasized the importance of interactive tasks to explain wage differences between native and foreign workers.[17] Similarly, other studies have highlighted rising returns of social skills in recent decades (Deming 2017, Michaels, Rauch & Redding 2019) and how those have especially helped females in reducing the gender pay gap.[18] To test this hypothesis, I revisit the wage implications of task variation by disaggregating abstract task measures into NR Analytic and NR Interactive and routine task measures into Routine Cognitive and Routine Manual. Hence, NR Manual remains the relevant base group. The results of this exercise are summarized in Table (A.1) in Appendix A.1.

Qualitatively, the main conclusions carry over in the sense that most coefficients are positive and statistically significant. Regardless of which task measure is being used, all tasks continue to be jointly significant in their own right (columns 1-3). Nonetheless, a few interesting observations stand out. First, the positive coefficients for routine tasks are unsurprisingly driven by Routine Cognitive.[19] Hence, performing more routine manual tasks instead of NR Manual has no positive wage effects. Second, the positive impact of abstract tasks is primarily driven by NR Analytic, especially for either occupation-level measures (1 & 3).[20]

[17]See, e.g., Peri & Sparber (2009, 2011), Amuedo-Dorantes & de La Rica (2011) and Haas, Lucht & Schanne (2013).

[18]See Black & Spitz-Oener (2010), Cortes, Jaimovich & Siu (2018), and Yamaguchi (2018).

[19]One might object that this result is driven by the broader selection of activities outlined in section 2.2.2. Including activities in the definition of the task content for which workers reported required skill levels does indeed bolster the importance of Routine Cognitive. Restricting the analysis only to activities which workers perform "often", "sometimes", or "'never" does not change these results substantially, however. Applying this definition of the task content alleviates the importance of routine cognitive tasks to some extent, but they remain statistically and economically significant throughout specifications. These results are not reported but are available from the author upon request.

[20]These findings are consistent with Stinebrickner, Stinebrickner & Sullivan (2019) who find information tasks to be relatively more important in the determination of wages compared to people tasks. Conceptually, this distinction is similar to NR Analytic vs NR Interactive. Possibly, an increasing amount of time devoted to

Once occupation-level measures are combined with worker-level information (4 & 5), much of the predictive elements in tasks is absorbed by individual variation. For instance, compare the benchmark case of utilizing only Expert data (column 3) with model (5). Inclusion of individual task information substantially attenuates coefficients of Expert-based data, at least cutting them by half. Notably, individual variation in interactive activities entirely absorbs task information embedded in Expert data. This finding suggests that the use of Survey data on tasks is especially pronounced in the migration and gender gap literature due to reasons discussed above. Conditioning on occupational FE (column 6) even raises point coefficients, indicating that task specialization within occupations also takes place in narrowly defined task groups.

1.5.2.2 Finer Occupational Classification: 3-digit Codes

An additional caveat in the baseline specification is the dimension of occupations. This aspect matters especially with respect to the transferability of skills as employment in an occupation allows workers to accumulate task-specific human capital. Hence, if occupational groups are defined too broadly, occupations lumped together may be too different in regards to their task requirements. As a consequence, tasks become less portable, leading to a greater depreciation of task-specific human capital in the aftermath of an occupational transition.[21] Vice versa, sufficiently narrow definitions make it easier to transfer skills. Following this logic, occupation-level measures should be more important for 3-digit occupations as they capture occupation-specific task requirements more accurately.

Indeed, estimates displayed in Table (A.2) suggest that occupation-level measures explain about as much of the variation in log was as worker-level tasks. Neither of the point estimates have changed substantially, however, compared to the baseline specification in which 2-digit occupations are used. Importantly, both information criteria still favor a model comprising only individual-level information on tasks. A key takeaway of this exercise is that practitioners employing occupation-level task data should strive to use

information tasks is an important reason for these findings, as suggested by their longitudinal data. Hence, next to variation in skill levels, the time dimension may contribute to the dominance of NR Analytic among narrow task categories.

[21] See Poletaev & Robinson (2008), Kambourov & Manovskii (2009), Gathmann & Schönberg (2010), Yamaguchi (2012), and Robinson (2018).

fine occupational codes to reduce measurement error resulting from aggregation.

1.5.2.3 Different Task Definition: Principal Component Analysis

The main downside of the task content as defined in (1.5) is multicollinearity, forcing the researcher to drop one of the task variables. To test whether results are robust to the construction of the task content, one can alternatively assume a different base in the denominator, e.g. total no. of activities within a task group. For instance, Spitz-Oener (2006), Black & Spitz-Oener (2010), and Cassidy (2017) use this definition instead. While appealing due to the possibility of including all tasks, this measure confounds the time dimension of activities within a task group with the overall number of tasks performed. Since the latter characteristic sheds light on overall job complexity (e.g. if all or most activities are of abstract nature), conflicting both dimensions reduces the interpretative value compared to the baseline definition in the present study.[22]

Alternatively, one may conduct a Principal Component Analysis (PCA). This technique aims at reducing the dimension of the data, thereby mitigating problems related to overfitting a model. In essence, a PCA is based on linearly transforming the data by subtracting the mean of each variable and performing an Eigendecomposition of the Covariance matrix of covariates. Normalizing each of the (orthogonalized) eigenvectors then yields principal components (PCs), which can be included as covariates in a simple OLS regression. The premise of a PCA is that a small number of PCs suffices to explain most of the variability in the data. In principle, one could use as many PCs as covariates. Yet, the first PC contains the most information as it minimizes the initial sum of the squared residuals, thus capturing the direction of the data along which the observations vary the most. All subsequent PCs must be orthogonal to the direction of the first one, thus only capturing variance subject to this constraint, containing less information.

[22]Using this alternative task measurement does not change the main results, however. Performing more routine and especially abstract tasks is correlated with wage gains while performing more manual tasks implies wage losses (not reported). Importantly, individual-level variation remains the dominant predictor among the task measures considered. Results of this exercise are available from the author upon request.

For these reasons, I follow Autor & Handel (2013) and use the first component of a PCA to condense the task content into a single measure for abstract, routine, and manual tasks. Specifically, I extract information embodied in task groups based on the single activities displayed in Table (1.1). A PCA is then conducted for each of the three task categories where the first PC is a linear combination of underlying activities. To make the interpretation more intuitive, I standardize all resulting components (individual and occupational) with mean zero and a variance equal to one.

Table (A.3) summarizes the results of this exercise. Qualitatively, the estimates are in line with previous specifications, highlighting the explanatory power of worker-level task data and its benefits over occupation-level measures.[23] For instance, a one standard deviation increase in individual-level variation in abstract tasks raises wages by 11% (column 2). Performing more manual tasks, on the other hand, implies wage losses on the order of 5% as these activities are predominant in low-wage occupations. Notably, individual-level variation remains not only robust to inclusion of occupation-level measures, but also quantitatively larger.[24]

1.5.2.4 Time Dimension of Tasks

Most task measures provide imperfect identification on the importance of job-related activities as they confound the skill and time dimension. It is generally not clear whether explanatory power of variation in tasks can be attributed to greater level of skill, more time devoted to a task, or a combination of both. A key interest lies in abstract tasks who have shown to be of particular importance.[25] This limitation also applies to the present

[23] Note that the estimates from Expert-based Survey data are scaled. Occupation-level tasks are more dispersed in this data compared to information derived from the surveys. This implies larger jumps along the wage distribution resulting from an increase by one standard deviation.

[24] This is not true in Autor & Handel (2013) in which O*Net coefficients are about 50% larger in magnitude compared to individual-level measures.

[25] For instance, Stinebrickner, Stinebrickner & Sullivan (2019) show that, even though most workers spend some time on almost all tasks throughout the year, the time devoted to information tasks, similar to NR Analytic, has increased substantially over time at the detriment of people tasks. Hence, one might suspect that the time dimension has become disproportionately more important for information tasks relative to other activities.

study. Baseline specifications are based on eq. (1.4), imposing that workers only carry out an abstract task if they perform underlying activities "often".

Thinking of the skill dimension by education, the breakdown of time allocation devoted to tasks displayed in Table (1.2) shows the implications of this alternative assumption in the construction of tasks measures. With respect to abstract (and routine cognitive) tasks, college graduates are over-represented among workers who perform them "often" whereas workers with some or no vocational degree are under-represented in most instances. Hence, including "sometimes" in the definition of the task content adds a disproportionate amount of Non-college graduates to the group of workers performing abstract tasks, making the skill-specific distinction between who's performing a task and who isn't less sharp. The baseline task definition thus implies that a disproportionate amount of the variation in wages is driven by differences in skill.

In Table (A.4) I relax this assumption, creating dummies based on the following classification instead:

$$d_{iaj} = \begin{cases} 1, & \text{if } a = \text{“often”} \vee a = \text{“sometimes”} \\ 0, & \text{if } a = \text{“never”} \end{cases} \tag{1.10}$$

While the most skilled workers are still assumed to perform tasks, workers who are less skilled, but spend *some* time on tasks, are now likewise accounted for.[26] The average skill level for the group performing tasks thus becomes more diluted, reducing the impact of variation in skill as a driver of wage differences altogether.[27] Larger coefficients on task measures compared to the baseline analysis in section 1.5.1 would thus provide exploratory evidence that the time dimension in tasks is meaningful, e.g. by facilitating learning-by-doing (Yamaguchi 2012, Stinebrickner, Stinebrickner & Sullivan 2019). For reference, a 1 pp. increase in the individual abstract content in the baseline regression implies wage gains on the order of 58%, relative to manual tasks. Indeed, adding more

[26]For instance, Yamaguchi (2012) shows that returns to skills increase with task complexity (e.g. abstract tasks). Moreover, skills grow faster when the worker is employed in an occupation intensive in complex tasks. These findings can be interpreted in the sense that occupations provide different learning opportunities. Performing more complex tasks therefore helps workers develop their skills faster, e.g. via learning-by-doing.

[27]Another way to see this is to keep in mind that the three time categories "often", "sometimes", and "never" still consist of workers of all three education groups. Yet, we now have a sharp distinction between workers who are never performing a task and those who are performing it at least once in a while.

importance to the time dimension raises the coefficient to 92% (column 2). These findings are thus consistent with the hypothesis that the predictive power of task variation does not merely reflect variation in skill, but also time workers differentially devote to a task.

1.5.3 Degree of Specialization within Occupations

In this section I provide results of eq. (1.9), illustrating wage gains stemming from task specialization within occupations. Table (1.7) displays task measures from Survey (columns 1 & 2) and Expert data (3 & 4) and accounts for some of the aspects in the robustness analysis discussed above. In particular, results are displayed for different occupational classifications and time considerations implied in the task content. Regardless of data source or dimension of the task measure, abstract interaction terms show statistically significant positive estimates, consistent with the idea of efficiency gains from an enhanced degree of specialization relative to peers. For reference, consider model (2), assuming 3-digit occupational Survey data in which workers need to perform a task "often". Relative to the omitted task category Manual, the average task endowment of abstract activities implies wage gains of 97%. An incremental specialization by 1 pp. beyond that average adds another 47% in relative wage gains compared to performing manual tasks.

Hence, efficiency gains are incrementally about half as large as the base wage gains resulting from matching the average task endowment of workers employed in an occupation. The summary statistics at the bottom of Table (1.7) for the distribution of the abstract task endowment suggests that these efficiency gains are essentially irrelevant for the median worker. However, for workers in the upper quartile of the distribution of the abstract task endowment these gains are sizable. Relative to manual tasks, their efficiency gains due to intra-occupational specialization are cumulatively six times as large compared to the base wage gains at the occupation-level (15 x 0.47 vs. 0.96). Likewise, workers at the bottom quartile, who are less efficient at performing abstract tasks, face relative wage losses compared to their more efficient peers. Based on Expert data, the incremental efficiency gains are about half as large, yet, nonetheless statistically and economically meaningful. In contrast, the routine task endowment displays statistically insignificant estimates.

Dependent Variable: Log Hourly Real Wage	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Abstract (Occ.)	0.94***	0.97***			1.45***	1.51***		
	(0.07)	(0.06)			(0.09)	(0.08)		
Abstract (Occ.) × Abstract Deviation from Occ. Avg.	0.55***	0.47***			1.58***	1.44***		
	(0.06)	(0.06)			(0.12)	(0.13)		
Routine (Occ.)	0.43***	0.47***			0.64***	0.68***		
	(0.08)	(0.08)			(0.14)	(0.13)		
Routine (Occ.) × Routine Deviation from Occ. Avg.	0.28***	0.21**			1.12***	0.97***		
	(0.08)	(0.08)			(0.17)	(0.18)		
Abstract (Exp.)			0.51***	0.53***			0.63***	0.63***
			(0.03)	(0.03)			(0.03)	(0.03)
Abstract (Exp.) × Abstract Deviation from Occ. Avg. (Exp.)			0.35***	0.22***			0.62***	0.42***
			(0.04)	(0.04)			(0.06)	(0.06)
Routine (Exp.)			0.22***	0.22***			0.16***	0.17***
			(0.04)	(0.04)			(0.05)	(0.04)
Routine (Exp.) × Routine Deviation from Occ. Avg. (Exp.)			-0.01	-0.07			-0.11	-0.17**
			(0.05)	(0.05)			(0.08)	(0.08)
Survey tasks (Occupational)	✓	✓			✓	✓		
Survey tasks (Individual)	✓	✓	✓	✓	✓	✓	✓	✓
Expert tasks (Occupational)			✓	✓			✓	✓
2-digit Occupations	✓		✓		✓		✓	
3-digit Occupations		✓		✓		✓		✓
Task Time Dimension: "Often"	✓	✓	✓	✓				
Task Time Dimension: "Often" & "Sometimes"					✓	✓	✓	✓
Abstract Deviation from Occ. Avg. (p25)	-0.12	-0.14			-0.07	-0.06		
Abstract Deviation from Occ. Avg. (p50)	0.00	0.00			0.00	0.00		
Abstract Deviation from Occ. Avg. (p75)	0.14	0.15			0.08	0.07		
Abstract Deviation from Occ. Avg. (Exp.) (p25)			-0.14	-0.16			-0.13	-0.17
Abstract Deviation from Occ. Avg. (Exp.) (p50)			0.05	0.04			0.04	0.02
Abstract Deviation from Occ. Avg. (Exp.) (p75)			0.24	0.23			0.20	0.21
Observations	32003	32003	32003	32003	32003	32003	32003	32003
R-squared	0.196	0.198	0.193	0.195	0.201	0.202	0.193	0.196
Adj. R-squared	0.195	0.196	0.191	0.194	0.199	0.201	0.192	0.194

Robust standard errors in parentheses

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

* Note: Above estimates are based on eq. (1.9) to describe wage gains resulting from task specialization within occupations. The first four rows display occupation-level averages based on survey data ("(Occ.)") as base estimates and interacted with individual deviations from those averages. The last four rows display occupation-level averages based on Expert data ("(Exp.)") as base estimates and interacted with individual deviations from those averages. All specifications include controls for gender, age, age squared, a dummy for living in an urban area, education dummies, occupational tenure, firm tenure, squared tenure for each dimension of experience, and a categorical variable reflecting firm size. The omitted task category is "Manual". The first four columns assume a worker performs a task if she carries out activities "often". In contrast, the last four columns assume a worker performs a task if she carries out activities "often" or "sometimes".

Table 1.7: Task Measures as Wage Predictors: Interaction between Occupation-level Averages and Individual Deviations from Mean Task Content (Broad Task Categories, 2-digit Occupations)

To address the time dimension of tasks, columns (5)-(8) display results when workers need to perform a task at least "sometimes". Notably, adding more weight to the time dimension makes incremental efficiency gains in abstract tasks as important as base gains (columns 5 & 6). In case of enhanced specialization in routine tasks, efficiency gains are even more pronounced.[28] Yet, the cumulative effects of incremental gains for workers at the top quartile of the task distribution remain steady, being six times as large as base gains (7 x 1.44 vs 1.51). The incremental efficiency gains in abstract tasks are instead about two thirds of the base gains when Expert data is used. Based on these findings it could be speculated that the skill dimension is relatively more relevant at the occupation-level, e.g. via self-selection embedded in a Roy model.[29] Within occupations, however, workers have similar skill endowments and may thus increasingly specialize along the time margin. Ideally, one would use longitudinal data to test whether workers attach more weight to the time dimension as their career in an occupation progresses. This questions is beyond the scope of this paper, however, and is left for future research.

1.6 Conclusions

This paper contributes to the growing literature on the task-approach to labor markets, adding new theoretical and empirical insights. Employing a sizable cross-section of more than 32,000 workers in Germany since 2012, I compare task measures derived from Survey data with recently made available German Expert-based task data and conduct formal tests of the underlying assumptions of more commonly used Expert data, especially pertaining to the assumption of a common set of tasks within occupations. The evidence reveals that worker-level information on tasks is uniquely predictive of wage differences between *and* within occupations. Several goodness-of-fit measures and information criteria suggest that models comprising worker-level information are statistically superior to models relying on occupation-level measures only. Notably, individual-level tasks explain 8% of the variation in wages that other covariates cannot address, including occupation-level measures. Combined, these findings reject the implicit assumption of common tasks

[28]These effects are driven by enhanced specialization in routine cognitive tasks (not reported). An analysis on the degree of specialization based on the five narrow task groups is available from the author upon request.

[29]See, e.g., Heckman & Sedlacek (1985), Heckman & Scheinkman (1987), Keane & Wolpin (1997), Lee (2005), Sullivan (2010), Yamaguchi (2012), and Autor & Handel (2013).

within occupations, a takeaway consistent with Autor & Handel (2013) who conduct a similar analysis for the US.

To conceptualize the benefits of using worker-level information on tasks, I empirically test a wage equation accounting for task specialization within occupations. This framework is based on the idea that more efficient workers have an incentive to specialize in occupation-specific core tasks. The results strongly support the notion that these intra-occupational efficiency gains are an important component of wage differences within occupations. Relative to performing manual tasks, occupational averages imply base wage gains in abstract tasks on the order of 97%. Incremental individual deviations from that average imply additional wage gains of 47%.

The evidence presented in this study supports using worker-level information on tasks, whenever feasible. On the one hand, sufficiently detailed information on occupational affiliation may not always be available, thus distorting measurement of the task content. On the other hand, a growing body of research has pointed to rising heterogeneity within important dimensions of interest, such as occupations[30] or firms[31]. Using detailed information on what workers do at their job can help shed light on these phenomena. Moreover, it is worth exploring time-related aspects of tasks in more detail. Typically, the time dimension relating a worker's skills to time spent on job-related activities is not observed by the practitioner, yet exploratory findings in this paper indicate they are a component of the skill endowment as wage premia resulting from task specialization within occupations are more pronounced in specifications in which time dimension of tasks is given more importance. These findings are in in line with novel research explicitly investigating the time dimension using longitudinal data (Stinebrickner, Stinebrickner & Sullivan 2018, 2019). Future research should continue to shed light on these questions, perhaps within in a Roy framework in which workers sort themselves into occupations based on their skill endowment and job preferences incorporating time spent on specific activities.

[30]See Hershbein & Kahn (2018), Atalay, Phongthiengtham, Sotelo & Tannenbaum (2018a,b, 2019), Deming & Noray (2019), and Modestino, Shoag & Ballance (2019).

[31]See Card, Heining & Kline (2013), Barth, Bryson, Davis & Freeman (2016), Song, Price, Guvenen, Bloom & von Wachter (2019), and Dostie, Li, Card & Parent (2020).

Chapter 2

THE NATIVE-FOREIGN WAGE GAP: EVIDENCE FROM INDIVIDUAL TASK DATA

2.1 Introduction

Economists have long discussed the wage effects of immigration. Early research has exploited heterogeneous immigrant concentration at the local level. These "area studies" usually find little to no adverse effects of immigration, in part because they ignore skill differences between natives and foreigners.[1] To provide remedy, a popular approach has been to follow Borjas (2003) and estimate a CES production function by assigning workers into education-experience cells, thus accounting for different types of skill in the labor aggregate. These studies find comparably larger wage effects among less-skilled workers, but nonetheless a small impact at the aggregate level.[2]

A shortcoming of this "cell-approach" is that workers are distinguished by means of formal qualification. This introduces measurement error when otherwise similar workers workers are located in different parts of the wage distribution due to unobserved differences.[3]In light of this identification problem, Peri & Sparber (2009) propose measuring skill differences between native and foreign-born workers by utilizing data about task requirements at work. Within a CES framework they show that less-educated natives in

[1]See Altonji & Card (1991), LaLonde & Topel (1991), Pischke & Velling (1997) for notable early studies. More recent papers have accounted for different skill types, finding stronger adverse effects on incumbent workers whose observed education and experience level is similar to location-specific immigrant groups (Card 2001, Glitz 2012).

[2]See, e.g., Borjas (2003), Bonin (2005), D'Amuri, Ottaviano & Peri (2010), Steinhardt (2011), Manacorda, Manning & Wadsworth (2012), and Ottaviano & Peri (2012).

[3]See, e.g., Friedberg (2001), Dustmann & Preston (2012), Dustmann et al. (2013), Warman et al. (2015), Dustmann et al. (2016) for empirical evidence on occupational downgrading of immigrants upon arrival in the destination country. Moreover, Altonji, Kahn & Speer (2014) document an increase in inequality among US college graduates, emphasizing differences in majors and corresponding skill prices as driving forces.

states with large inflows of less-educated immigrants respond by specializing in occupations intensive in interactive tasks. Peri & Sparber (2011) show similar specialization patterns among skilled labor as native college graduates tend to specialize in interactive occupations, whereas foreign-born college graduates are concentrated in STEM occupations intensive in analytic tasks.

This empirical strategy has gained popularity in recent years, highlighting occupational segregation as a key source for imperfect substitutability between native and foreign workers and providing a compelling argument for the modest migration-induced wage effects usually found in the literature.[4] Existing studies measure task requirements at the occupation-level, thus implicitly assuming that workers within occupations perform the same set of tasks. However, an extensive literature has documented how occupations experienced substantial changes in job task requirements as technological change has automated many routine tasks. This development has led to the re-allocation of workers previously employed in routine-heavy occupations and widespread employment polarization,[5]implying that workers are 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.

The present study contributes to this growing literature exploring the relationship between skills, tasks, and wages. First, I demonstrate that individual-level information on tasks at work has explanatory power that differs from data at the occupational level. Only a couple of studies have explored the heterogeneous adoption of tasks within occupations. Combining occupation-level task measures from the *Occuptional Information Network* (O*Net) database with survey data on individual-level task measures, Autor & 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) uses survey data on German workers, the same data set used in the present study, confirming that

[4]Among papers building upon this strategy are, e.g., Amuedo-Dorantes & de La Rica (2011), Haas, Lucht & Schanne (2013), and Sebastian & Ulceluse (2019).

[5]See Autor, Levy & Murnane (2003), Spitz-Oener (2006), Goos & Manning (2007), Autor & Dorn (2013), Goos, Manning & Salomons (2014), Senftleben & Wielandt (2014), Hershbein & Kahn (2018) and the references therein for international evidence on employment polarization and its implications on the wages.

individual task variation is likewise predictive of wage differences in Germany from 1986-92. These studies focus on a rather short-term time horizon, however. I expand on their findings by providing long-term evidence on the explanatory power of worker-level tasks from 1992-2018.

Second, I demonstrate that worker-level variation in tasks is predictive of wage differences between native and foreign workers. Unlike previous studies in the migration literature, I highlight that both groups of workers perform distinct activities within occupations and that these disparities are an important factor of the wage gap. Applying a Oaxaca-Blinder (OB) decomposition, I conduct a Between- vs Within-occupation comparison of task specialization and show that both channels are statistically and economically significant. On average, the Between-occupation component contributes 30% to the explained wage gap between 1992-2018, compared to 20% for Within-occupation effects.

Third, I decompose the native-foreign wage gap along the wage distribution, focusing primarily on the role of tasks.[6]Generalizing the conventional OB decomposition, I follow Firpo, Fortin & Lemieux (2009) and construct Recentered Influence Functions (RIF) to perform quantile regressions on the wage gap. Applying this methodology, I show that individual-level variation in tasks (i) is more pronounced among high-wage earners and (ii) has become increasingly important since the 2000s. This, in turn, implies that occupation-level measures have become relatively less important over the past 20 years. The sole exception is variation in interactive tasks whose contribution to the wage gap has remained substantial at the detriment of variation in analytic tasks, which are dominant in STEM occupations. These findings are consistent with Peri & Sparber (2011), who document occupational segregation among college graduates. Yet, my results are only partially consistent with Peri & Sparber (2009), who focus on less-educated workers instead. While I do find native workers below the median to become increasingly specialized in communication-heavy occupations, there is no indication that foreign workers below the median increasingly specialize in occupations intensive in manual tasks.

[6]In a recent study Ingwersen & Thomsen (2019) likewise decompose the wage gap between native and foreign workers in Germany, using the same technique as the present paper. However, their focus is on differential effects among subgroups of foreigners with a core interest in cultural factors.

Instead, contributions to the gap among low-wage earners that are associated with variation in manual tasks, around 10%, are due to discrepancies at the worker-level. Similarly, up to 25% of the explained wage gap near the top of the distribution between 2006-2018 can be attributed to individual differences in interactive tasks alone. Hence, there is substantial heterogeneity in the measurement of skills which traditional proxies fail to address. This development explains why, despite educational assimilation (Algan, Dustmann, Glitz & Manning 2010), the rise in the German native-foreign wage gap has been driven by workers near the top of the wage distribution. Idiosyncratic differences in job-related activities are more pronounced among skilled workers and have allowed Within-occupation differences in tasks to become more important relative to Between-occupation effects. If otherwise similar workers perform distinct tasks with distinct prices, the implied productivity differences will translate into wage differences (Gottschalk, Green & Sand 2015, Boehm 2017, Cortes, Jaimovich & Siu 2018). Previous studies emphasizing occupational segregation have thus underestimated the degree of task specialization between native and foreign workers. The findings of this study 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.

2.2 Data

2.2.1 Data Source & Key Features

The data source are 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 each of the seven waves: 1979, 1986, 1992, 1999, 2006, 2012, 2018. I exclude the first two surveys as they contain no identifier on a worker's nativity.[7]

[7] See Bundesinstitut Für Berufsbildung (Berlin) & Institut Für Arbeitsmarkt- Und Berufsforschung Der Bundesanstalt Für Arbeit (Nürnberg) (1995), Jansen & Dostal (2001), Hall & Beermann (2009), Hall, Siefer &

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.[8] The frequently used O*Net and *Dictionary of Occupational Titles* (DOT) databases in the US, for example, are based on occupational analysts (and job incumbents in the case of O*NET). As a consequence, this method of measuring tasks limits the scope of any analysis on the occupation level and relies on the external assessment about the importance of occupation-specific tasks. Second, the employment surveys enable an investigation of long-term trends. Comparable data sources providing self-reported information, such as the the Princeton Data Improvement Initiative (PDII) and the survey of Skills, Technology, and Management Practices (STAMP) in the US, 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.[9]

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 1992 classification, using the conversion tables provided by the German Federal Employment Agency (BA).[10] Second, various occupations contain few observations on foreign workers.[11]As a consequence, any analysis based on occupation-specific averages is constrained due to the influence of outliers. To address this limitation, I aggregate the 3-digit occupations into closely related

Tiemann (2014), and Hall, Hünefeld & Rohrbach-Schmidt (2020) for data manuals for each of the surveys used in this study. Moreover, Appendix B.1 presents Document Object Identifiers (DOI) for all data.

[8]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".

[9]See Rohrbach-Schmidt & Tiemann (2013) for a comprehensive comparison among task data sets.

[10]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/Umsteigeschluessel/Umsteigeschluessel-Nav.html` (Date accessed: 01/18/2020).

[11]Workers are distinguished by citizenship, i.e. 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 (Riphahn & Trübswetter 2013, Klein, Barg & Kühhirt 2019).

occupational groups following the methodology of the IAB.[12] While this strategy increases statistical precision, it still leaves several occupational groups with few foreign workers. Therefore, parts of the analysis centered around occupation-level averages is limited to groups with at least 10 observations on foreign individuals. This restriction reduces the set of occupational groups from 118 to 75. An overview of the occupations along with composition of the native and foreign workforce can be found in Table B.1 in Appendix B.2.1.1. 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.[13] Finally, income levels are converted into real terms using CPI=100 as of 2015 and used to calculate the hourly wage rate using information on weekly hours worked from the surveys.[14]

The baseline sample is restricted to West German civilian workers aged 18-65 who are not self-employed, no civil servants and work at least 15 hours a week, thus containing only workers who are subject to social security payments. Applying these restrictions leaves a sample size of 63,456 workers (male and female) for whom individual-level information on tasks is available. Among those, 61,229 (96.5%) are natives. The remaining 3.5% of observations are from foreign workers. Official data from the German employment agency, however, suggests that almost 12% of workers subject to social security payments and working in West Germany had been foreign citizens in 2017, compared to some 8% in 1999.[15] Therefore, the employment surveys under-represent foreign workers by

[12]The occupational groups can be found in Ganzer, Schmucker, Vom Berge & Wurdack (2017, p. 60). Note that I exclude two occupational categories, Elected Officials and Soldiers/Judicial Enforcers, as my sample restrictions exclude soldiers and civil servants.

[13]The bin midpoints are: 300, 800, 1250, 1750, 2250, 2750, 3250, 3750, 4250, 4750, 5250, 5750. Income levels beyond that are capped at 6000.

[14]By constructing hourly wage rates, I assume that each worker works 8 hours per day. This assumption is supported by descriptive statistics in the sample as the average weekly hours worked for natives (foreigners) amounts to 38.7 hours (39.3) with a standard deviation of 12.8 (12.8). Furthermore, note that the CPI data is taken from the Federal Reserve Bank of St. Louis (FRED) and can be downloaded under the following link: https://fred.stlouisfed.org/series/DEUCPIALLAINMEI (Date accessed: 01/18/2020).

[15]https://statistik.arbeitsagentur.de/Statistikdaten/Detail/201712/analyse/analyse-arbeitsmarkt-zeitreihen/analyse-arbeitsmarkt-zeitreihen-d-0-201712-pdf.pdf, P. 30 (Date accessed: 03/25/2020).

at least a half. A key reason for this discrepancy are requirements on proficiency of the German knowledge: only foreign workers with sufficient command of the German language were 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 BIBB/IAB and BIBB/BAuA employment surveys with other commonly used German labor market data suggests the data is able to capture key trends in the native-foreign wage gap. Specifically, the data correctly characterizes (i) the rising wage gap for most parts of the past 20 years and (ii) a pronounced gap at the tails of the distribution. Moreover, command of the German language among immigrants deteriorated since the 1990s. Any contributions to the wage gap stemming from natives' comparative advantage in interactive tasks can thus be viewed a lower bound in regards to the overall foreign population. More details are presented in Appendix B.2.2.

2.2.2 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 consistently asked throughout the sample period 1992-2018. In this regard, I follow Rohrbach-Schmidt & Tiemann (2013) who compare different classifications of tasks among the older (BIBB/IAB) and more recent (BIBB/BAuA) surveys from 1979-2006. Across these samples, they select tasks that appear in two out of five samples. Recognizing that the surveys released in 2012 and 2018 are conceptually alike, I follow this strategy by including only those tasks that were questioned at least three out of five times.[16]

[16] The key difference among tasks selected in my study compared to Rohrbach-Schmidt & Tiemann (2013) is with respect to the domain of routine cognitive tasks. While Rohrbach-Schmidt & Tiemann (2013) use three task groups in this domain (measuring, writing, calculating), the infrequent question for routine cognitive tasks in more recent surveys limits my analysis to one single task group - measuring/ writing/ calculating. While in 1992 "measuring" was not part of the task space, "writing" and "calculating" have been removed in subsequent surveys. Hence, I aggregate the three distinct tasks groups into one domain to create a single measure for routine cognitive tasks.

Subsequently, I follow Spitz-Oener (2006) and pool activities into five narrow task categories: (i) non-routine (NR) analytic tasks, (ii) NR interactive tasks, (iii) routine cognitive tasks, (iv) routine manual tasks, and (v) NR manual tasks. This task classification is based on Autor, Levy & Murnane (2003), the landmark study in the literature employing task data. Table (2.1) illustrates the single task elements comprised in those five categories (column 3) along with descriptions about underlying activities (column 4). Several studies in the literature use related, yet, broader definitions of tasks. For instance, in Acemoglu & Autor (2011) analytic and interactive tasks are subsumed under "Abstract". Similarly, routine cognitive and routine manual tasks are subsumed under "Routine". Non-routine manual tasks, on the other hand, are not categorized further and will be described interchangeably as "Manual".

Task Category (Broad)	Task Category (Narrow)	Task Group(s)	Task Content
Abstract	Non-Routine Analytic	Investigating Organizing Researching Programming	Gathering Information, Investigating Organizing, Making Plans, Decision Making Researching, Evaluating, Developing Working with Computers, Programming
	Non-Routine Interactive	Teaching Consulting Buying/Selling Promoting	Teaching, Training, Educating Consulting, Advising Purchasing, Procuring, Selling Marketing, PR, Presenting
Routine	Routine Cognitive	Measuring/Writing/Calculating	Measuring, Testing, Quality Control, Clerical Work, Calculating, Bookkeeping
	Routine Manual	Operating Manufacturing Storing	Operating, Controlling Machines Manufacturing of Goods, Planting Storing, Transporting, Stocking, Posting
Non-Routine	Non-Routine Manual	Repairing Accomodating Caring Cleaning Protecting	Repairing, Renovating, Restoring Accomodating, Preparing Food, Serving Taking Care, Healing Cleaning, Recycling, Waste Disposal Guarding, Observing, Controlling Traffic

Table 2.1: Task Categories and their Contents

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 to NR tasks. Lastly, NR tasks require 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 Antonczyk, Fitzenberger & Leuschner (2009), I define task measures T_{ijt} for individual i at time t as

$$T_{ijt} = \frac{\text{No. of activities performed by i in task category j at time t}}{\text{Total no. of activitites by i across } \textit{all} \text{ j's at time t}} \tag{2.1}$$

where $t \in (1992, 1999, 2006, 2012, 2018)$ and $j = 1$ (NR Analytic), $j = 2$ (NR Interactive), $j = 3$ (Routine Cognitive), $j = 4$ (Routine Manual), $j = 5$ (NR Manual) reflect the task categories defined above. This definition implies that the number of task-specific activities is proportional to all activities, adding up to 1 over all tasks. Intuitively, it thus describes the relative importance of each task category j. For example, if employee i performs two analytic, two interactive, and one routine cognitive task, then her analytic, interactive, and routine cognitive task content, respectively, is 0.4, 0.4, and 0.2. Therefore, 80% of her overall activities comprise abstract tasks with equal contributions from NR Analytic and NR Interactive. The remaining 20% involve routine cognitive activities.[17]

By collecting the individual task content T_{ijt} for each of the N_o workers employed in occupation o, we can compute occupational averages, the common task dimension used in the literature:

$$T_{jo} = \frac{1}{N_o} \sum_i \sum_t T_{ijt} \tag{2.2}$$

where T_{jo} simply reflects occupation-specific averages for each j and has an interpretation analogous to eq. (2.1), defining the importance of each task category at the occupation-level instead. Note that occupational averages are computed across all t. To conduct the decomposition of the wage gap, eq. (2.2) will be calculated separately for natives and foreign workers. Calculating averages at the occupation-level for each t, however, is not feasible due to the under-representation of the latter group in the sample.

[17] Intuitively, this measures is related to the skill-weight approach in Lazear (2009) in which returns to skills are determined by weights firms attach to core skills. Constructing these weights implies that a high weight attached to a particular skill means a low weight on the other skills.

2.2.3 Trends in the Task Content

Figure (2.1) depicts the relative importance of each of the narrow task categories from 1992-2018. Panel (2.1a) illustrates aggregate trends, whereas panel (2.1b) illustrates trends by nativity. Unsurprisingly, routine tasks experienced a substantial drop over time in aggregate terms. While they comprised more than 40% of all tasks in 1992, this share decreased to 25% by 2018. Notably, the bulk of this drop occurred in routine manual tasks whose share has been cut by half.[18] This reduction has been complemented by a rise in abstract tasks. Compared to 1992, the combined share of analytic and interactive tasks increased from 38% to 59% by 2018 with nearly identical contributions by both task categories.

Overall, the stylized facts on tasks assignments support the well-known increase in occupational skill requirements documented since the 1970s.[19] In response to increasing automation of activities, routine tasks have subsequently been substituted by abstract and, albeit by a smaller amount, manual tasks. This mechanism has been a key contributor to employment polarization as workers who used to mainly perform routine tasks were allocated to occupations utilizing abstract or manual tasks more extensively.[20] Yet, different specialization patterns among workers likewise suggest these trends have been differentially experienced by native and foreign workers.[21]

Interestingly, though, Figure (2.1b) shows an assimilation of average tasks assignments between both groups, mirroring trends in educational assimilation (see Figure B.4 in Appendix B.2.2.2). Foreign workers still perform relatively more manual tasks. Yet, abstract tasks have become a more integral part of foreign worker's job activities. In the 1990s, natives performed some 20 pp. more abstract tasks with equal contributions from analytic

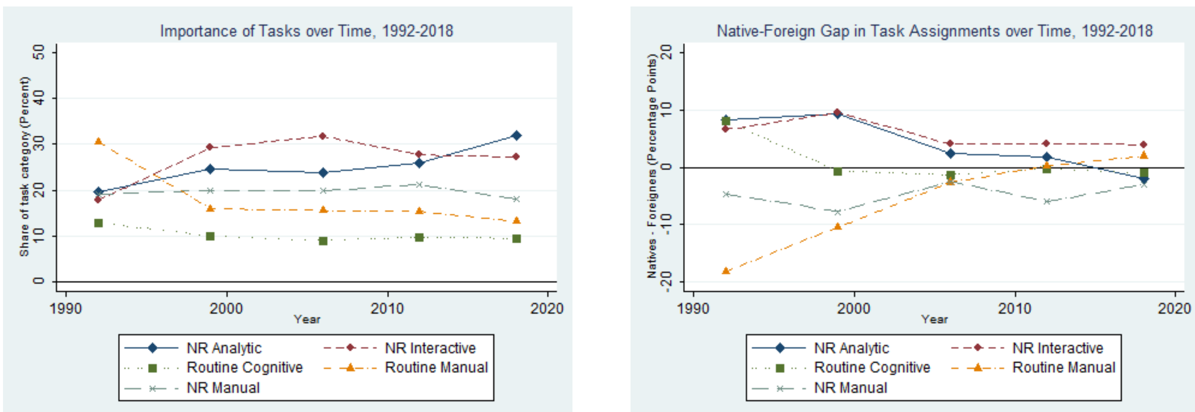
[18]Note, however, that routine cognitive tasks are underrepresented in this sample due to inconsistent appearances in the employment surveys. Spitz-Oener (2006), whose analysis ends in 1999, reports a share of routine cognitive tasks of 27% as of 1992 whereas routine manual represented 23%. Hence, the measure for the broad category "Routine" in this study disproportionately includes routine manual tasks at the detriment of routine cognitive tasks.

[19]See Autor, Levy & Murnane (2003), Spitz-Oener (2006), Acemoglu & Autor (2011), Beaudry, Green & Sand (2016), Deming (2017), Hershbein & Kahn (2018), Atalay, Phongthiengtham, Sotelo & Tannenbaum (2018a,b, 2019), Deming & Noray (2019), Modestino, Shoag & Ballance (2019), and the references therein.

[20]See Autor, Levy & Murnane (2003), Spitz-Oener (2006), Goos & Manning (2007), Autor & Dorn (2013), Goos, Manning & Salomons (2014), Senftleben & Wielandt (2014), and Hershbein & Kahn (2018).

[21]See Peri & Sparber (2009, 2011), Haas, Lucht & Schanne (2013), and Cassidy (2019).

and interactive activities. This gap in abstract tasks has closed by 2018, seemingly at odds with the rising wage gap illustrated in Figure (2.2). While (2.2a) illustrates that the wage gap between native and foreign workers remained mostly flat just short of 15% between the mid 1990s and mid 2000s, it increased steadily from 14% in 2008 to 20% in 2014. If foreign workers assimilate in terms of education outcomes and increasingly perform the same tasks as natives, then why do we not observe a convergence in wages?

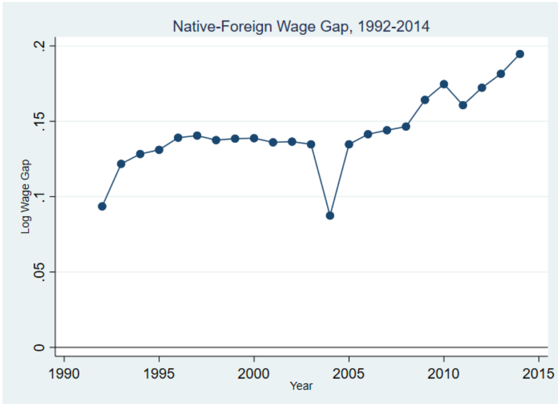


(a) Tasks across all Workers

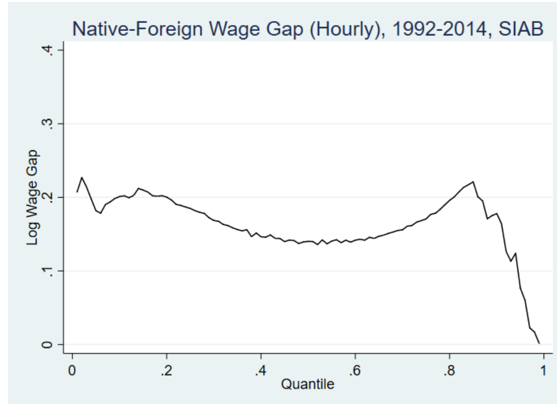
(b) Task Gaps by Nativity

Figure 2.1: Task Assignments in Germany, 1992-2018

This study explores two hypotheses to answer this question. First, while native and foreign workers perform the same set of tasks in aggregate terms nowadays, there are still crucial differences in the allocation of narrow task categories. Despite the convergence regarding NR Analytic to the point of equality by 2018, Figure (2.1b) clearly illustrates that the gap regarding NR Interactive has remained steady over the past 15 years, implying heterogeneous adoption of NR tasks between the two groups. Second, simple average measures are not adequate to capture differences in task assignments between natives and foreigners. In particular, the wage gap follows a U-shaped pattern along the wage distribution, displayed in Figure (2.2b). A distributional analysis thus appears more appropriate to reconcile the opposing stylized facts.



(a) Wage Gap over Time



(b) Wage Gap across the Wage Distribution

Figure 2.2: Native-Foreign Wage Gap in Germany, 1992-2014
Source: SIAB-R 7514

2.3 Empirical Analysis

To address the trends in task assignments and the wage gap, I employ the following strategies. First, compare the relative contribution of task measures at the individual and occupation-level. To my knowledge, no paper has explored individual-level variation in tasks in the context of immigration. As the rise in the native-foreign wage gap coincided with an assimilation of tasks in aggregate terms, it can be hypothesized that individual variation has become more important over time. Second, explore the dimension of the degree of specialization between natives and foreign workers. If native and foreign workers perform different tasks according to their comparative advantage, skill-biased technological change should amplify preexisting specialization patterns beyond occupational borders. "Between-Occupation" effects are the standard measure in the literature and are proxied by averaging out individual responses of workers within an occupation per eq. (2.2). On the other hand, "Within-Occupation" effects are based on individual-level tasks and conditioned on occupational affiliation via fixed effects (FE). Previous studies have not addressed this element of wage differences, but have pointed to specialization of native workers in occupations intensive in interactive tasks. Should this channel have gained more importance over time, it is expected to be true specifically for interactive tasks.

2.3.1 Oaxaca-Blinder Decomposition

As a benchmark, I first employ the Oaxaca-Blinder (OB) decomposition (Oaxaca 1973, Blinder 1973) to highlight the relevance of tasks as a predictor of the wage gap at the occupational and individual level. This conventional method has been widely used to study mean differences between two groups. In the present context, this amounts to decomposing the mean wage gap between native (N) and foreign (F) workers:

$$\overline{w}_N - \overline{w}_F = \underbrace{(\overline{X}_F - \overline{X}_N)\hat{\beta}_N}_{\text{Explained Part}} + \underbrace{\overline{X}_F(\hat{\beta}_N - \hat{\beta}_F)}_{\text{Unexplained Part}} \tag{2.3}$$

where the first term captures the explained part due to mean differences in covariates. The second term reflects the residual which cannot be explained by the model, including a constant term which has been omitted to simplify the exposition. The decomposition can be implemented by running OLS by groups $g = N, F$ and plugging sample means and coefficients into (2.3). In the specification below, the dependent variable is the log hourly real wage $ln\ w_{it}$ of individual i performing task category j at time t:

$$ln\ w_{it} = \alpha + \boldsymbol{\beta T_{it}} + \boldsymbol{\gamma X_{it}} + \delta_t + \lambda_r + \eta_s + \epsilon_{it} \tag{2.4}$$

where the vector $\boldsymbol{X_{it}}$ 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 time, region (state-level), and sectoral dummies.[22]

The key variable is the vector $\boldsymbol{T_{it}} = \left(T_{i1t}, T_{i2t}, ..., T_{iJt}\right)$, comprising NR analytic, NR interactive, Routine Manual and NR Manual task measures. Routine Cognitive is the excluded task group, the coefficients thus have to be interpreted relative to this category. On the one hand, native and foreign workers included in the sample have been most

[22] To be specific, the dummies encompass 5 years, 11 states (Western Germany), and 34 sectoral groups. For the empirical implementation one group has to be removed for each dummy, thus serving as a reference group. For the same reasons one education group has to be removed, in this case workers who have not earned a vocational degree.

similar with respect to routine cognitive activities. On the other hand, this paper explores whether native workers specialize in interactive tasks, while foreign workers specialize in manual tasks. Choosing Routine Cognitive as the reference group is conform with this hypothesis. The benchmark specification includes occupation-level task measures $\boldsymbol{T_{jo}}$ instead of $\boldsymbol{T_{ijt}}$ to provide a reference to previous research. Subsequently, individual-level task measures are included to test whether worker-level information on tasks adds explanatory power which is not picked up by occupation-level data. Augmenting eq. (2.4) by up to 118 occupational dummies θ_o stresses the importance of idiosyncratic factors embodied in the task content by exploring task specialization *within* occupations.

Table 2.2 summarizes the key results from this baseline decomposition. The mean wage difference is between 9-10 pp depending on specification and can be entirely explained by mean differences in observable outcomes. Due to the under-representation of the foreign workforce in the BIBB/IAB and BIBB/BAuA surveys, I restrict baseline specifications including occupation-level task measures to occupations with observations on at least 10 foreign workers. Columns (1)-(5) are based on this restricted sample, removing occupations which are particularly prone to outliers. Specifications in columns (6)-(10), in turn, comprise the full sample with all occupations.

Estimates in column (1) suggest that 25% of the explained wage gap can be attributed to occupational choice in the restricted model with no task measures (0.023/0.092). In comparison, columns (2) and (3), respectively, introduce occupation-level and individual-level task measures. Both specifications display even larger point estimates for the contribution of tasks to the explained gap (collectively), implying that individual-level tasks pick up some of variation that is usually attributed to occupational affiliation and in line with previous findings (Autor & Handel 2013, Cassidy 2017). Including both task measures (column 4) reveals that they are able to explain different kinds of variation in the native-foreign wage gap. In particular, individual task measures remain statistically and economically significant, combined accounting for 2.1 log points of the explained wage difference. Column (5) proxies within-occupation discrepancies in task assignments by conditioning the wage gap on worker-level tasks and occupational FE. If variation in tasks merely reflect differences in occupational requirements, we would expect the coefficients on tasks to be insignificant. However, conditional on occupational choice, variation in task measures remains significant and contributes more than 25% to the explained mean gap (0.024/0.090).

Dependent Variable: Log Hourly Real Wage	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Native-Foreign Wage Gap	0.094***	0.094***	0.095***	0.095***	0.095***	0.097***	0.097***	0.099***	0.099***	0.099***
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Explained Difference	0.092***	0.093***	0.086***	0.089***	0.090***	0.102***	0.102***	0.096***	0.099***	0.101***
	(0.011)	(0.012)	(0.012)	(0.012)	(0.012)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Occupation	0.023***				0.011***	0.032***				0.019***
	(0.003)				(0.003)	(0.004)				(0.004)
NR Analytic (Occup.)		0.025***		0.023***			0.024***		0.022***	
		(0.003)		(0.003)			(0.003)		(0.003)	
NR Interactive (Occup.)		0.002		0.002			0.003**		0.003*	
		(0.001)		(0.002)			(0.001)		(0.001)	
Routine Manual (Occup.)		0.002		-0.006**			0.003		-0.005**	
		(0.002)		(0.003)			(0.002)		(0.002)	
NR Manual (Occup.)		0.002**		-0.002*			0.003***		-0.001	
		(0.001)		(0.001)			(0.001)		(0.001)	
NR Analytic (Indiv.)			0.011***	0.007***	0.008***			0.010***	0.007***	0.007***
			(0.002)	(0.001)	(0.002)			(0.002)	(0.001)	(0.001)
NR Interactive (Indiv.)			0.006***	0.006***	0.006***			0.005***	0.005***	0.005***
			(0.001)	(0.001)	(0.001)			(0.001)	(0.001)	(0.001)
Routine Manual (Indiv.)			0.006***	0.003**	0.003***			0.007***	0.003***	0.003***
			(0.001)	(0.001)	(0.001)			(0.001)	(0.001)	(0.001)
NR Manual (Indiv.)			0.008***	0.005***	0.007***			0.008***	0.005***	0.005***
			(0.002)	(0.001)	(0.001)			(0.001)	(0.001)	(0.001)
Restriction: $\geq$ 10 Foreigners by Occupation	✓	✓	✓	✓	✓					
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Occupation Dummies	✓				✓					
Task Measure (Occupational)		✓		✓			✓		✓	
Task Measure (Individual)			✓	✓	✓			✓	✓	✓
Observations	56963	56963	55036	55036	55036	65613	65613	63456	63456	63456

Robust standard errors in parentheses

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

* Note: The Decomposition is based on regressions of log wages by nativity on a set of controls, 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) and dummies to capture time, region (state-level), sectoral, and occupational effects.

Table 2.2: Tasks and the Native-Foreign Wage Gap - OB Decomposition

Models based on the full sample display quantitatively similar results. Notably, however, occupational FE become more important. For instance, the point estimate of occupational FE in a specification with individual task measures (column 10) nearly doubles compared to the restricted sample (column 5). A potential caveat is bias due to removal of occupations with too few observation on foreigners. If this set of occupations bears any systematic relationship between the amount of foreigners employed and task requirements, it introduces a bias in estimates of the restricted sample. Indeed, a closer inspection reveals that excluded occupations rely disproportionately on routine manual tasks, thus diminishing the importance of between-occupation differences in task requirements in the restricted sample. The interested reader is referred to Appendix B.2.1.2 for more details. Moving forward, I will focus on specification (10) in Table (2.2) in applications in which a between- vs within-occupation comparison is not of central interest. This proceeding alleviates any bias resulting from occupational restrictions and moreover increases statistical precision.

2.3.2 RIF Decomposition: 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. It stands to reason, however, that individual characteristics have differential contributions to the wage gap along the distribution. For instance, performing more abstract tasks may affect high-wage workers differently than low-wage workers as many of them are already specialized in those activities, thus being more equipped in executing them. 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, Fortin & Lemieux (2009) show formally how to construct an IF as a measure of robustness and, importantly, demonstrate how this tool can be used to perform quantile regressions. 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 influence function $IF(y;v;F_{Y(g)})$ 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 we need to construct a recentered influence function (RIF), i.e. centre 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:

$$E(RIF(y;v;F_{Y(g)})|X) = X\beta_g \tag{2.5}$$

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 $p_\tau, \tau = 0.1, ..., 0.9$. Collecting the β_g's from eq. (2.5) and using $RIF(y;v;F_{Y(g)})$ as dependent variable, we can decompose the contributions of X in spirit of the OB method:

$$RIF_\tau^N - RIF_\tau^F = \underbrace{(\overline{X}_\tau^F - \overline{X}_\tau^N)\hat{\beta}_\tau^N}_{\text{Explained Part}} + \underbrace{\overline{X}_\tau^F(\hat{\beta}_\tau^N - \hat{\beta}_\tau^F)}_{\text{Unexplained Part}} \tag{2.6}$$

Note that eq. (2.6) is merely a generalization of eq. (2.3) in section 2.3.1, applying the OB decomposition along the wage distribution and replacing mean wages for $g = N, F$ by their corresponding RIF on the LHS. A decomposition based on an RIF has several key features that makes 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, 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, Fortin & Lemieux (2009), I specify $RIF(y;v;F_{Y(g)})$ as follows:

$$RIF_g(w_g, p_\tau) = \frac{\tau - I(w_g \leq p_\tau)}{f_{w_g}(p_\tau)} + p_\tau \tag{2.7}$$

where the first term illustrates $IF(y;v;F_{Y(g)})$ and the second term illustrates the statistic of interest, namely the log wage at decile $p_\tau, \tau = 0.1, ..., 0.9$. 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.[23]

[23] Intuitively, a RIF decomposition is closely related to a model for proportions. Specifically, eq. (2.7) estimates the proportion of workers for each group falling below the first decile, the second decile, and so on. Weighting each indicator by the corresponding group-specific wage density, we can account for the

In practice, a RIF decomposition can be implemented in two steps. First, using kernel methods, compute the wage density associated with native and foreign workers, respectively, over the entire sample horizon (1992-2018). The estimated densities are subsequently plugged into (2.7), yielding the RIF for both groups evaluated at each decile of their respective wage distribution. Second, replace the dependent variable by its corresponding RIF from the first step and run simple quantile regressions:

$$RIF_g(\widehat{lnw_{it}, p_\tau}|\boldsymbol{T},\boldsymbol{X}) = \alpha + \boldsymbol{\beta T_{it}} + \boldsymbol{\gamma X_{it}} + \delta_t + \lambda_r + \eta_s + \epsilon_{it} \tag{2.8}$$

where $\boldsymbol{T}$, $\boldsymbol{X}$, γ, δ, and η, respectively, have the same interpretation as in eq. (2.3). By replacing $ln\ w_{it}$ by the group-specific RIF, we can identify distinct distributional effects of changes in task assignments on the native-foreign wage gap. 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.

2.3.3 RIF Decomposition: Results

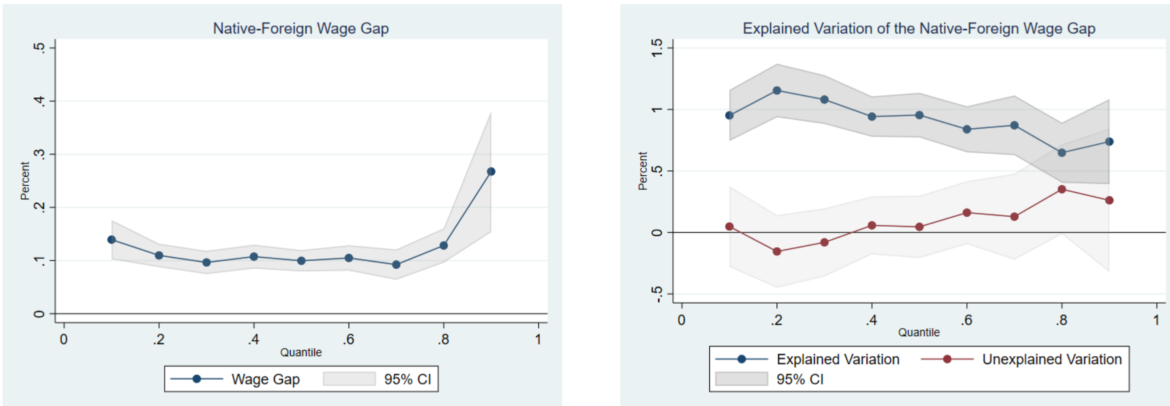
2.3.3.1 Baseline

Before analyzing the contributions of tasks to the gap, let's first inspect the model's ability to explain the native-foreign wage gap in Figure (2.3a). Along the 90-10 range, the wage gap initially decreases from 13% at the first decile to 10% in the middle of the distribution. Beyond the 7th decile, it starts to rise before jumping to around 25% at the highest decile. Overall, the RIF Decomposition does a good job capturing the variation in the wage gap. While the point estimates decrease somewhat for high-wage earners, we cannot reject the hypothesis of explaining the entire model at most deciles (2.3b).[24] The unexplained variation in wages can thus assumed to be zero throughout the distribution,

differing likelihood of a native or foreign worker falling below the decile of interest. Therefore, the model in eq. (2.7) simply divides a model for proportions by its density to get a decomposition model for deciles (Fortin, Lemieux & Firpo 2011).

[24] In contrast, Ingwersen & Thomsen (2019) find low explanation of the gap near the bottom of the wage distribution using German household survey data.

implying that eq. (2.6) can be viewed as $RIF_\tau^N - RIF_\tau^F \approx (\overline{X}_\tau^F - \overline{X}_\tau^N)\hat{\beta}_\tau^N$.



(a) Wage Gap: Distribution

(b) Wage Gap: Explained vs Unexplained

Note: All point estimates are supplemented by a 95% Confidence Interval (CI) based on bootstrapped standard errors with 100 replications.

Figure 2.3: Explained Variation of the German Native-Foreign Wage Gap, 1992-2018

To gauge the relative importance of different task dimensions, I now compare occupation-level task measures with information at the individual level. In maintaining a consistent sample definition, only occupations with at least 10 observations on foreign workers are considered to reduce the influence of outliers. Hence, the results displayed below are based on a restricted model comprising both task measures (model (4) in Table (2.2)). Let $\Delta T_{j,\tau} = \overline{T}_{j,\tau}^F - \overline{T}_{j,\tau}^N$ denote the difference in the overall task content in category j at decile τ between foreign and native workers and let $\Delta X_{j,\tau}^{'} = \overline{X}_\tau^{F'} - \overline{X}_\tau^{N'}$ denote the difference at τ between both groups in the remaining covariates. Expanding on eq. (2.6), we can then differentiate the explained wage gap by its task-related components:

$$
\begin{aligned}
\underbrace{RIF_\tau^N - RIF_\tau^F}_{\text{Explained Wage Gap}} &= \sum_{j=1}^{J} \underbrace{\Delta T_{j,\tau}\hat{\beta}_{j,\tau}^N}_{\text{Total Task Variation}} + \underbrace{\Delta X_\tau' \hat{\beta}_\tau^N}_{\text{Controls}} \\
&= \sum_{j=1}^{J} \Big[\underbrace{(\overline{T}_{ij,\tau}^F - \overline{T}_{ij,\tau}^N)\hat{\beta}_{j(i),\tau}^N}_{\text{Individual-level Tasks}} + \underbrace{(\overline{T}_{jo,\tau}^F - \overline{T}_{jo,\tau}^N)\hat{\beta}_{j(o),\tau}^N}_{\text{Occupation-level Tasks}} \Big] + \Delta X_\tau' \hat{\beta}_\tau^N \\
&\equiv \sum_{j=1}^{J} \Big[\Delta T_{j,\tau}^I \hat{\beta}_{j(i),\tau}^N + \Delta T_{j,\tau}^O \hat{\beta}_{j(o),\tau}^N \Big] + \Delta X_\tau' \hat{\beta}_\tau^N
\end{aligned}
\tag{2.9}
$$

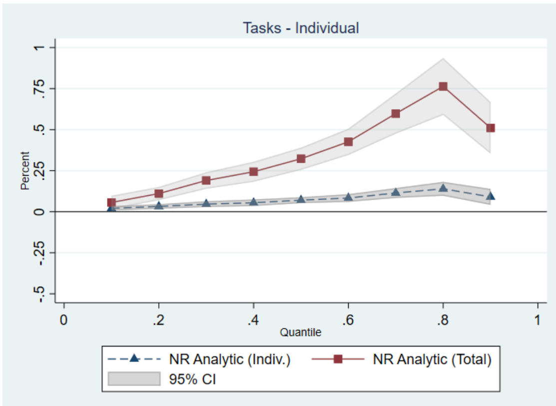
where the total contribution of tasks is disaggregated into variation at the individual level, $\Delta T_{j,\tau}^I$, and occupation-level, $\Delta T_{j,\tau}^O$, across all $J = 5$ task categories. Moreover, note that both task dimensions are evaluated at different coefficients. While $\Delta T_{j,\tau}^I$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

Figure (2.4) illustrates this comparison for each j and τ. Evaluated at the 8th decile, Figure (2.4a) shows that up to 75% of the explained wage gap among high-wage earners can be contributed to total variation in NR Analytic activities ($\Delta T_{j,\tau}$). Specifically, up to 15% is due to individual variation ($\Delta T_{j,\tau}^I$). Since $\Delta T_{j,\tau} = \Delta T_{j,\tau}^I + \Delta T_{j,\tau}^O$, the vertical distance between both lines indicates that up to 75% − 15% = 60% of the explained wage gap is associated with occupational segregation in the task content, i.e. occupation-level variation. The smaller this gap, the more important is individual-level variation.

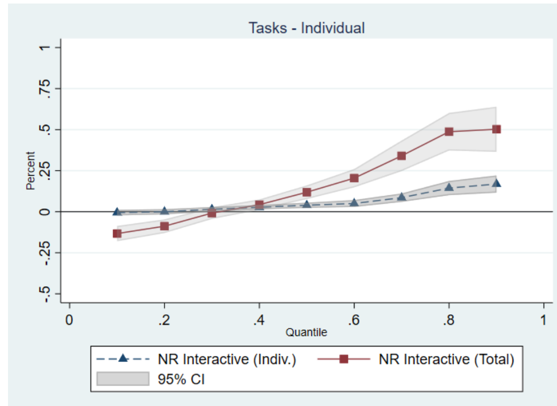
A consistent way to assess the relative importance of task dimensions is thus to compare the ratio of individual- to occupation-level variation (IOV) in j at τ:

$$
IOV_j^\tau = \frac{\Delta T_{j,\tau}^I}{\Delta T_{j,\tau}^O} = \frac{\Delta T_{j,\tau}^I}{(\Delta T_{j,\tau} - \Delta T_{j,\tau}^I)} \tag{2.10}
$$

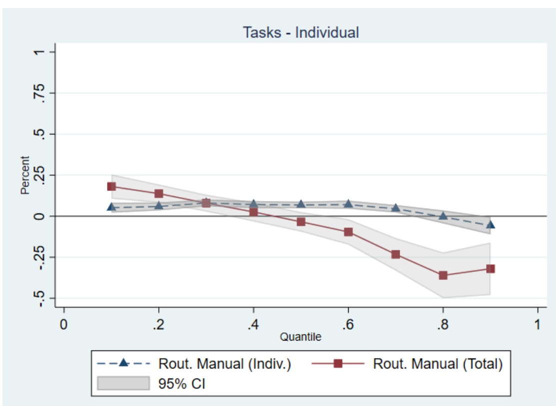
implying that individual- and occupation-level variation in tasks are equally important if $IOV_j^\tau = 1$. In regards to NR Analytic, however, $IOV_{NRA}^{\tau=8} = 0.25$ (0.15/0.60). Consequently, occupation-level variation is up to four times as important. In contrast, individual variation is relatively more pronounced in NR Interactive tasks. For workers near the top of the wage distribution, 50% of the explained wage gap is related to overall variation in interactive tasks and some 20% specifically associated with individual differences. This implies $IOV_{NRI}^{\tau\geq 8} = 0.67$ (0.2/0.3). Therefore, while both abstract task measures display qualitatively similar results, individual-level variation is almost three times as important for NR Interactive compared to NR Analytic.



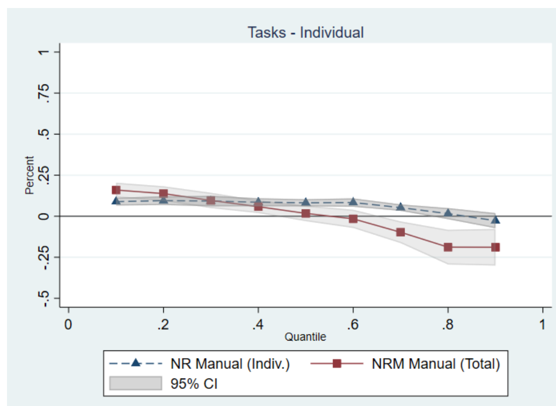
(a) NR Analytic



(b) NR Interactive



(c) Routine Manual



(d) NR Manual

Note: All point estimates are supplemented by a 95% Confidence Interval (CI) based on bootstrapped standard errors with 100 replications.

Figure 2.4: Individual-level Contribution of Tasks to the Wage Gap, Relative to Overall Contribution of Task Group

The comparison does have opposing implications for manual tasks, however. While individual differences are negligible among high-wage earners, differences at the occupation-level are quite sizable. Combined, the contributions of Routine Manual and NR Manual implies that the wage gap should be smaller by some 35-50% for workers near the top of the distribution.

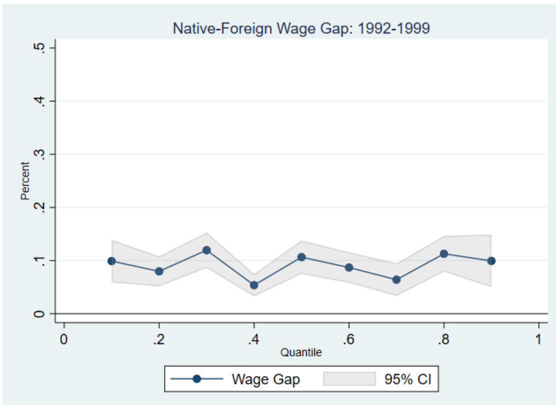
Above results can be interpreted in terms of long-term trends, covering 1992-2018, and suggesting that the native-foreign wage gap is primarily driven by distinct activities involving abstract tasks. This finding lends credence to models assuming differences in skill endowments to be more sensitive for non-routine activities, relative to routine tasks (Jung & Mercenier 2014). It is likewise consistent with greater wage inequality in occupations with a high degree of non-routine activities (van der Velde 2020). Importantly, the robust and rising contribution of individual variation in abstract tasks above the median reveals distributional implications which 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.

2.3.3.2 Trends in Tasks and their Contribution to the Wage Gap

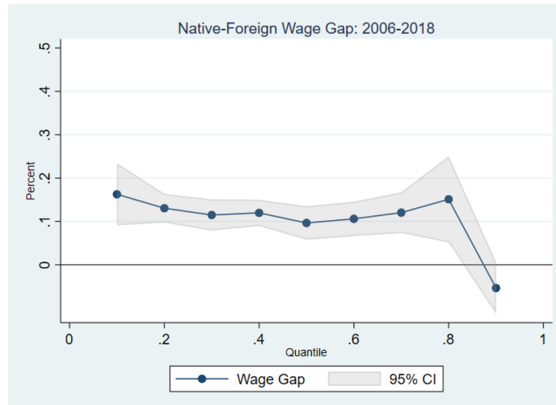
Despite increasingly performing abstract tasks in aggregate terms (Figure 2.1b), foreign workers may not reap the benefits if they continue sorting themselves into manual-heavy occupations. This explanation fits into key findings of several papers documenting the rise in occupation-level abstract task prices.[25] The key implication of this research is wage gains for workers in occupations relying heavily on abstract tasks and wage losses for workers in occupations intensive in manual tasks. On the other hand, a couple of papers have documented an inverted U-shaped pattern of the price of abstract tasks, with the downturn beginning in the early 2000s (Gottschalk, Green & Sand 2015, Beaudry, Green & Sand 2016). Following this logic, the gap should have decreased as wage differences between natives and foreigners have been driven by high-wage earners. In fact, though, the wage gap has *increased* since the 2000s. Combined, the conflicting evidence on trends in task prices motivates a closer inspection of the relative importance of individual- and

[25]See, e.g., Autor & Dorn (2013), Boehm (2017), Deming (2017), and Cortes, Jaimovich & Siu (2018).

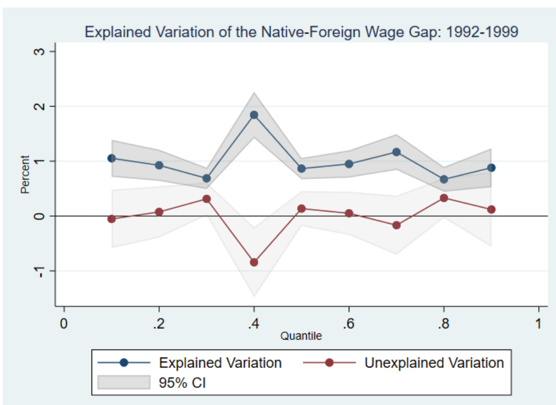
occupation-level task measures and their evolution over time.[26]



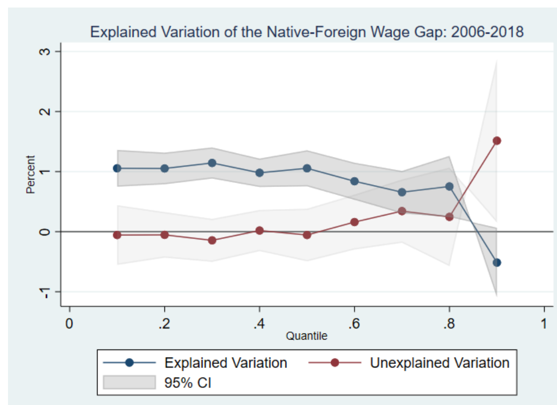
(a) Wage Gap: Distribution, 1992-1999



(b) Wage Gap: Distribution, 2006-2018



(c) Explained Wage Gap, 1992-1999



(d) Explained Wage Gap, 2006-2018

Note: All point estimates are supplemented by a 95% Confidence Interval (CI) based on bootstrapped standard errors with 100 replications.

Figure 2.5: Trends in the Native-Foreign Wage Gap, 1992-2018

To inspect this hypothesis more thoroughly, I split the sample by comparing estimates from the surveys in 1992 and 1999 with those from 2006 until 2018. Figure (2.5) displays the wage gap separately for the 1990s (2.5a) and 2000s (2.5b). Notably, the U-shaped

[26] On a related note, several recent studies employ US job vacancy data and document rapid changes of tasks within occupations since the Great Recession 2007/08 (Hershbein & Kahn 2018, Atalay, Phongthiengtham, Sotelo & Tannenbaum 2018a,b, 2019, Deming & Noray 2019), and Modestino, Shoag & Ballance (2019). Similarly, Michaels, Rauch & Redding (2019) measure the relative importance of tasks within occupations by tracking the frequency of verbs characterizing job-related activities in occupations listed in the DOT over time. Data limitations, however, do not allow these papers to explore wage implications at the individual level due to within-occupations discrepancies in the task content, let alone wage differences between native and foreign workers. This is where the present study can provide novel insight as the detailed survey data allows a one-to-one correspondence of tasks to wages.

pattern we saw earlier is driven by developments in the last couple of decades. While the wage wage gap fluctuated around 10% throughout the 1990s (2.5a), it reached 15% at its tails since the 2000s (2.5b). The model is not able to explain the sharp reversal in the wage gap in the 2000s, however.[27] For these reasons, the ensuing analysis will concentrate on developments up until the 8th decile of the wage distribution.

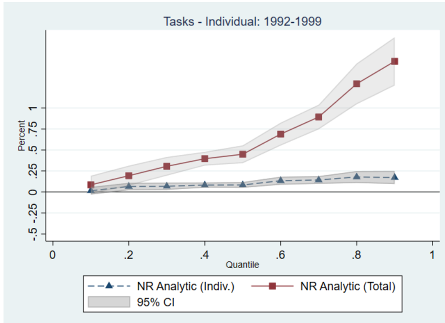
A. Invididual - vs Occupation-level Task measures

Figure (2.6) displays the relative importance of individual-level tasks for the two sub-samples. Focusing on abstract task measures for the moment (Panels 2.6a-2.6d), a couple of observations stand out. On the one hand, individual variation in NR Analytic displays statistically insignificant contributions to the wage gap since the 2000s, suggesting $IOV^{\tau}_{NRA} = 0\ \forall \tau$ as of late. On the other hand, individual variation in NR Interactive has become increasingly important over the past 20 years. Using the 8th decile as a focal point, discrepancies in terms of interactive tasks account for 50% of the explained wage gap between 1992-99, compared to around 65% from 2006-2018. At the same time, contributions from individual variation rose from 10% to 25%. Therefore, $IOV^{\tau=8}_{NRI}$ increased from 0.25 (0.1/0.4) to 0.625 (0.25/0.40), indicating that individual-level variation in interactive tasks gained importance by a factor of 2.5 relative to the occupational dimension.

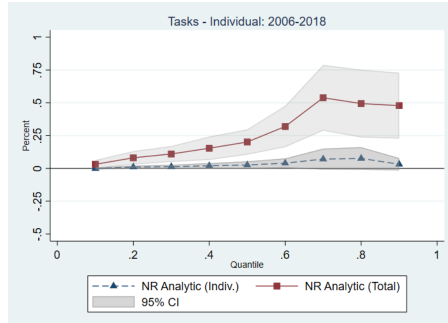
Among low-wage earners, worker-level variation has overall been negligible in economic terms.[28] Yet, there has been an interesting development in terms of NR Manual tasks. From 1992-99, $IOV^{\tau\leq 3}_{NRM} = 0.5$ (0.125/0.250) for workers below the fourth decile. Since 2006, however, $IOV^{\tau\leq 6}_{NRM} \rightarrow \infty$ as all the variation in this task group is associated with idiosyncratic factors. This observation opposes Peri & Sparber (2009) who find low-skilled natives to specialize in occupations intensive in interactive tasks, whereas low-skilled

[27] Ingwersen & Thomsen (2019) have shown that wage gaps differ for various ethnic subgroups. Hence, the reversal of the wage gap near the top of the distribution may be the influenced by specific foreign groups. For instance, this change of direction may be related to the skilled immigration to Germany from Southern Europe following the Great Recession 2007/08.

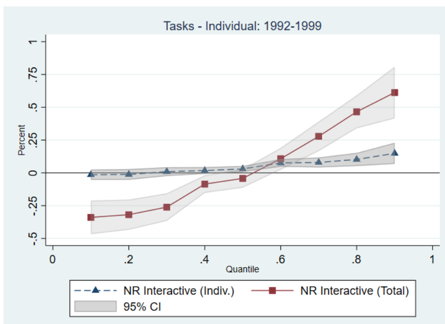
[28] These findings are consistent with the idea of lopsided learning-by-doing, according to which only high-wage earners become more productive by gaining experience in carrying out a task. Being able to earn a wage premium resulting from learning-by-doing thus favors their human capital formation disproportionately (Stinebrickner, Stinebrickner & Sullivan 2019).



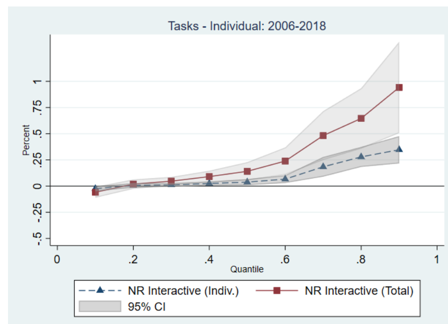
(a) 1992-1999 (NRA)



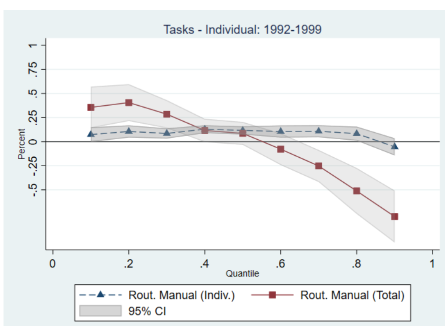
(b) 2006-2018 (NRA)



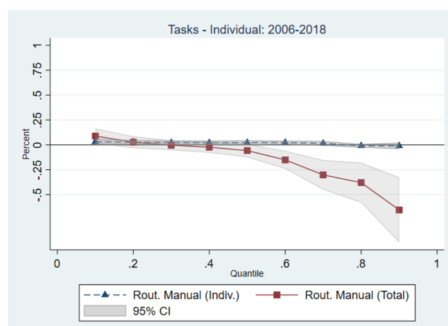
(c) 1992-1999 (NRI)



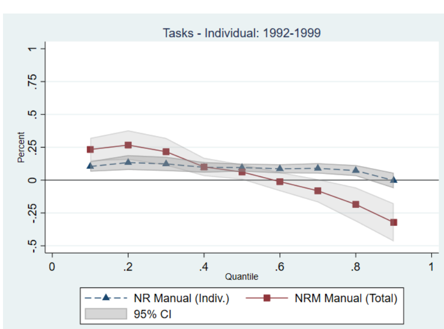
(d) 2006-2018 (NRI)



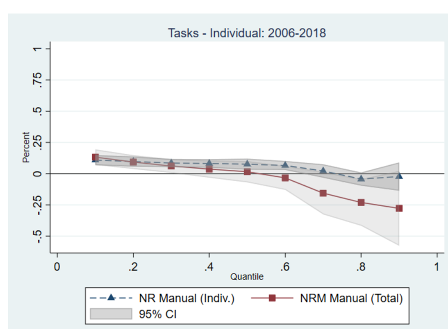
(e) 1992-1999 (RM)



(f) 2006-2018 (RM)



(g) 1992-1999 (NRM)



(h) 2006-2018 (NRM)

Note: All point estimates are supplemented by a 95% Confidence Interval (CI) based on bootstrapped standard errors with 100 replications.

Figure 2.6: Individual- vs Occupation-level Effects over Time, 1992-2018

foreigners specialize in occupations intensive in manual tasks. Yet, the present study finds that foreigners are relatively less specialized in manual-heavy occupations than they used to. These implications should be treated with caution, though, as the foreign sample is not representative of the entire foreign working population. The survey data only consists of workers with sufficient command of the German language. As recent immigrant cohorts are less proficient in German than previous generations (see Appendix B.2.2.2), it is reasonable to assume that a disproportionate amount of workers excluded from the surveys are employed in occupations intensive in manual tasks.

This measurement error, in turn, reinforces the importance of interactive tasks for native workers. In regards to the interactive task content, wage gaps for this group should have been smaller by about 25% in the 1990s, with no economically meaningful contributions in the 2000s. This implies rising occupational segregation among low-wage earners in interactive activities, which may be even larger in the entire working population. If there has been a divergence in interactive-heavy occupations (consistent with Peri & Sparber (2009)) and a convergence in manual-heavy occupations (inconsistent with Peri & Sparber (2009)), then where have the remaining tasks been allocated to? The answers lies in NR Analytic. Comparing its importance in the wage gap below the median over time, it has been roughly cut in half. Evaluated at the 4th decile, the total variation dropped from 40% to 15%, in large parts driven from occupation-level variation. This finding is consistent with an increasing assimilation of native and foreign workers in problem-solving tasks, yet, mostly limited to non-verbal activities (Figure 2.1b). Hence, within the abstract task category, there has been a re-allocation of native workers away from NR Analytic towards NR Interactive.[29]

[29] For instance, evaluated at the 8th decile, the ratio in total variation of NR Analytic to NR Interactive in 1992-99 was 2.5 (1/0.4), implying that differences in NR Analytic explained two and a half times more variation in the native-foreign wage gap. During 2006-18, this ratio dropped to roughly 1.5 in (0.45/0.30), suggesting that variation in interactive tasks has become a relatively more important factor in explaining wage differences between natives and foreigners.

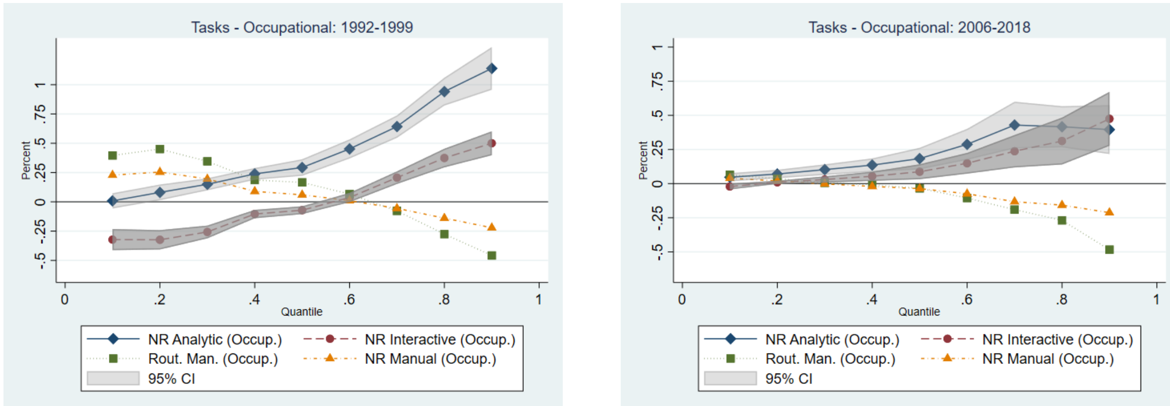
B. Between vs Within-Occupation Task measures

Increasing relevance of individual-level tasks since the 2000s suggests an important role for idiosyncratic factors in the rising native-foreign wage gap and is consistent with rising heterogeneity in worker- and firm-specific factors. Using German establishment-level data, Card, Heining & Kline (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. Accompanied by greater dispersion of individual wage components and rising assortativeness between high-wage workers and high-wage firms, this mechanism likewise facilitated occupational segregation. Put differently, skilled workers increasingly work together in high-wage paying firms, while at the same time concentrating in a set of high-wage occupations.[30] The relevance of these findings in the migration context is reinforced in Dostie, Li, Card & Parent (2020) who show that different hiring patterns among firms contribute around 20% to the Native-Foreign wage gap in Canada.

Figure (2.7) displays results of the standard model based on occupation-level task measures.[31] In order to avoid overlapping confidence intervals, only the range of estimates for abstract task measures is displayed. In line with results from section 2.3.3.2, A, both abstract task measures are significant and economically meaningful contributors to the wage gap above the median. Likewise, compared to the 1990s, their magnitude has declined in recent decades, suggesting declining importance of between-occupation differences in tasks over time. Notably, though, interactive tasks have become relatively more important compared to analytic tasks. While the point estimates have been more than twice as large for the latter throughout the 1990s (2.7a), interactive tasks have closed the gap since the 2000s (2.7b). The flattening of NR Analytic among high-wage earners may also suggest that the U-shaped pattern of returns to abstract tasks documented in Gottschalk, Green & Sand (2015) and Beaudry, Green & Sand (2016) is primarily driven by this narrow task group.

[30]Barth, Bryson, Davis & Freeman (2016) and Song, Price, Guvenen, Bloom & von Wachter (2019) find similar results, arguing that heterogeneous worker effects may be even more pronounced in the US. Notably, Song, Price, Guvenen, Bloom & von Wachter (2019) suspect that rising returns to skills have been a key contributor to greater dispersion of worker-specific effects.

[31]Specifically, the results correspond to model (2) in Table (2.2).



(a) Between-Occupation Effects, 1992-1999 (b) Between-Occupation Effects, 2006-2018

Note: All point estimates are supplemented by a 95% Confidence Interval (CI) based on bootstrapped standard errors with 100 replications.

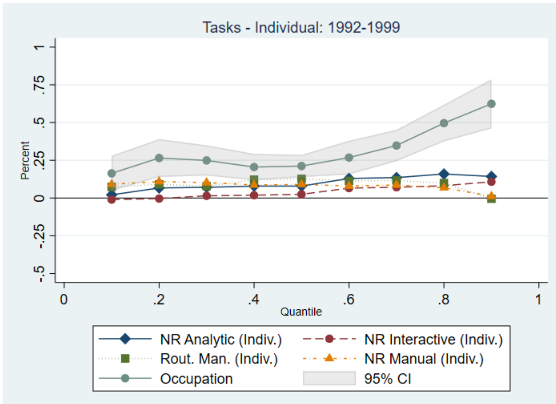
Figure 2.7: Between-Occupation Effects over Time, 1992-2018

This finding could have been reinforced by rising assimilation of natives and foreigners in analytic activities which are prominent in STEM occupations. These professions tend to be less verbal than, for instance, managerial jobs (Peri & Sparber 2011), thereby creating a more leveled playing field by alleviating comparative advantages.[32] Consistent with this mechanism, research on employment polarization argues that recent college graduates increasingly shy away from STEM careers towards occupations that have previously been routine-heavy (Hershbein & Kahn 2018, Deming & Noray 2019). These occupations underwent substantial automation, making them complementary to skilled labor. Not only did this readjustment devalue the role of occupations, it also raised competition among skilled workers by making individual skill elements more valuable.[33] Especially in occupations with a relatively diverse set of tasks, these developments would provide more room to

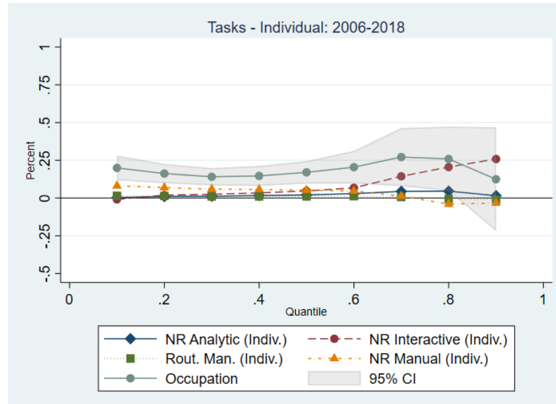
[32] See Bound, Braga, Golden & Khanna (2015), Hanson & Slaughter (2016), and Jaimovich & Siu (2017).

[33] Following similar logic, Modestino, Shoag & Ballance (2019) explore changes in skill requirements within firm-job title pairs in the US based on job vacancy data. They show that upskilling within firms is especially pronounced during a recession and accelerated by a large supply of skilled workers. Hence, improvements in schooling between 1992 and 2018 combined with assimilation of educational outcomes can explain the rising importance of skills within occupations and how, based on historical comparative advantages, natives have been able to maintain their wage advantages due to rising task specialization. In a series of papers focused on the long-term evolution of skill requirements in the US, Atalay, Phongthiengtham, Sotelo & Tannenbaum (2018a,b, 2019) have likewise documented a rise in changes of task assignments within occupations from 1950-2000.

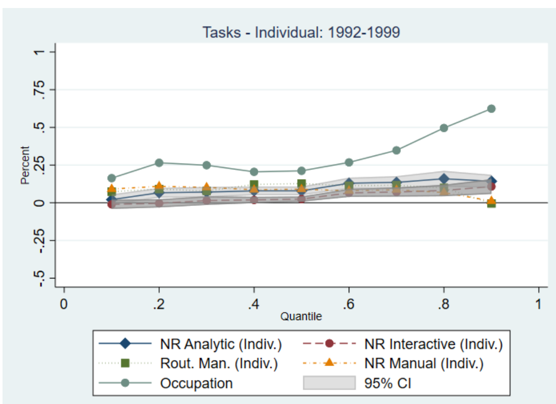
raise the level of task specialization within occupations.



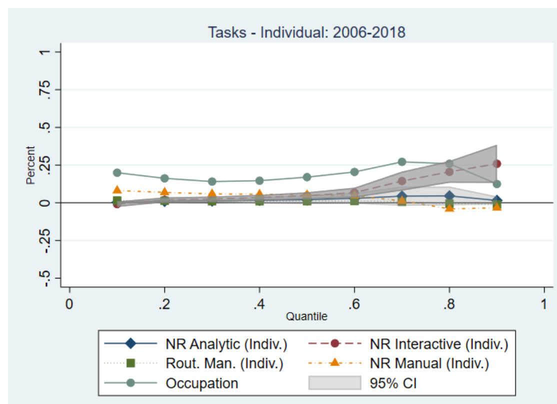
(a) 1992-1999 (Occupation FE highlighted)



(b) 2006-2018 (Occupation FE highlighted)



(c) 1992-1999 (Tasks highlighted)



(d) 2006-2018 (Tasks highlighted)

Note: All point estimates are supplemented by a 95% Confidence Interval (CI) based on bootstrapped standard errors with 100 replications.

Figure 2.8: Within-Occupation Effects over Time, 1992-2018

Figure (2.8) helps to shed light on this issue, illustrating the importance of within-occupation differences over time. This model is based on augmenting eq. (2.8) by θ_o, i.e. individual-level task measures conditional on occupational FE (model (10) in Table (2.2)). Similar to the IOV measure, we can assess the relative importance of within-occupation adjustments in the task content by comparing contributions of individual task variation relative to occupational FE ($IFEV$):

$$IFEV_j^{\tau} = \frac{\Delta T_{j,\tau}^{I}}{\Delta FE_{\tau}} \tag{2.11}$$

where $\Delta FE_{\tau} = \overline{FE}_o^F - \overline{FE}_o^N$ is the difference in occupational characteristics for foreign and native workers at decile τ. For reference, if $IFEV_j^{\tau} = 1$, individual-level variation in task j and occupational FE are equally important elements of the explained wage gap at τ.

Panels (2.8a - 2.8b) emphasize the trend of occupational characteristics, showing that its economic impact has diminished substantially over time. Evaluated at the 8th decile, its contribution to the explained wage gap shrank from 50% in the 1990s to 25% since the 2000s. On the other hand, panels (2.8c - 2.8d) reveal a striking increase in the importance of interactive tasks. Specifically, around 10% of the explained wage gap within occupations from 1992-99 is attributed to individual task variation, compared to 25% from 2006-18. Hence, $IFEV_{NRI}^{\tau=8}$ increased from 0.2 (0.1/0.5) to 1.0 (0.25/0.25). Put differently, variation in interactive activities within occupations gained importance by a factor of five over the past 20 years. In comparison, $IFEV_{NRA}^{\tau=8}$ decreased from 0.4 (0.2/0.5) to 0.0 (0/0.25), in line with findings from section 2.3.3.2, A on the recently diminished role of analytic tasks.

These trends may be motivated by the cost of switching occupations. Within an occupation, workers accumulate task-specific human capital. The more different the new source occupation, the less portable are tasks and the greater the cost incurred by the worker.[34] On the one hand, transitions into communication-heavy occupations are less costly for natives than foreign workers. This is especially true if gains from occupational switching are motivated by rising returns to social skills (Deming 2017, Michaels, Rauch & Redding 2019). On the other hand, it may be more lucrative for workers to simply specialize within their profession and avoid the cost altogether. Using novel longitudinal data with information on time spent on tasks, Stinebrickner, Stinebrickner & Sullivan (2019) show that workers who spend more time on "high-skilled people tasks" (similar to NR Interactive) experience larger wage gains compared to corresponding moves in "high-skilled information tasks" (similar to NR Analytic). The human capital stock of natives therefore receives relatively more favorable shocks over a lifetime career, diminishing the effect of

[34]See, e.g., Poletaev & Robinson (2008), Kambourov & Manovskii (2009), Gathmann & Schönberg (2010), Yamaguchi (2012), and Robinson (2018).

initial skill endowments (Yamaguchi 2012). This mechanism mitigates assimilation in educational outcomes and prevents foreigners from catching up.[35]While not explicitly explored in this paper, thus speculative, the rising importance of worker-level variation in tasks and especially within-occupation task specialization between natives and foreigners is consistent with an outward shift of the production function, giving rise to production complementarities as found in Ma (2020).[36] If true, research in the migration literature employing occupation-level data has understated migration-induced wage *gains*.

2.3.3.3 Robustness

The above analysis highlights the importance of individual job activities in explaining wage differences between native and foreign workers and how this development favored task specialization within occupations. This channel is particularly pronounced for interactive tasks and robust to various specifications. Appendix B.3 provides robustness exercises, showing that the rising importance of individual tasks in general and interactive tasks in particular is likewise valid in the unrestricted sample (Appendix B.3.1). Therefore, the key takeaway from this study is robust to the influence of outliers due to occupations with few observations on foreigners. In the same vein, restricting the analysis on trends in

[35]In contrast, Speer (2017) finds pre-market skill differences, measured by ASVAB test scores from NLSY data, to be persistent drivers of occupational choices and contributing to gender and racial gaps. At the same time, pre-market skills are less important for wage gaps compared to occupation gaps, suggesting a role for task specialization *within* occupations as a key component of wage differences. Notably, Speer (2017) finds faster growth in verbal tasks for individuals with high verbal test scores in school. In the migration context this entails that initial skill differences with respect to interactive tasks, e.g. language proficiency, are persistent over a career. Along the same line, Sanders (2016) estimates a structural life-cycle model of occupational choice to gauge the relative importance of skill accumulation versus skill uncertainty. Relevance of the latter would imply workers have an incomplete understanding of their own skills, inducing them to experiment a lot in their career. He finds, however, that wage growth over a career is largely driven by skill accumulation, implying workers have sufficient knowledge of their career match and especially their own skills. Hence, there is little to gain from switching occupations, making task specialization within occupations more compelling instead.

[36]Moreover, Ma (2020) shows how native and foreign Computer Scientists in the US are imperfect substitutes, yet, in Other-STEM occupations they are complements. Using the O*NET database, she provides suggestive evidence at the occupation-level that Other-STEM occupations have a more diverse set of tasks, which, in turn, induces greater within-occupation task specialization. The findings of the present study show strong support for this hypothesis based on worker-level information.

within-occupation task variation to occupations with at least ten observations on foreigners reinforces the important role of individual-level variation in tasks in recent decades, especially among interactive activities (B.3.2).

Including civil servants (B.3.3) does not affect the main conclusion either. Yet, occupation-level measures, and thus between-occupation differences, become somewhat more important when civil servants are included. This is true for both sub-samples, presumably because foreign workers are under-represented in this group due to a higher degree of communicative activities. Restricting the sample to males only, which is common in much of the related literature, does not substantially affect the results either (B.3.4). However, excluding females implies a prolonged decrease in the wage gap among high-wage earners since 2006, implying that wage differences near the top of the wage distribution are more pronounced among females. There is research arguing that the rise of abstract skills favored females disproportionaly and thus enabled them to increasingly compete with males in high-wage occupations.[37] The robustness exercise in Appendix B.3.4 may thus point to rising abstract skills favoring native females disproportionately, perhaps due to a comparative advantage in interactive tasks compared to foreign female workers. This question is left for future research. Lastly, the under-representation of routine cognitive activities in the data is not worrisome. Replacing Routine Cognitive as reference task group by Routine Manual does not affect the key takeaways from the RIF decomposition (B.3.5). If anything, individual-level variation in interactive tasks becomes even more meaningful, reinforcing its importance in explaining the native-foreign wage gap.

2.4 Conclusions

This paper presents evidence of substantial heterogeneity in skills inferred from a high degree of specialization in job-related activities. Using survey data from Germany, I observe the number and type of activities workers perform at the workplace and provide novel evidence that task specialization is more far-reaching than previously documented. A key role is attributed to interactive tasks. While previous studies have shown how

[37] See Black & Spitz-Oener (2010), Cortes, Jaimovich & Siu (2018), and Yamaguchi (2018).

native workers utilize their comparative advantage against foreign workers by specializing in occupations intensive in interactive tasks, I find that individual variation in communication-heavy activities has in fact gained importance. Notably, its contribution to the explained wage gap has increased from 10% to 25% over the past 20 years. An important implication of this finding is that natives have increasingly been utilizing their comparative advantage in interactive tasks *within* occupations, offering new insight into the imperfect substitutability of native and foreign workers at the core of small migration-induced wage effects.

Employing a RIF Decomposition, I moreover add to the literature by demonstrating distributional implications on the effects of tasks on wages. The key takeaway is that the rising importance of individual tasks in general and interactive tasks in particular is more pronounced among workers near the top of the wage distribution. This enhanced degree of task specialization has contributed to greater within-occupation variation in tasks in the last two decades and serves as a plausible explanation for the rising native-foreign wage gap since the 2000s, which has been primarily driven by high-wage workers. The growing importance of task specialization may thus have contributed to the widening of the aggregate German wage distribution (Rinawi & Backes-Gellner 2019).

Taken together, the fragmentation of the labor market along the task dimension is more severe than previously documented. This finding has important implications on the integration of immigrant workers. Worldwide, countries counter aging populations by competing for the best talents. Germany is no exception to this competition, yet, has struggled in the past to retain its international students.[38] The Government has recognized this problem by implementing policies to improve the integration of workers. First, the *Federal Recognition Act* of 2012 has been passed with the goal to "improve the use of professional qualifications acquired abroad so that holders of such qualifications can find work commensurate with those qualifications on the German labour market".[39] Second,

[38]See a recent report by the Council of German Foundations on Integration and Migration discussing this dilemma: https://www.svr-migration.de/wp-content/uploads/2015/08/Study_Train-and-Retain_SVR-research-unit_WEB.pdf (Date accessed: 01/18/2020).

[39]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).

the *Skilled Immigration Act* of 2020 extends the previous act, improving recognition of skilled labor from Non-EU countries and relaxing occupational requirements.

While early evaluations of the *Federal Recognition Act* show promising improvements in terms of labor market entry[40], the findings in the present study suggest room for improvement regarding the management of skilled workers. The key priority of both acts is to improve occupational recognition. Yet, variation in tasks within occupations implies that successful integration of immigrants requires more than accepting qualifications and getting them into good jobs. In light of the prevalent specialization patterns between native and foreign workers and rising importance of interactive skills, advanced communication training and management programs are paramount in making domestic labor markets more attractive and thus retaining skilled foreign workers.

[40]See Ekert, Larsen, Valtin, Schroeder & Orning (2017) and the most recent report published by the Federal Ministry of Education and Science (BMBF 2020).

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Appendix A: Chapter 1 Appendix

A.1 Robustness: Regression Tables

Dependent Variable: Log Hourly Real Wage	(1)	(2)	(3)	(4)	(5)	(6)
NR Analytic (Occ.)	0.49***			0.06		
	(0.18)			(0.17)		
NR Interactive (Occ.)	0.30***			-0.09		
	(0.11)			(0.12)		
Routine Cognitive (Occ.)	0.63***			0.28***		
	(0.08)			(0.08)		
Routine Manual (Occ.)	-0.27**			-0.34**		
	(0.13)			(0.13)		
NR Analytic (Ind.)		0.58***		0.52***	0.50***	0.52***
		(0.04)		(0.04)	(0.04)	(0.04)
NR Interactive (Ind.)		0.44***		0.39***	0.36***	0.39***
		(0.04)		(0.04)	(0.04)	(0.04)
Routine Cognitive (Ind.)		0.48***		0.38***	0.38***	0.38***
		(0.04)		(0.04)	(0.04)	(0.04)
Routine Manual (Ind.)		0.06		0.09*	0.04	0.08*
		(0.05)		(0.05)	(0.05)	(0.05)
NR Analytic (Exp.)			0.46***		0.24***	
			(0.04)		(0.04)	
NR Interactive (Exp.)			0.17***		0.02	
			(0.05)		(0.05)	
Routine Cognitive (Exp.)			0.28***		0.10***	
			(0.04)		(0.04)	
Routine Manual (Exp.)			-0.02		-0.02	
			(0.05)		(0.05)	
Survey tasks (Occupational)	✓			✓		
Survey tasks (Individual)		✓		✓	✓	✓
Expert tasks (Occupational)			✓		✓	
Occupation Dummies						✓
F (Task Measures, Occ.)	93.45		86.57	17.43	17.45	
F-pval (Task Measures, Occ.)	(0.00)		(0.00)	(0.00)	(0.00)	
F (Task Measures, Ind.)		126.87		65.56	73.70	67.31
F-pval (Task Measures, Ind.)		(0.00)		(0.00)	(0.00)	(0.00)
R-squared	0.194	0.204	0.192	0.207	0.207	0.212
Adj. R-squared	0.192	0.203	0.190	0.205	0.205	0.210
AIC	60209.98	59801.64	60279.94	59699.09	59706.33	59543.13
BIC	60729.14	60337.54	60807.47	60260.12	60258.98	60346.99
Observations	32003	32003	32003	32003	32003	32003

Robust standard errors in parentheses

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

* Note: The first four rows display coefficients based on occupational averages derived from individual responses in the employment surveys ("(Occ.)"). Point estimates corresponding to those individual responses are displayed in rows five to eight ("(Ind.)"). Lastly, the last four rows display coefficients based on occupational averages derived from the Expert database ("(Exp.)"). All specifications include controls for gender, age, age squared, a dummy for living in an urban area, education dummies, occupational tenure, firm tenure, squared tenure for each dimension of experience, and a categorical variable reflecting firm size. The omitted task category is "NR Manual".

Table A.1: Task Measures as Wage Predictors: Survey vs Expert Data (Narrow Task Categories, 2-digit Occupations)

Dependent Variable: Log Hourly Real Wage	(1)	(2)	(3)	(4)	(5)	(6)
Abstract (Occ.)	0.97***			0.56***		
	(0.06)			(0.07)		
Routine (Occ.)	0.51***			0.25***		
	(0.07)			(0.07)		
Abstract (Ind.)		0.58***		0.43***	0.43***	0.46***
		(0.04)		(0.04)	(0.04)	(0.04)
Routine (Ind.)		0.38***		0.27***	0.28***	0.29***
		(0.04)		(0.04)	(0.04)	(0.04)
Abstract (Exp.)			0.48***		0.32***	
			(0.03)		(0.03)	
Routine (Exp.)			0.26***		0.16***	
			(0.03)		(0.03)	
Survey tasks (Occupational)	✓			✓		
Survey tasks (Individual)		✓		✓	✓	✓
Expert tasks (Occupational)			✓		✓	
Occupation Dummies						✓
F (Task Measures, Occ.)	128.98		180.55	36.36	70.49	
F-pval (Task Measures, Occ.)	(0.00)		(0.00)	(0.00)	(0.00)	
F (Task Measures, Ind.)		146.41		63.97	70.56	74.12
F-pval (Task Measures, Ind.)		(0.00)		(0.00)	(0.00)	(0.00)
R-squared	0.193	0.197	0.194	0.200	0.202	0.222
Adj. R-squared	0.192	0.195	0.192	0.199	0.201	0.217
AIC	60235.15	60090.77	60206.25	59946.82	59870.43	59338.34
BIC	60745.93	60593.19	60717.04	60474.35	60397.96	60987.93
Observations	32003	32003	32003	32003	32003	32003

Robust standard errors in parentheses

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

* Note: The first two rows display coefficients based on occupational averages derived from individual responses in the employment surveys ("(Occ.)"). Point estimates corresponding to those individual responses are displayed in the third and fourth row ("(Ind.)"). Lastly, the last two rows display coefficients based on occupational averages derived from the Expert database ("(Exp.)"). All specifications include controls for gender, age, age squared, a dummy for living in an urban area, education dummies, occupational tenure, firm tenure, squared tenure for each dimension of experience, and a categorical variable reflecting firm size. The omitted task category is "Manual".

Table A.2: Task Measures as Wage Predictors: Survey vs Expert Data (Broad Task Categories, 3-digit Occupations)

Dependent Variable: Log Hourly Real Wage	(1)	(2)	(3)	(4)	(5)	(6)
Abstract (Occ.)	0.07***			0.04***		
	(0.01)			(0.01)		
Routine (Occ.)	0.04***			0.01		
	(0.01)			(0.01)		
Manual (Occ.)	-0.03**			-0.02*		
	(0.01)			(0.01)		
Abstract (Ind.)		0.10***		0.10***	0.10***	0.10***
		(0.00)		(0.01)	(0.01)	(0.01)
Routine (Ind.)		0.07***		0.05***	0.06***	0.05***
		(0.01)		(0.01)	(0.01)	(0.01)
Manual (Ind.)		-0.04***		-0.04***	-0.04***	-0.04***
		(0.01)		(0.01)	(0.01)	(0.01)
Abstract (Exp.)/100			0.060*		0.053	
			(0.034)		(0.033)	
Routine (Exp.)/100			0.048*		0.042	
			(0.027)		(0.027)	
Manual (Exp.)/100			0.048*		0.043	
			(0.028)		(0.027)	
Survey tasks (Occupational)	✓			✓		
Survey tasks (Individual)		✓		✓	✓	✓
Expert tasks (Occupational)			✓		✓	
Occupation Dummies						✓
F (Task Measures, Occ.)	127.59		74.07	19.90	16.29	
F-pval (Task Measures, Occ.)	(0.00)		(0.00)	(0.00)	(0.00)	
F (Task Measures, Ind.)		322.50		197.59	229.29	198.66
F-pval (Task Measures, Ind.)		(0.00)		(0.00)	(0.00)	(0.00)
R-squared	0.193	0.210	0.188	0.213	0.212	0.218
Adj. R-squared	0.191	0.209	0.187	0.211	0.211	0.216
AIC	61171.97	60470.20	61346.62	60372.03	60390.97	60202.50
BIC	61683.28	60981.51	61874.70	60916.87	60935.82	61007.19
Observations	32003	32003	32003	32003	32003	32003

Robust standard errors in parentheses

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

* Note: Above results are based on the first component of a Principal Component Analysis. Hence, the activities displayed in Table (1.1) have been condensed into a single measure for abstract, routine, and manual tasks. All task measures are standardized with mean zero and a variance equal to one. The first three rows display coefficients based on occupational averages derived from individual responses in the employment surveys ("(Occ.)"). Point estimates corresponding to those individual responses are displayed in the fourth, fifth, and sixth row ("(Ind.)"). Lastly, the last three rows display coefficients based on occupational averages derived from the Expert database ("(Exp.)"). All specifications include controls for gender, age, age squared, a dummy for living in an urban area, education dummies, occupational tenure, firm tenure, squared tenure for each dimension of experience, and a categorical variable reflecting firm size. The omitted task category is "Manual".

Table A.3: Task Measures as Wage Predictors: Survey vs Expert Data (Broad Task Categories, 2-digit Occupations)

Dependent Variable: Log Hourly Real Wage	(1)	(2)	(3)	(4)	(5)	(6)
Abstract (Occ.)	1.37***			0.67***		
	(0.09)			(0.10)		
Routine (Occ.)	0.57***			0.19		
	(0.14)			(0.14)		
Abstract (Ind.)		0.92***		0.75***	0.78***	0.77***
		(0.05)		(0.06)	(0.06)	(0.06)
Routine (Ind.)		0.56***		0.44***	0.45***	0.44***
		(0.06)		(0.07)	(0.07)	(0.07)
Abstract (Exp.)			0.44***		0.24***	
			(0.03)		(0.03)	
Routine (Exp.)			0.26***		0.14***	
			(0.03)		(0.03)	
Survey tasks (Occupational)	✓			✓		
Survey tasks (Individual)		✓		✓	✓	✓
Expert tasks (Occupational)			✓		✓	
Occupation Dummies						✓
F (Task Measures, Occ.)	121.93		119.55	25.12	31.81	
F-pval (Task Measures, Occ.)	(0.00)		(0.00)	(0.00)	(0.00)	
F (Task Measures, Ind.)		159.65		88.91	101.08	94.29
F-pval (Task Measures, Ind.)		(0.00)		(0.00)	(0.00)	(0.00)
R-squared	0.190	0.199	0.189	0.201	0.202	0.210
Adj. R-squared	0.189	0.197	0.187	0.200	0.200	0.207
AIC	61129.28	60783.11	61193.48	60689.99	60675.16	60412.23
BIC	61632.18	61294.39	61696.38	61209.66	61203.21	61216.87
Observations	32003	32003	32003	32003	32003	32003

Robust standard errors in parentheses

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

* Note: In contrast to baseline results, above estimates are based on a different assumption in the construction of the task content. In the baseline definition, a dummy indicating whether a worker performs task is equal to one if she carries out the task “often”. Instead, above estimates assume she carries out the task “often” or “sometimes”. The first two rows display coefficients based on occupational averages derived from individual responses in the employment surveys (“(Occ.)”). Point estimates corresponding to those individual responses are displayed in the third and fourth row (“(Ind.)”). Lastly, the last two rows display coefficients based on occupational averages derived from the Expert database (“(Exp.)”). All specifications include controls for gender, age, age squared, a dummy for living in an urban area, education dummies, occupational tenure, firm tenure, squared tenure for each dimension of experience, and a categorical variable reflecting firm size. The omitted task category is “Manual”.

Table A.4: Task Measures as Wage Predictors: Survey vs Expert Data (Broad Task Categories, 2-digit Occupations)

Appendix B: Chapter 2 Appendix

B.1 Data DOI

B.1.1 BIBB/IAB & BIBB/BAuA Employment Surveys

- 1992: https://doi.org/10.4232/1.2565
- 1999: https://doi.org/10.4232/1.12247
- 2006: https://doi.org/10.4232/1.13481
- 2012: https://doi.org/10.4232/1.13480
- 2018: https://doi.org/10.4232/1.13433

B.1.2 SIAB-R 7514

- Data for years 1975-2014: http://doku.iab.de/fdz/reporte/2017/DR_01-17_EN.pdf

B.1.3 SOEP Public Use File (95% Version)

- Data for years 1984-2015: https://doi.org/10.5684/soep.v32

B.2 Details on Data

B.2.1 Details on Sample

B.2.1.1 Occupations

#	Occupational Group	N (Total)	N (Native)	N (Foreign)	Full Sample
1	Office Specialists	5278	5178	100	
2	Salespersons	2442	2371	71	
3	Assistants	2337	2209	128	
4	Nurses	2242	2171	71	
5	Other Technicians	2118	2082	36	
6	Wholesale/ Retail Buyers	2059	1995	64	
7	Bank Specialists	1763	1741	22	
8	Survey Engineers	1361	1324	37	
9	Consultants, Tax Advisers	1329	1291	38	
10	Managers	1228	1181	47	
11	Data Processing Specialists	1180	1138	42	
12	Social Workers	1105	1071	34	
13	Electrical Fitters, Mechanics	1063	1030	33	
14	Tourism Special.,Ticket Sellers	1043	1003	40	
15	Mechanical Engineering Techn.	994	951	43	
16	Motor Vehicle Drivers	973	934	39	
17	Higher Education Teachers	963	926	37	
18	Nursery Teachers, Child Nurses	912	890	22	
19	Insurance Specialists	861	853	8	X
20	Cost Accountants, Valuers	848	823	25	
21	Mechanical/ Motor Engineers	817	789	28	
22	Stenographers, Typists	785	775	10	
23	Engine Fitters	803	771	32	
24	Medical Receptionists	790	769	21	
25	Motor Vehicle Repairers	794	761	33	
26	Locksmiths	801	760	41	
27	Gardeners, Forest Workers	787	760	27	
28	Machinists	781	744	37	
29	Forwarding Business Dealers	730	715	15	
30	Cooks	714	661	53	
31	Home Wardens	637	625	12	
32	Bricklayers, Concrete Workers	635	613	22	
33	HH/Glass/Building Cleaners	630	603	27	
34	Physicians, Pharmacists	612	594	18	
35	Carpeneters	574	560	14	
36	Rest./Bar/Hotel Proprietors	559	515	44	
37	Railway Engine Drivers	527	512	15	
38	Electrical Engr./ Building Techn.	506	493	13	
39	Plumbers	486	468	18	
40	Social Scientists, Statisticians	481	467	14	
41	Post Masters, Telephonists	471	456	15	
42	Dental Techn., Model Makers	453	441	12	
43	Turners	460	432	28	
44	Goods Examiers, Sorters	460	425	35	
45	Warehouse Managers	445	425	20	
46	Packagers, Goods Receivers	445	417	28	
47	Dietary/ Pharm. Assistants	422	416	6	X
48	Masseurs, Physiotherapists	417	410	7	X
49	Journalists, Librarians	420	405	15	
50	Electrical Engineers	410	400	10	
51	Hairdressers, Body Care Occ.	416	388	28	
52	Radio-/Sound Equip. Mechanics	375	370	5	X
53	Doormen, Caretakers	347	336	11	
54	Stowers	369	334	35	
55	Watch-/Clockmakers	343	327	16	

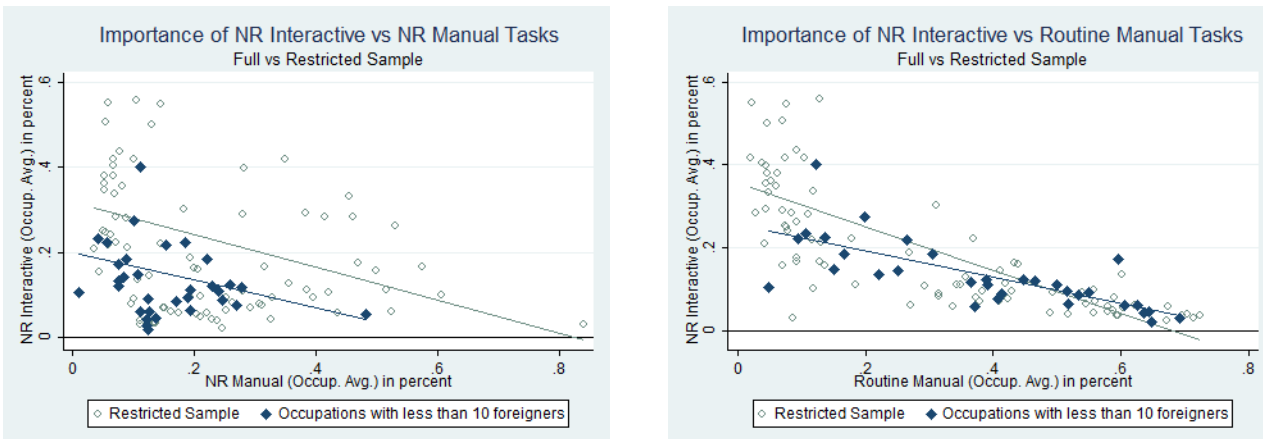
#	Occupational Group	N (Total)	N (Native)	N (Foreign)	Full Sample
56	Foremen, Master Mechanics	317	313	4	X
57	Architects, Civil Engineers	321	312	9	X
58	Measurement Techn., Manufact. Techn.	310	307	3	X
59	Sheet Metal Workers	318	306	12	
60	Plant Fitters	315	306	9	X
61	Bakers, Confectioners	312	297	15	
62	Commercial Agents, Travellers	292	287	5	X
63	Electrical Appliance Fitters	295	285	10	
64	Housekeeping Mangers	294	283	11	
65	Cashiers	291	281	10	
66	Chemical Plant Operatives	301	276	25	
67	Factory Guards, Custodians	287	275	12	
68	Compositors, Printers	277	274	3	X
69	Biological Specialists	271	265	6	X
70	Music Teachers	269	262	7	X
71	Painters, Lacquerers	274	261	13	
72	Toolmakers	264	257	7	X
73	Technical Draughtspersons	257	251	6	X
74	Cutters, Textile Finishers	255	242	13	
75	Steel Smiths	251	241	10	
76	Chemical Lab. Assist.	246	238	8	X
77	Spinners, Skin Proc. Operatives	247	236	11	
78	Welders	235	213	22	
79	Nursing Assistants	227	212	15	
80	Publishing House Dealers, Booksellers	212	209	3	X
81	Miners, Block Makers	216	203	13	
82	Metal Workers	223	202	21	
83	Agricult. Machinery Repair.	187	184	3	X
84	Scaffolders	189	181	8	X
85	Paper/ Cellulose Makers	191	180	11	
86	Chemists, Physicists, Mathematicians	166	164	2	X
87	Farmers, Animal Keepers	164	162	2	X
88	Artistic Performers, Athletes	162	161	1	X
89	Building Labourer	166	153	13	
90	Musicians, Painters	164	153	11	
91	Metal Prod., Melters	163	149	14	
92	Machine Attendants/Setters	154	149	5	X
93	Butchers, Fish Processing	149	145	4	X
94	Wood Preparers	145	141	4	X
95	Street Cleaners, Disposers	141	128	13	
96	Roofers	131	123	8	X
97	Tile Setters, Terrazzo Layers	126	119	7	X
98	Other Assemblers	129	111	18	
99	Paviors, Road Makers	125	110	15	
100	Ceramics Workers	112	108	4	X
101	Chemical lab. workers	114	106	8	X
102	Wine Coopers, Sweets/Ice-Cream Makers	106	100	6	X
103	Metal Pressers, Drawers	104	98	6	X
104	Tracklayers, Civil Engr Workers	103	98	5	X
105	Stucco Workers, Plasterers	106	94	12	
106	Metal Polishers	95	93	2	X
107	Plastics Processors	98	92	6	X
108	Transportation Equip. Drivers	99	88	11	
109	Wood Equip. Makers	95	88	7	X
110	Navigating Ships Officers	86	81	5	X
111	Drillers, Borers	81	77	4	X
112	Goods/Ceramics/Glass Painters	85	76	9	X
113	Metal Grinders	78	74	4	X
114	Attending on Guests	79	73	6	X
115	Textile Cleaners/ Dyers	67	64	3	X
116	Special Printers, Screeners	55	53	2	X
117	Office Auxiliary Workers	55	52	3	X
118	Electrical Appliance Assemblers	8	8	0	X
	Observations Full Sample	63,456	61,229	2,227	
	Observations Restricted Sample	55,036	53,029	2,007	

* Note: The "X" in the last column indicates occupational groups which are excluded in parts of the analysis requiring occupation-level averages. These occupations have less than 10 observations on foreign individuals.

Table B.1: Overview of occupations and composition of workforce

B.2.1.2 Full vs Restricted Sample: Task Measures

To gauge any potential bias resulting from removing occupations with less than observations on foreign workers, I compare the full versus the restricted sample in terms of the relative importance of task employed across all workers. Notably, the task content in interactive tasks across all workers in the full sample is higher by about 5pp. Figure B.1 compares the relative importance of interactive tasks in each sample by plotting it against both manual task measures. The average ratio of interactive to NR manual tasks does not change substantially in the restricted sample, implied by the common linear fit for each task measure (B.1a).



(a) Reference Task: NR Manual

(b) Reference Task: Routine Manual

Figure B.1: Interactive vs Manual Tasks across Occupations

In panel (B.1b), however, we can see that the linear fit in the ratio of interactive to routine manual tasks crosses. This illustration illustrates that the task content in routine manual tasks is lower by some 6pp in the full sample. Put differently, excluded occupations in the restricted sample rely disproportionaly on routine manual tasks. As a consequence, restricting the sample to occupations with a minimum amount of foreign workers, diminishes the importance of between-occupation differences in task requirements and thus the comparative advantage of natives in communication-heavy occupations.

B.2.2 Data Validity

The two key limitations of the BIBB/IAB and BIBB/BAuA surveys are imprecise measurement of wages and under-representation of foreign workers. First, the two surveys released in 1992 and 1999 only provide (monthly) income information in binned form, thus presumably understating the variability in wages. Second, foreign workers are under-represented foreign workers by at least a half compared to the true population due to exclusion of individual with insufficient command of the German language. To inspect whether the employment surveys are nonetheless able to characterize key trends in the native-foreign wage gap, I compare them with other commonly used German labor market data. Of particular importance are (i) the rising wage gap for most parts of the past 20 years and (ii) a pronounced gap at the tails of the distribution. Moreover, to get a sense for the direction of the bias resulting from self-selection of foreign workers, socio-economic characteristics are compared to nationally representative data.

B.2.2.1 Wage Measurement

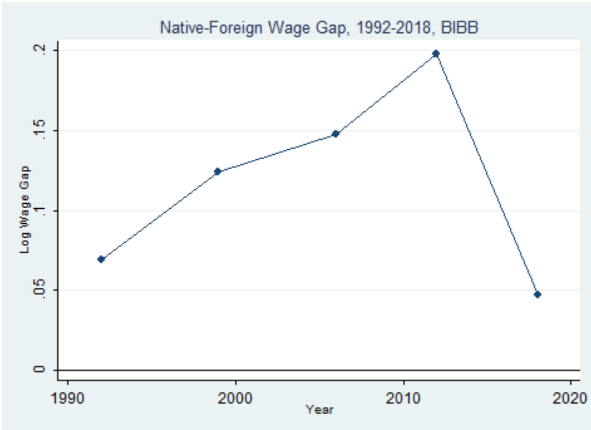
Figure (B.2) compares the (real hourly) wage gap over time using the (i) BIBB/IAB and BIBB/BAuA surveys, (ii) the Sample of Integrated Labor Market Biographies Regional File (SIAB-R 7514), a 2% random sample of social security records in Germany[1], and (iii) household surveys from the Socio-Economic Panel (SOEP).[2] The SIAB-R data is the most reliable data source on wages given its administrative nature, however, it is restricted to workers subject to social security payments. The SOEP data, on the other hand, is a nationally representative sample, thus providing a reference for the bias introduced through the self-selection of foreign workers into the employment surveys.

Panel (B.2a) demonstrates that the BIBB/IAB and BIBB/BAuA surveys are able to replicate the increase in the native-foreign wage gap from 1992-2012 which can likewise be found using administrative data (B.2b). Both data sources suggest a wage gap fluctuating around 10% throughout the 1990s, before rising to 15-20% up until the mid 2010s. The SOEP data, on the other hand, is not able to replicate this recent surge in the wage gap, illustrated in panel (B.2c).

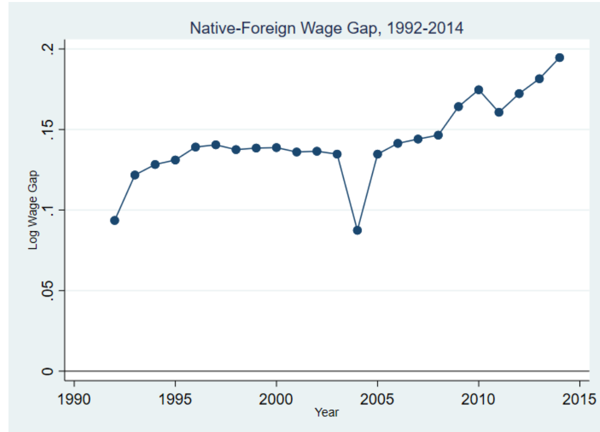
To gauge distributional information embedded in the data sets, Figure (B.3) displays the wage gap along the wage distribution. Panels (B.3a) and (B.3b) demonstrate that the BIBB/IAB and BIBB/BAuA surveys capture key trends in the wage gap between native and foreign workers in recent decades. Accordingly, the native-foreign wage gap is most pronounced at the tails of the distribution with more than 20 pp. compared to around 15 pp. in the middle of the distribution. The SOEP data is not able to reflect these stylized facts, potentially because of self-reporting of various income sources and oversampling of foreign individuals (B.3c).

[1]See Ganzer, Schmucker, Vom Berge & Wurdack (2017) for the data manual.

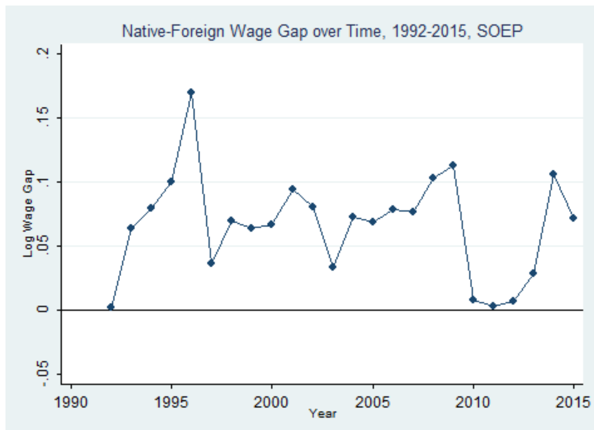
[2]See Schupp, Goebel, Kroh, Schröder, Bartels, Grabka, Fedorets, Erhardt, Giesselmann, Krause, Kühne, Richter, Siegers, Schmelzer, Schmitt, Schnitzlein, Wenzig, Schacht & Deutsches Institut Für Wirtschaftsforschung (2016) for the data manual and Goebel, Grabka, Liebig, Kroh, Richter, Schröder & Schupp (2019) describing the SOEP data more generally. Moreover, see Frick, Jenkings, Lillard, Lipps & Wooden (2007) for a description of the Public Use File of the SOEP, i.e. the international distributed 95% sample of the data.



(a) Data Source: BIBB/IAB/BAuA



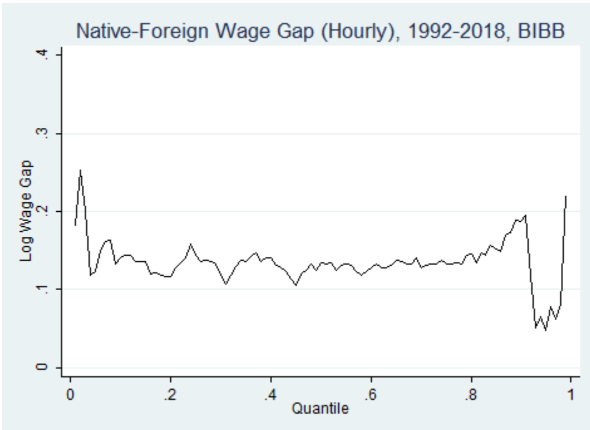
(b) SIAB



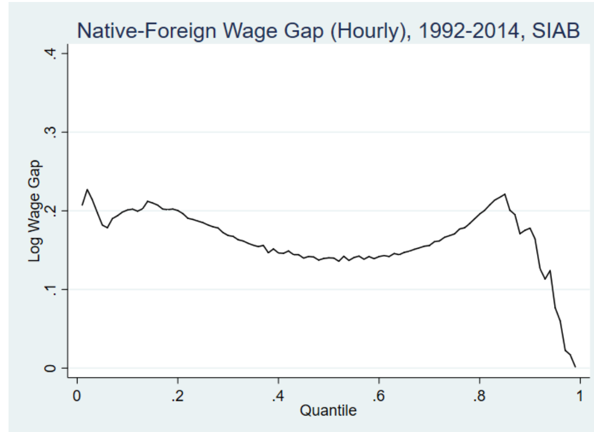
(c) SOEP

Figure B.2: Comparison of the Native-Foreign Wage Gap across different Data Sources - Over Time

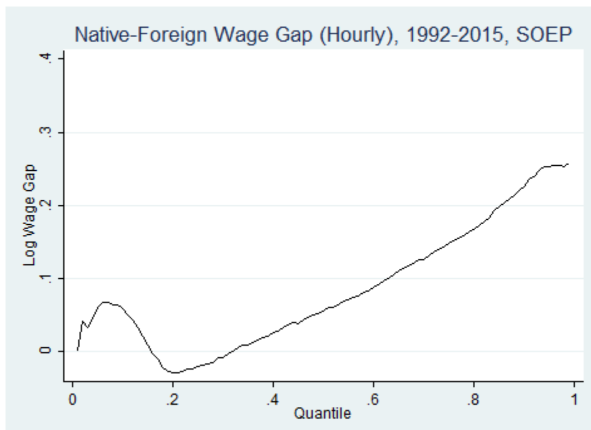
Notably, the BIBB/IAB and BIBB/BAuA data imply a sharp reversal of the wage gap above the 90th percentile, while exaggerating it slightly below the 10th percentile. Both local trends cannot be found using the administrative data, pointing to measurement error resulting from a comparably small sample and the imprecise nature of income reporting in the BIBB surveys. The visual comparison of the employment surveys with administrative data indicates that a distributional analysis concentrated between the 10th and 90th percentile adequately captures trends in the native-foreign wage gap.



(a) Data Source: BIBB/IAB/BAuA



(b) Data Source: SIAB



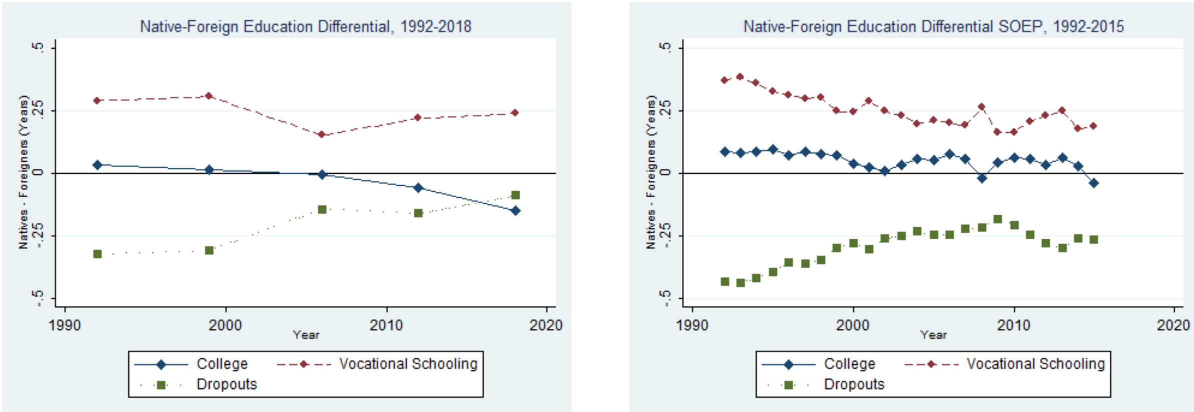
(c) Data Source: SOEP

Figure B.3: Comparison of the Native-Foreign Wage Gap across different Data Sources - Across Wage Distribution

B.2.2.2 Under-representation of Foreign Workers

To gauge the impact of the bias resulting from self-selection of foreign workers, I compare socio-economic characteristics taken from the BIBB/IAB and BIBB/BAuA and SOEP surveys, respectively.

First, a comparison among education outcomes of the foreign population suggests similar developments, irrespective of the data source. Figure (B.4) demonstrates a convergence in educational outcomes between native and foreign workers from 1992 onward, especially due to a reduction in the share of dropouts among foreign individuals.



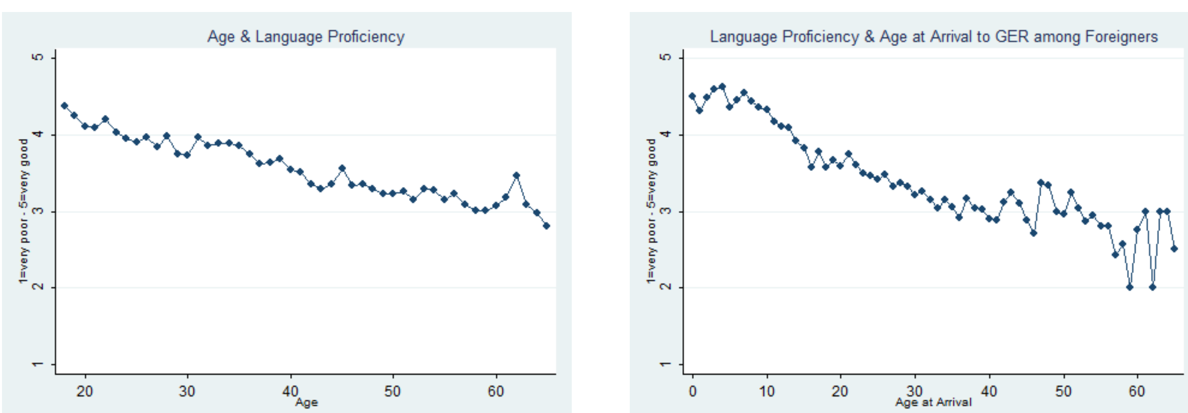
(a) Data Source: BIBB/IAB/BAuA

(b) Data Source: SOEP

Figure B.4: Native-Foreign Education Differentials

Second, changes in the age structure have important implications on the proficiency in the German language among the foreign population. Figure (B.5) establishes a negative relationship between age and language proficiency. Regardless of current age (B.5a) or age at arrival to Germany (B.5b), foreign individuals report worse command of the German language the older they are. Changes in the age structure of immigrant cohorts over time will thus affect the average language proficiency among the foreign population.

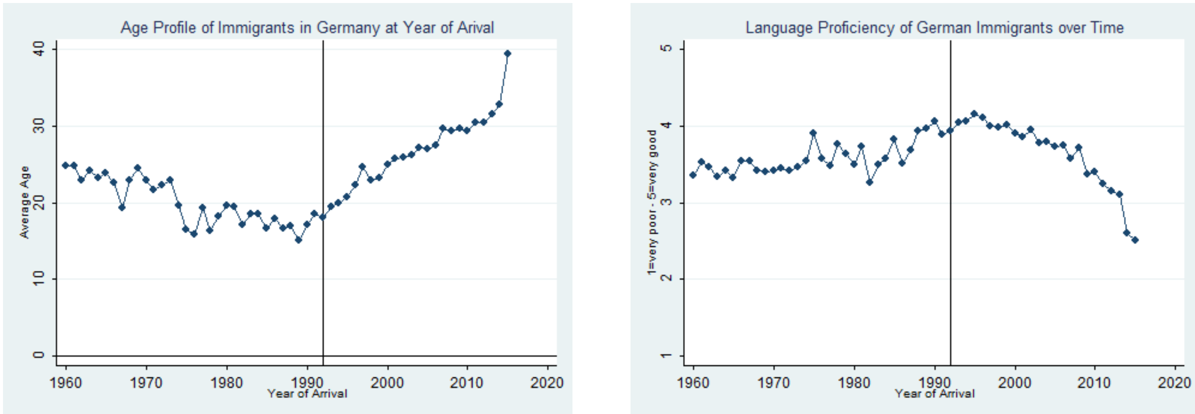
Figure (B.6a) demonstrates that the average age of immigrants in Germany has been 16-25 between 1960 and 1992. Over the past three decades, however, the average age has increased steadily. More recently, the average immigrant has been at least 30 years old, i.e. more 10 years older compared to the early 1990s. As a consequence, the language proficiency of immigrant cohorts deteriorated during that time (B.6b). While foreigners reported to speak German 'good' in 1992, they only reported to have 'fair' command of the language or worse since 2010.



(a) Data Source: SOEP

(b) Data Source: SOEP

Figure B.5: Age & Language Proficiency



(a) Data Source: SOEP

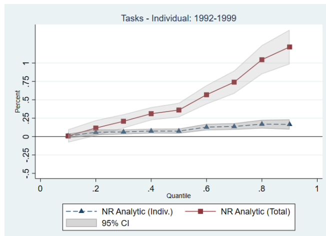
(b) Data Source: SOEP

Figure B.6: Foreigners & Language Proficiency: Cohort-Analysis

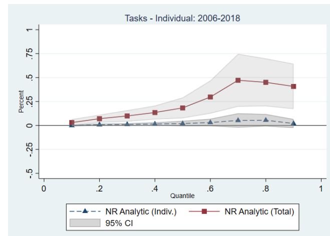
Recall that the BIBB/IAB and BIBB/BAuA surveys selected only foreign workers with sufficient knowledge of the German language. If the surveys were representative of the actual composition of the workforce, they would therefore include *more* foreigners with poor German language skills. Hence, any bias stemming from self-selection of workers in the sample in fact works against the key findings of this study. In particular, any results emphasizing that natives' comparative advantage in interactive tasks contributes to the native-foreign wage gap can be viewed a lower bound for the actual impact.

B.3 RIF Decomposition: Robustness

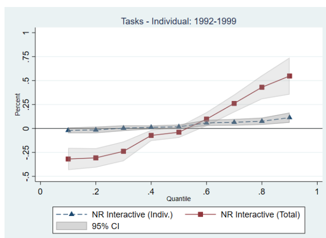
B.3.1 Individual vs Occupation-level Tasks: Unrestricted Sample



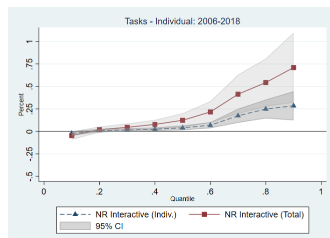
(a) 1992-1999 (NRA)



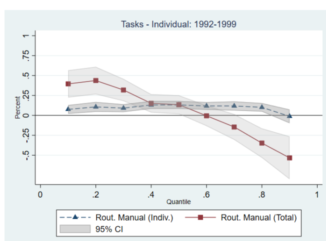
(b) 2006-2018 (NRA)



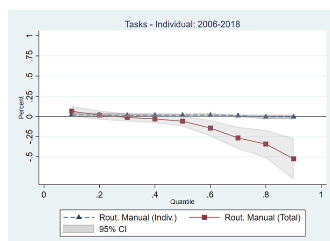
(c) 1992-1999 (NRI)



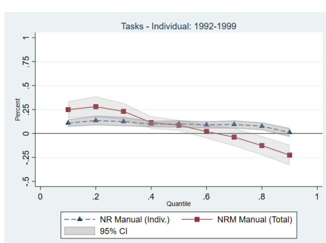
(d) 2006-2018 (NRI)



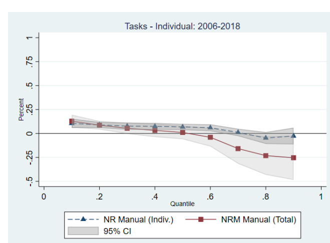
(e) 1992-1999 (RM)



(f) 2006-2018 (RM)



(g) 1992-1999 (NRM)

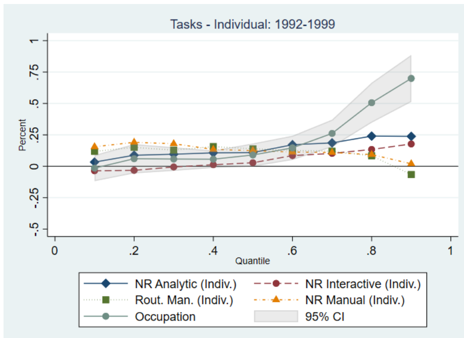


(h) 2006-2018 (NRM)

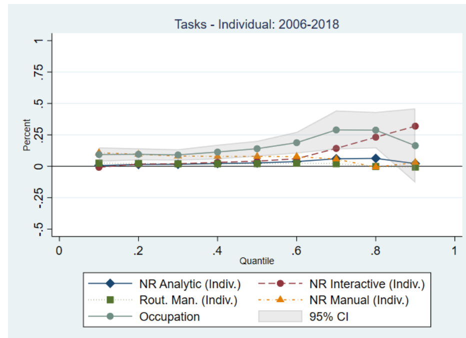
Note: All point estimates are supplemented by a 95% Confidence Interval (CI) based on bootstrapped standard errors with 100 replications.

Figure B.7: Within- vs Between-Occupation Effects over Time, 1992-2018 (Unrestricted Sample)

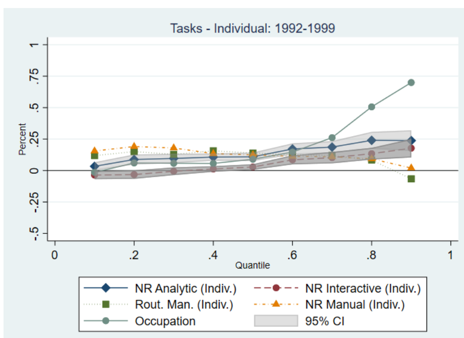
B.3.2 Within-Occupation Tasks: Restricted Sample (≥ 10 foreigners by occupation)



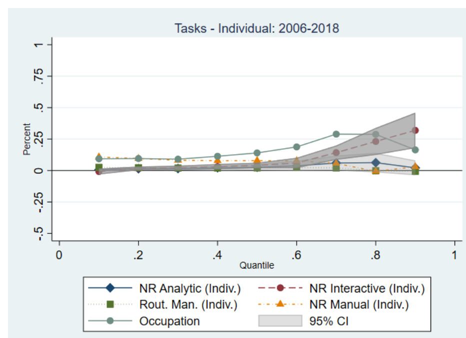
(a) 1992-1999 (Occupation FE highlighted)



(b) 2006-2018 (Occupation FE highlighted)



(c) 1992-1999 (Tasks highlighted)

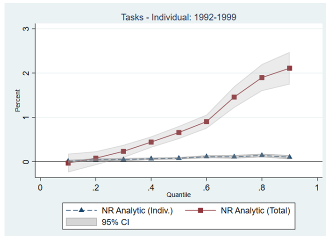


(d) 2006-2018 (Tasks highlighted)

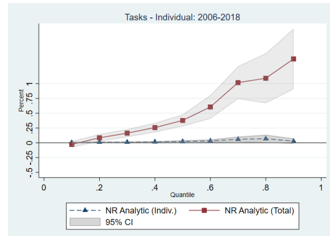
Note: All point estimates are supplemented by a 95% Confidence Interval (CI) based on bootstrapped standard errors with 100 replications.

Figure B.8: Within-Occupation Effects over Time, 1992-2018 (Restricted Sample)

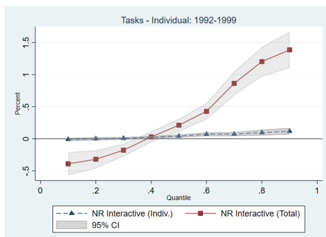
B.3.3 Trends in Task Measures: Include Civil Servants



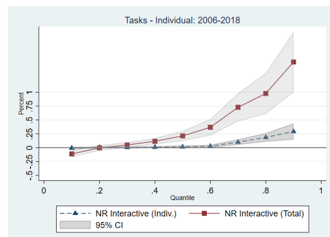
(a) 1992-1999 (NRA)



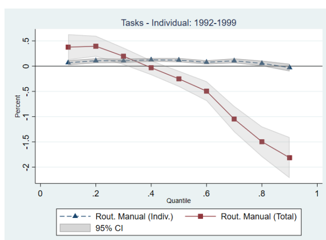
(b) 2006-2018 (NRA)



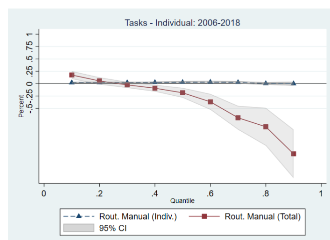
(c) 1992-1999 (NRI)



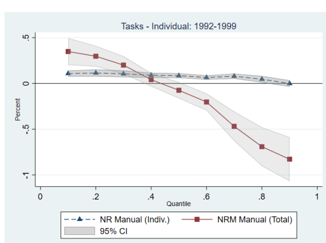
(d) 2006-2018 (NRI)



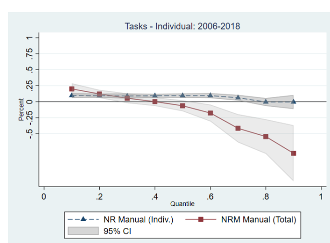
(e) 1992-1999 (RM)



(f) 2006-2018 (RM)



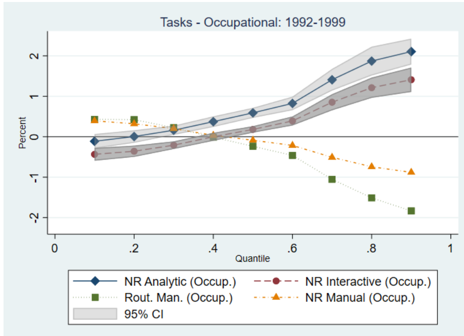
(g) 1992-1999 (NRM)



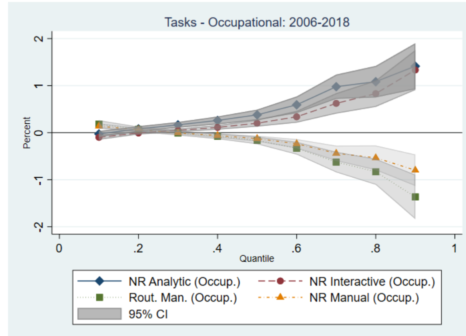
(h) 2006-2018 (NRM)

Note: All point estimates are supplemented by a 95% Confidence Interval (CI) based on bootstrapped standard errors with 100 replications.

Figure B.9: Individual- vs Occupation-level Tasks over Time, 1992-2018 (Include Civil Servants)



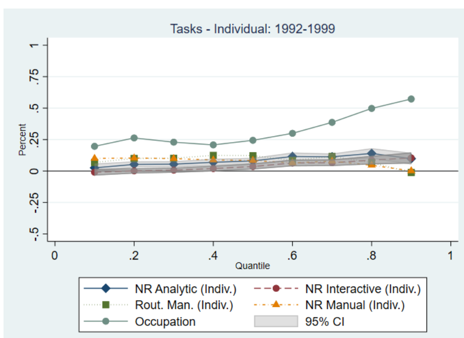
(a) Between-Occupation Effects, 1992-1999



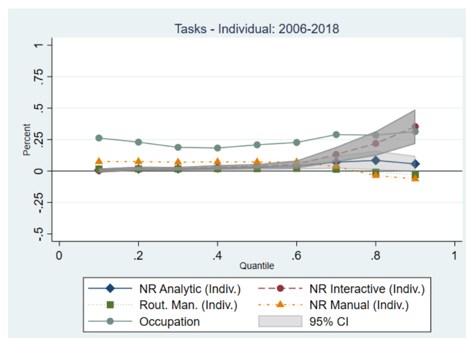
(b) Between-Occupation Effects, 2006-2018

Note: All point estimates are supplemented by a 95% Confidence Interval (CI) based on bootstrapped standard errors with 100 replications.

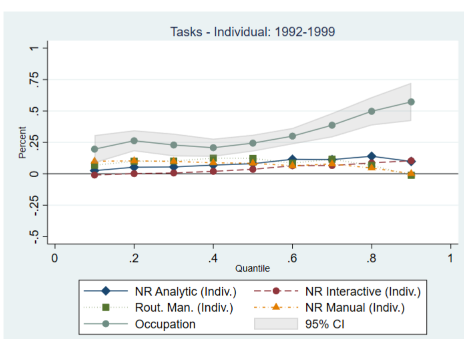
Figure B.10: Between-Occupation Effects over Time, 1992-2018 (Include Civil Servants)



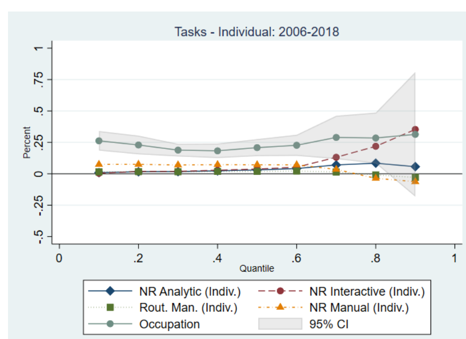
(a) 1992-1999 (Occupation FE highlighted)



(b) 2006-2018 (Occupation FE highlighted)



(c) 1992-1999 (Tasks highlighted)

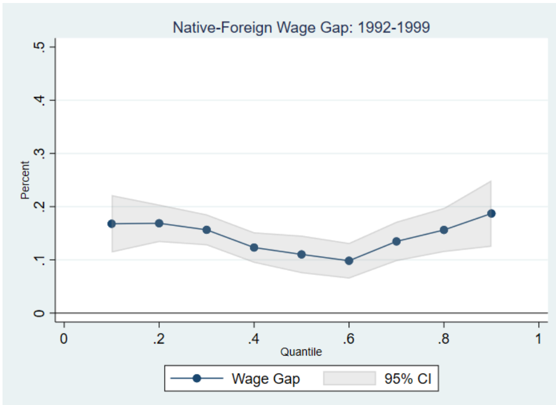


(d) 2006-2018 (Tasks highlighted)

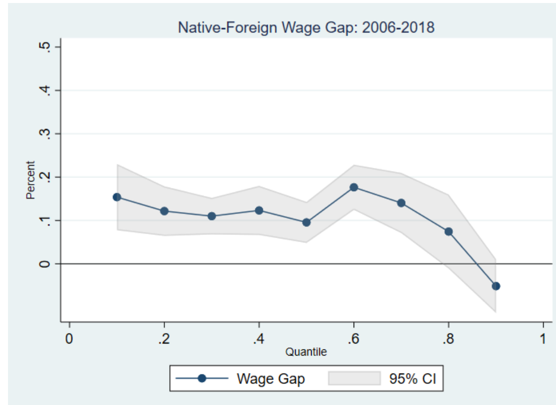
Note: All point estimates are supplemented by a 95% Confidence Interval (CI) based on bootstrapped standard errors with 100 replications.

Figure B.11: Within-Occupation Effects over Time, 1992-2018 (Include Civil Servants)

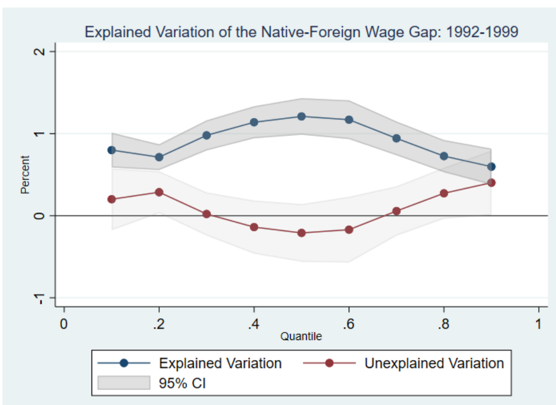
B.3.4 Trends in Task Measures: Exclude Females



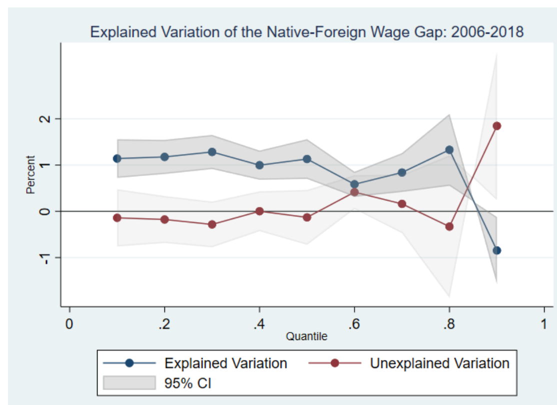
(a) Wage Gap: Distribution, 1992-1999



(b) Wage Gap: Distribution, 2006-2018



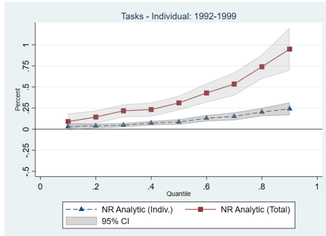
(c) Wage Gap: Explained vs Unexplained, 1992-1999



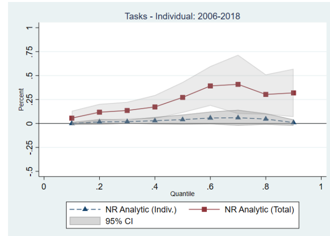
(d) Wage Gap: Explained vs Unexplained, 2006-2018

Note: All point estimates are supplemented by a 95% Confidence Interval (CI) based on bootstrapped standard errors with 100 replications.

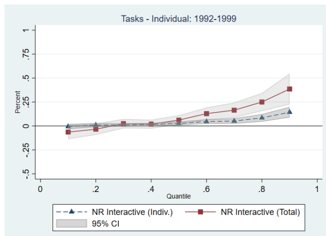
Figure B.12: Trends in the Native-Foreign Wage Gap, 1992-2018 (Exclude Females)



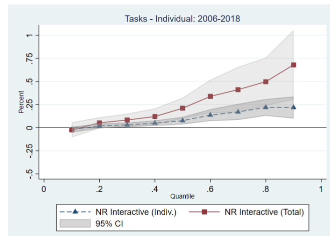
(a) 1992-1999 (NRA)



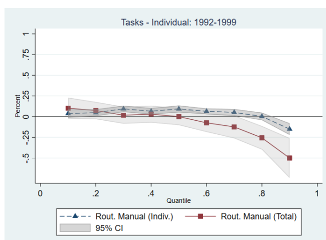
(b) 2006-2018 (NRA)



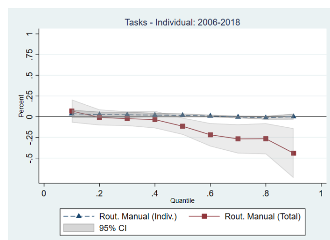
(c) 1992-1999 (NRI)



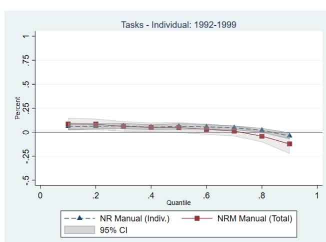
(d) 2006-2018 (NRI)



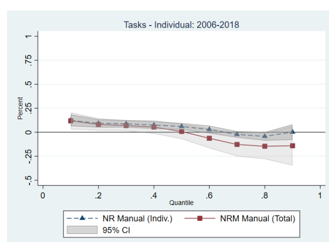
(e) 1992-1999 (RM)



(f) 2006-2018 (RM)



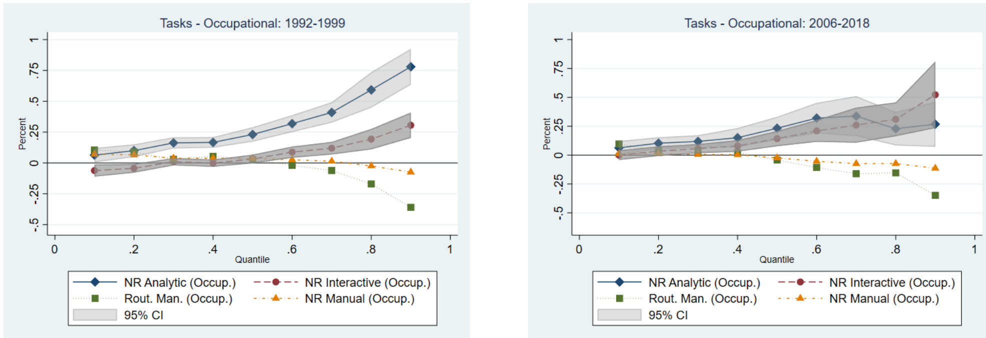
(g) 1992-1999 (NRM)



(h) 2006-2018 (NRM)

Note: All point estimates are supplemented by a 95% Confidence Interval (CI) based on bootstrapped standard errors with 100 replications.

Figure B.13: Individual- vs Occupation-level Tasks over Time, 1992-2018 (Exclude Females)

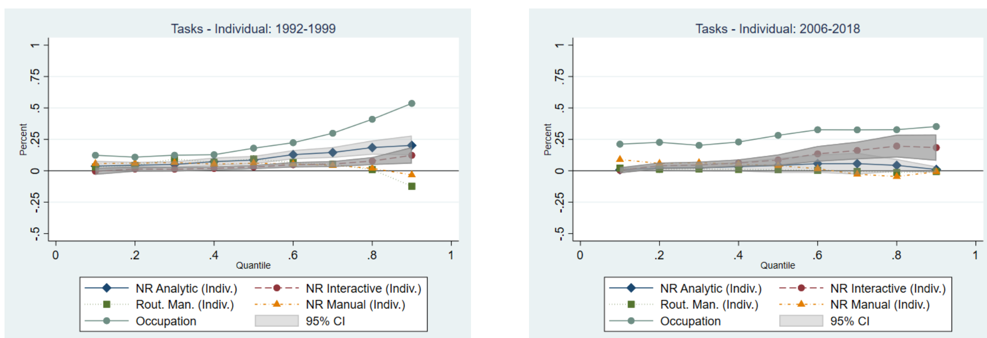


(a) Between-Occupation Effects, 1992-1999

(b) Between-Occupation Effects, 2006-2018

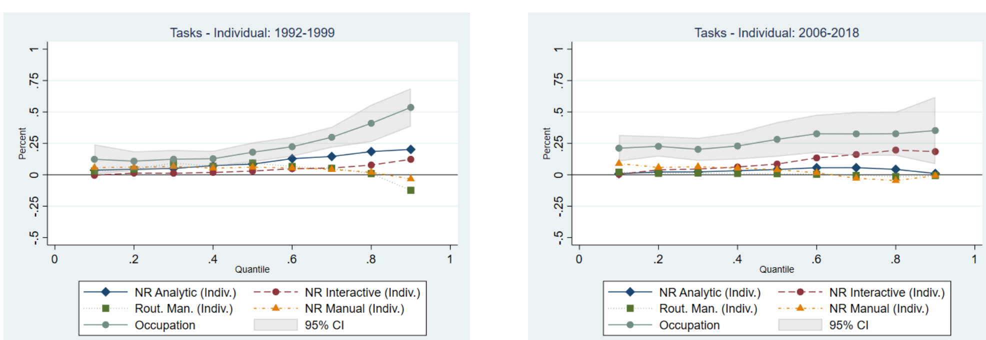
Note: All point estimates are supplemented by a 95% Confidence Interval (CI) based on bootstrapped standard errors with 100 replications.

Figure B.14: Between-Occupation Effects over Time, 1992-2018 (Exclude Females)



(a) 1992-1999 (Occupation FE highlighted)

(b) 2006-2018 (Occupation FE highlighted)



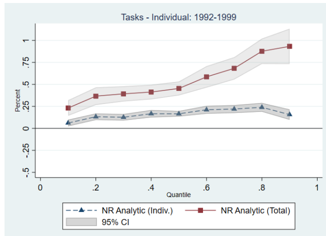
(c) 1992-1999 (Tasks highlighted)

(d) 2006-2018 (Tasks highlighted)

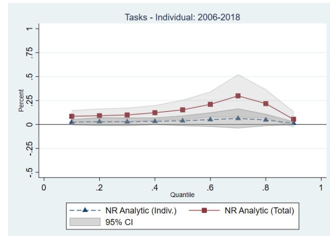
Note: All point estimates are supplemented by a 95% Confidence Interval (CI) based on bootstrapped standard errors with 100 replications.

Figure B.15: Within-Occupation Effects over Time, 1992-2018 (Exclude Females)

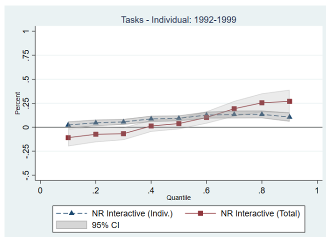
B.3.5 Trends in Task Measures: Base Task Group "Routine Manual"



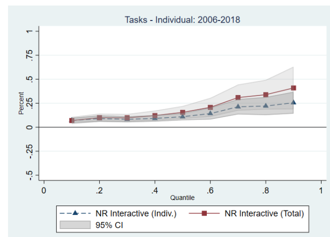
(a) 1992-1999 (NRA)



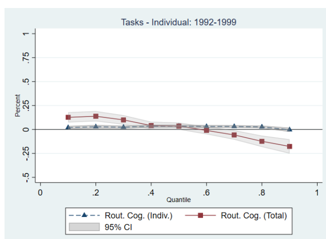
(b) 2006-2018 (NRA)



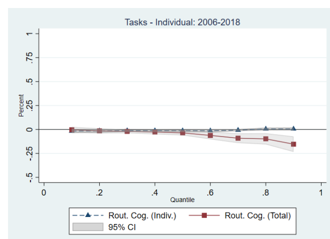
(c) 1992-1999 (NRI)



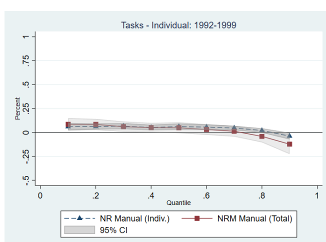
(d) 2006-2018 (NRI)



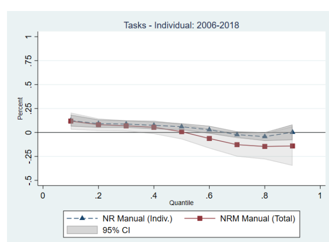
(e) 1992-1999 (RC)



(f) 2006-2018 (RC)



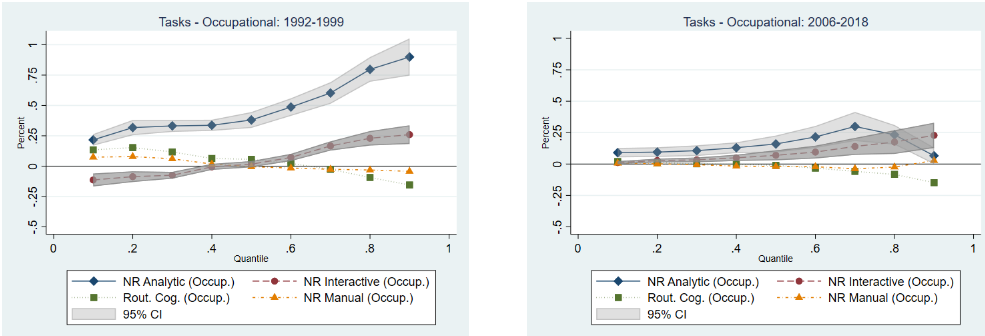
(g) 1992-1999 (NRM)



(h) 2006-2018 (NRM)

Note: All point estimates are supplemented by a 95% Confidence Interval (CI) based on bootstrapped standard errors with 100 replications.

Figure B.16: Individual- vs Occupation-level Tasks over Time, 1992-2018 (Base Group: "Routine Manual")

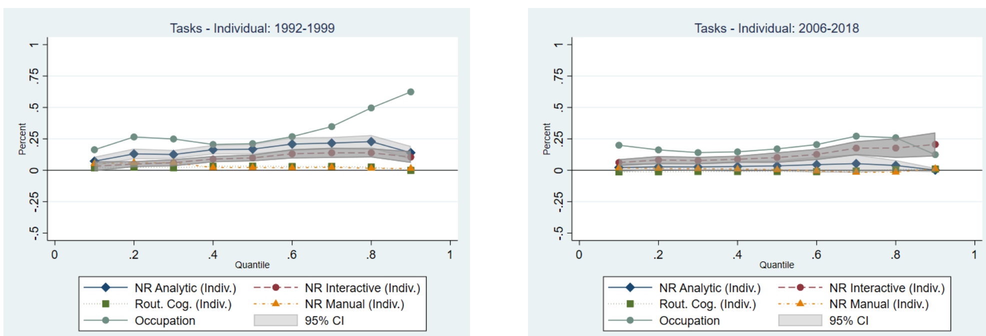


(a) Between-Occupation Effects, 1992-1999

(b) Between-Occupation Effects, 2006-2018

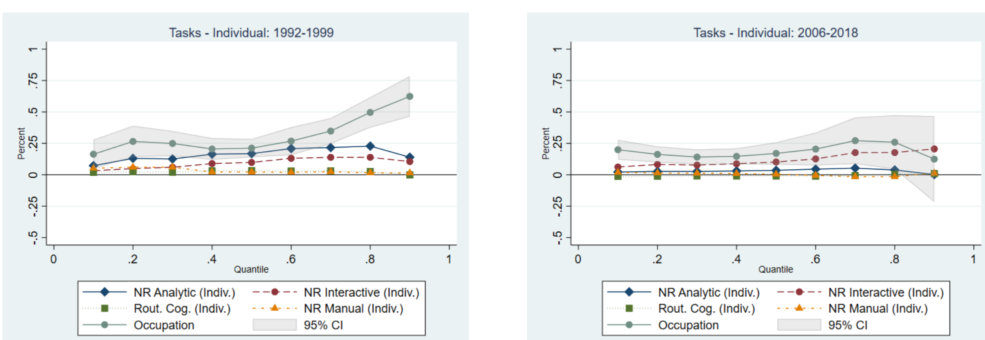
Note: All point estimates are supplemented by a 95% Confidence Interval (CI) based on bootstrapped standard errors with 100 replications.

Figure B.17: Between-Occupation Effects over Time, 1992-2018 (Base Group: "Routine Manual")



(a) 1992-1999 (Occupation FE highlighted)

(b) 2006-2018 (Occupation FE highlighted)



(c) 1992-1999 (Tasks highlighted)

(d) 2006-2018 (Tasks highlighted)

Note: All point estimates are supplemented by a 95% Confidence Interval (CI) based on bootstrapped standard errors with 100 replications.

Figure B.18: Within-Occupation Effects over Time, 1992-2018 (Base Group: "Routine Manual")

EDUARD STORM

Curriculum Vitae

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Academic Appointments

Carleton College *2020*
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Education

University of Wisconsin-Milwaukee *Expected: 08/2020*
Ph.D., Economics
Ph.D. Thesis: "Skills, Tasks, and Wages in Labor Markets"
M.A., Economics *2014*

Justus Liebig University, Giessen, Germany
M.Sc., Economics *2015*

Research and Teaching Interests

Primary: Labor Economics, Education Economics

Secondary: Demographic Economics, International Economics, Economic History

Teaching Experience

Course Instructor *2016 – Present*
University of Wisconsin-Milwaukee

International Economic Relations	*(1 course)*
Economic Statistics	*(1 course)*
Economics of Personal Finance	*(4 courses)*
Principles of Macroeconomics	*(10 courses)*

Instructor (Summer Bridge Program) *2017 – Present*
University of Wisconsin-Milwaukee

Financial Literacy	*(4 courses)*

Teaching Assistant *2013 – 2016*
University of Wisconsin-Milwaukee

Principles of Microeconomics	*(4 sections)*
Principles of Macroeconomics	*(8 sections)*

Instructor (Honorary, Student Initiative) *2011 – 2015*
Justus Liebig University, Giessen, Germany

Foundations of Financial Markets *(6 courses)*

Working Papers

"On the Measurement of Tasks: Does Expert Data Get it Right?" *2020*

"The Native-Foreign Wage Gap Revisited: Evidence from Individual Task Data" *2020*

Research in Progress

"Does Immigration Induce more Natives to Enroll in College?"

"Wage Inequality: A Task-Based Approach"

"Tasks and the Gains from Specialization"

Awards and Honors

UWM Graduate Student Excellence Fellowship Award *2020*

(*Declined due to graduation ahead of conferral*)

William L. Holahan Prize for Outstanding Teaching in Economics *2019*

University of Wisconsin-Milwaukee Chancellor's Graduate Student Award *2016 – 2017*

Conference and Seminar Presentations (Economics Department unless otherwise listed)

Including scheduled – University of Wisconsin-Milwaukee Labor Workshop, Annual Conference of Macroeconomists from Liberal Arts Colleges, Southern Economic Association Annual Meeting 2020

University of Wisconsin-Milwaukee Labor Workshop 2019

Professional Activities

Employment	Student Employee: Mutual Fund Rating *FERI EuroRating Services AG*, Bad Homburg, Germany (Meanwhile acquired by *Scope Ratings GmbH*)	*2011 – 2015*
Service	Leadership Role: Student Initiative (Fin. Markets) Vice President Board Member for Communication	 *2014 – 2015* *2011 – 2013*
Reviewer	Journal of Economic Behavior and Organization	
Memberships	American Economic Association	

Skills

IT	EViews, LaTeX, MATLAB, R, STATA
Languages	German (native), English (fluent)

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