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The Composition of Wage Differentials between Migrants and Natives

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Abstract

We consider the role of unobservables, such as differences in search frictions, reservation wages, and productivities for the explanation of wage differentials between migrants and natives. We disentangle these by estimating an empirical general equilibrium search model with on-the-job search due to Bontemps et al. (1999) on segments of the labour market defined by occupation, age, and nationality using a large scale German administrative dataset.

The native-migrant wage differential is then decomposed into several parts, and we focus especially on the component that we label "migrant effect", being the difference in wage offers between natives and migrants in the same occupation-age segment in firms of the same productivity. Counterfactual decompositions of wage differentials allow us to identify and quantify their drivers, thus explaining within a common framework what is often labelled the unexplained wage gap.

Keywords: immigrants, decomposition of wage differentials, job search, turnover
JEL Classification: J31, J61, J63

1. Introduction

The empirical literature on the labour market experience of immigrants often focuses on differences in observable characteristics between migrants and natives to explain wage differentials. Less explored is the role of unobservables, such as differences in search frictions, reservation wages, and productivities. Yet, it is precisely

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these factors that modern search theory emphasises to be important for wage dispersion. We examine and disentangle the role of these various unobservables in explaining migrant-native wage differentials by adapting to the migrant context the empirical general equilibrium search model with on-the-job search due to Bontemps et al. (1999).

The estimation of this structural model on segments of the labour market defined by occupation, age, and nationality enables us to decompose the native-migrant wage differential into several parts. In particular, we focus on the component that we label "migrant effect", being the difference in wage offers between similar native and immigrant workers in firms of the same productivity. This effect is of interest as we thus control for firm-level differences as measured by their productivities, which have recently been shown using firm-level data to contribute systematically to the wage gap (Aydemir and Skuterud (2008) in the case of Canada, de Matos (2012) for Portugal, and Bartolucci (2013b) for the German case).[1] One particular advantage of our approach is that we do not require firm-level data (data confidentiality promises usually deny public access), as the productivity distribution emerges as an equilibrium relationship. We estimate the migrant effect on internationally accessible German administrative data, the scientific use file known as IABS which is a 2% subsample of the German employment register. This enables us to contribute to the recent literature on the immigrant-native wage gap as follows. While the role of observables is well understood for explaining the wage gap, the role of unobservables is less so. Such wage gaps arise when, for instance, migrants have systematically lower reservation wages (whose role is examined in detail in Albrecht and Axell (1984)), or when firms in a migrant-native segmented labour market (which we discuss below) are less productive in the migrant segment, or when wage-posting firms in one segment derive greater monopsony power from e.g. greater search frictions. Our analysis focuses on the roles of differences in the job turnover parameters, behavioural differences induced by differences in reservation wages, and productivity differences.[2] Within

[1] The migrant effect corresponds to within-firm wage differentials of workers with similar observable characteristics reported in these papers.

[2] The migrant effect is not synonymous with (taste-based) discrimination as we do not model this explicitly (for two approaches see Bowlus and Eckstein (2002), and Flabbi (2010)). Instead, similar to Bowlus (1997) and Bartolucci (2013a) in the context of the gender wage gap, we have an indirect link: if market discrimination exists and influences behavioural patterns, it will be captured in those parameters, while other avenues of wage-impacting discrimination will be picked up by the productivity distributions. In contrast to costly taste-based discrimination, the new monopsony theory suggests the possibility of profitable monopsonistic discrimination stemming e.g. from differential search friction (Manning (2003)). For instance Barth and Dale-Olsen (2009) and

a common framework, we establish the relative importance of each of these factors. Having estimated the model's parameters and thus the actual wage gap and migrant effect, we quantify the roles of the various unobservables in several counterfactual experiments.

The structural model is estimated on a large German administrative panel. Germany is a particularly interesting and relevant case since it hosts the largest numbers of foreign nationals in Europe, and immigration is known to be predominantly low-skilled. According to Eurostat, 7.13 million foreign nationals resided in Germany in 2010, about 8.7% of the total population. The size of the IABS allows us to stratify the analysis by nationality, occupation and age. The resulting subsamples are sufficiently large to permit precise estimation of the model's structural parameters. Moreover, since this is administrative data, the usual concerns about the quality of survey data in a migrant context (sample size, measurement accuracy, and use of retrospective information) are absent.

We briefly describe some aspects of our applications of the structural model. In order to control for heterogeneity in observables, we follow common estimation practice in the search-theory literature by partitioning the labour market into many segments. These segments are defined in terms of occupation, age, and nationality.[3] Given the skill profile of migrants, we consider only the low and medium skill occupations. Each segment is thus assumed to be potentially a separate labour market, characterised by its own job turnover parameters (the job arrival and separation rates). Turning to the unobservables (for the econometrician), firms in each segment differ in terms of productivity, and workers differ in terms of reservation wages. Such reservation wage heterogeneity is plausible given the absence of a legal minimum wage in Germany, and the fact that the location decisions of labour migrants in Roy-style models are usually based on comparisons of expected incomes in source and host country. Migrants might trade-off wage and non-wage job characteristics differently to natives, given their well-known clustering. Besides this preference component, reservation wages also feature an institutional one, but this is less important as contributory unemployment insurance benefits are independent of immigrant status.

The assumption of separate markets for natives and immigrants and the associ-

Hirsch et al. (2010) consider the gender wage gap in the light of this. We relate the migrant effect to the Hirsch and Jahn (2012) analysis of monopsonistic discrimination in Section 2.4.

[3]The term "nationality" rather than "immigrant status" is used here for greater precision given the coding practices of the German Statistical Office. Most German data sources record nationality and not country of birth since German nationality was conferred by descent until the year 2000, when Germany changed its legislation to *ius soli* (this change does not affect our sample).

ated notion of job segmentation conforms to existing international empirical evidence. For instance, using Portuguese data, de Matos (2012) shows that immigrants "work in different industries and occupations than natives" (p.10), and the sorting of immigrants is also observed by Aydemir and Skuterud (2008) for Canada. As regards Germany, D'Amuri et al. (2010) observe that recent immigrants are significantly more likely to compete with established immigrants rather than with natives. Velling (1995) is an early paper to report "evidence of strong occupational segregation" (p.1) between natives and immigrants. This finding has recently been reaffirmed by Lehmer and Ludsteck (2011), Brücker and Jahn (2011), Bartolucci (2013b), and Glitz (2012) who concludes that "ethnic segregation [..] is endemic in the German labour market" (p.15).[4] This segmentation is also consistent with the evidence of strong occupational immobility we find in our data (which has also been observed for other countries, e.g. by de Matos (2012) for Portugal).[5]

For each occupation-age segment, we estimate using maximum likelihood the job turnover parameters, the parameters characterising the reservation wage distribution, and the firms' productivity distribution. We find substantial differences in Germany between natives and foreigners. The segment-specific raw average log wage gaps in our data range from .09 to .45, the overall log wage gap being .22, which is in line with reports in the literature for Germany (e.g. Dustmann et al. (2010) report an unconditional average log wage gap of .23, Hirsch and Jahn (2012) report a gap of .2, while Lehmer and Ludsteck (2011) report predicted wage gaps ranging from .08 to .44 depending on nationality). Turning to the qualitative implications of our model estimates, we find that migrants experience job separations more often than natives but also find jobs more quickly. However, the net effect is such that migrants typically experience greater search frictions. The job turnover parameters decline in age. Across all segments and nationality, transitions into new jobs happen more

[4] At the same time, these papers provide complementary perspectives on the native-immigrant wage gap in Germany: descriptive Oaxaca-Blinder decompositions (Velling (1995), Lehmer and Ludsteck (2011)), wage setting (Brücker and Jahn (2011)), monopsonistic discrimination (Hirsch and Jahn (2012)), while Bartolucci (2013b) provides an interpretation in terms of taste-based discrimination. D'Amuri et al. (2010) pursue a different concern and estimate the wage and employment effects of recent immigration in Western Germany (and find little evidence for adverse effects on native wages and employment levels).

[5] The segmentation assumption has also been imposed routinely in recent search-based structural analyses of the gender wage gap. For instance, Flabbi (2010) considers only whites possessing a college degree, Bowlus (1997) considers two education groups, and Bartolucci (2013a) considers four sectors and two skill groups. Our partition is finer as we also consider three age groups in addition to our three occupation groups (and our estimates remain unbiased should the true partition be such that some segments be aggregated).

quickly than transitions into unemployment. This finding of migrants' higher job separation and offer rates is consistent with differences in employment protection; in particular, Sa (2011) reports that migrants in Germany are much more likely than natives to work on temporary contracts. As regards the reservation wage distribution, there are some workers in all segments with high reservation wages who turn down new job offers when wage offers are too low. However, migrant workers are less demanding on average than natives.

Migrants receive wage offers that are lower than those for natives controlling for the same productivity. This migrant effect is the largest for clerks and service workers, and small for unskilled workers. In particular, the average migrant effect for the skilled ranges between 12% and 15% of the average wage gap, and for clerks and service workers the range is 23% to 39%. For all occupation groups, the migrant effect declines across age groups. These estimates imply that the largest part of the within-group native-migrant wage gap is explained by differences in the productivity distribution (one explanation for such productivity differences is advanced in de Matos (2012)). At the same time, the migrant effect is significant in many segments, and, if expressed in terms of the average segment-specific wage of natives, it is found to be consistent with estimates of "unexplained wage differences" reported in the literature for Germany based on standard Oaxaca-Blinder decompositions (for instance, Lehmer and Ludsteck (2011) report a range from 4 to 17%) or complementary approaches (Hirsch and Jahn (2012) report 6% while Bartolucci (2013b) suggests discrimination effects ranging between 7 and 17%). Our counterfactual decomposition approach allows us to quantify the (marginal and joint) roles of the underlying drivers of the migrant effect in terms of labour market turnover parameters and behavioural differences captured by the reservation wage distribution. We find that reducing the job separation rate for migrants to that of natives typically leads to a large reduction in the migrant effect. This is of interest to policy makers since this parameter is targetable by e.g. deploying measures to improve migrants' employment protection.

This paper is organised as follows. In Section 2, we set out the model as well as the estimation approach. A validation exercise, reported in the Appendix, verifies that the estimation of the structural parameters works well. Section 2.4 introduces the migrant effect, the decomposition of the actual wage differential, and the counterfactual scenarios in the context of the simulated data (which are later re-examined in Section 5 with the real data). Section 3 describes the data used for the analysis. The estimation results are presented in Section 4, and the resulting decompositions in Section 5. Section 6 concludes.

2. The Analytical Framework

The search model with wage-posting and on-the-job search has been described and discussed extensively before in the literature. Therefore, only its most salient features will be outlined. We use the extension of the Burdett and Mortensen (1998) model, and the subsequent empirical generalisation and implementation of van den Berg and Ridder (1998), due to Bontemps et al. (1999). This extends the basic setting by introducing productivity heterogeneity among firms, which improves the fit of the model to wage data, and heterogeneity among workers in terms of the unobserved opportunity cost of employment, which improves the fit to the unemployment duration data. As discussed above, the latter is very plausible in the migration context against the background of Germany's institutional rules.

The labour market is partitioned into many segments, defined in our empirical implementation by age, occupation and nationality. Each segment is considered as a labour market for which the following model and estimation approach applies. The structural parameters are of course allowed to vary across segments, but for notational simplicity we suppress a segment index. This segmentation assumption precludes individuals moving from one segment to another, which is consistent with the evidence of occupational immobility in Germany presented below and the external evidence discussed in the Introduction. If the labour market is integrated over some stipulated segments, then the estimates of the structural parameters should be the same statistically; the segments can then be added to improve estimation efficiency. In line with the segmentation hypothesis we find that the estimated structural parameters differ across occupation-age-nationality groups. We proceed to outline the model for one labour market segment.

2.1. The Model of a Labour Market Segment

The labour market segment is populated by a fixed continuum of workers with measure M, and a fixed continuum of firms with measure normalised to one. Firms differ in terms of (the marginal) productivity (of labour) p with distribution Γ. Unemployed workers differ in terms of their reservation wages b with distribution H.

At any point in time, a worker is either unemployed or employed, and searches for jobs both off and on the job. Individuals draw offers by sampling firms using a uniform sampling scheme. Jobs are terminated at the exogenous rate δ, and job offers arrive at the common rate λ irrespective of the worker's state. This is a restrictive assumption but necessary for identification.[6] Let $k = \lambda/\delta$.

[6] This assumption yields, for the unemployed, a simple solution for the opportunity cost of

Job offers are, of course, unobservable to the econometrician. The job offer distribution is denoted by F, whereas the observable wage or earnings distribution (i.e. of accepted wages) is denoted by G. Let $[\underline{w}, \overline{w}]$ denote the support of F, and, for notational convenience, $\overline{F} = [1 - F]$. F is related to G through an equilibrium condition implied by the theoretical structure. Firms post wages and there is no bargaining.[7]

Workers are risk neutral and maximise their expected steady state discounted future income. Their optimal strategy has the reservation wage property: an employed individual moves to a new employer if the offered wage exceeds the current wage (so the model does not allow for wage cuts); an unemployed individual accepts a new job if the offer exceeds b, and otherwise rejects the offer and remains unemployed. On-the-job search thus generates further ex-post heterogeneity in reservation wages.

In steady-state equilibrium, the flows of workers into and out of the unemployment pool are equal, which determines the unemployment rate u. Consider the stock of employed workers who earn a wage less than or equal to w. Two sources constitute the outflow from this stock, namely: (i) exogenous job separations at rate δ and subsequent transits into unemployment, and (ii) wage upgrading as employed workers move to poaching firms. The combined outflow is thus $(1 - u)G(w)(\delta + \lambda\overline{F}(w))$. The flow into this stock consists of unemployed individuals who receive wage offers above their reservation wage. Conditional on b, the probability of this event is $u\lambda[F(w) - F(b)]$. The marginal inflow is obtained by integrating up to w over the distribution of b in the stock of the unemployed. Denoting the latter by H_u, the steady state equation for the labour market yields the relationship between H_u and H, namely $uH_u(b) = \int_{-\infty}^{b}[1 + k\overline{F}(x)]^{-1}dH(x)$.

Equating inflows and outflows relates the wage offer distribution F to the realised wage distribution G. To be precise, Bontemps et al. (1999, Proposition 2) show that the unemployment rate u and the actual wage distribution G satisfy

$$u = \left[\frac{1}{1+k}H\left(\underline{w}\right) + \int_{\underline{w}}^{\overline{w}} \frac{1}{1+k\overline{F}\left(x\right)} dH\left(x\right)\right] + \left[1 - H\left(\overline{w}\right)\right] \tag{1}$$

employment: it is simply equal to b. If job offer arrival rates were to differ, Mortensen and Neumann (1988) show that this opportunity cost would be an intractable function of all the primitives of the model, leading to feedback to workers' optimal strategies from wages and firm behaviour.

[7]For an analysis of wage determination in the presence of heterogeneity, search on-the-job, and strategic wage bargaining, see Cahuc et al. (2006). They find no significant bargaining power for intermediate and low skilled workers in France.

$$G(w) = \frac{H(w) - \left[1 + k\overline{F}(w)\right]\left[\frac{1}{1+k}H(\underline{w}) + \int_{\underline{w}}^{w} \frac{1}{1+k\overline{F}(x)} dH(x)\right]}{\left[1 + k\overline{F}(w)\right](1-u)}. \tag{2}$$

Risk neutral firms have constant-returns-to-scale technologies, and post wages that maximise steady state profit flows, the profit per worker being $p - w$. Firms do not observe the reservation wage of a potential employee. In equilibrium, firms offer wages to workers that are smaller than their productivity level, so firms have some monopsony power. Bontemps et al. (1999, Proposition 9) show that in equilibrium there exists an increasing function K which maps the productivity distribution Γ into the wage offer distribution F, so that the wage offer satisfies $w = K(p)$ with

$$K(p) = p - \left[\frac{\underline{p} - \underline{w}}{(1+k)^2} H(\underline{w}) + \int_{\underline{p}}^{p} \frac{H(K(x))}{1 + k\left[1 - \Gamma(x)\right]^2} dx\right] \frac{\left[1 + k\left[1 - \Gamma(p)\right]\right]^2}{H(K(p))} \tag{3}$$

and $F(w) = \Gamma\left(K^{-1}(w)\right)$. Hence given the frictional parameter k, the reservation wage distribution H and the productivity distribution Γ, equation (3) yields the wage offer distribution F, which then via (1) yields the equilibrium unemployment rate and through (2) the actual wage distribution G.

Our dataset does not include measures of firm productivity but, of course, extensive wage data. Using expressions of the key quantities in terms of the actual wage density g, the productivity distribution Γ becomes estimable. In particular, it can be shown that

$$(1-u) = \frac{k}{(1+k)\int_{\underline{w}}^{\overline{w}} \frac{g(t)}{H(t)} dt}, \tag{4}$$

$$\frac{1}{\left[1 + k\overline{F}(w)\right]} = (1-u)\int_{\underline{w}}^{w} \frac{g(t)}{H(t)} dt + \frac{1}{[1+k]}. \tag{5}$$

Equation (4) follows from (5) with $w = \overline{w}$. The equilibrium productivity levels are

$$p = K^{-1}(w) = w + \frac{H(w)}{2(1-u)\,g(w)\left[1 + k\overline{F}(w)\right] + h(w)}. \tag{6}$$

2.2. Identification

We seek to estimate this model using data by labour market segment on employment and unemployment durations, as well as data on wages and accepted wage offers. These data are sufficient to identify[8] the structural parameters, once the reservation wage distribution is parametrised. We assume that H is a normal distribution with unknown location and scale parameters, $(\mu, \sigma) \equiv \theta$. Since arrivals of job offers and separations are assumed to follow Poisson processes, sojourn times are exponentially distributed.

In particular, the wage data identify the wage distribution G, and the minimum and the maximum of the observed wages identify the infimum $\underline{w}$ and the supremum $\overline{w}$ of the wage offer distribution. The steady state flow equations in form of (4) and (5) then identify the wage offer distribution F given λ/δ and $H(.;\theta)$, which yield the productivity distribution Γ via (3). The job separation rate is identified from job durations ending in a transition to unemployment, as these are exponential variates with parameter δ, the mean duration being δ^{-1}. Job durations ending in a transition to another job with wage w are exponential with parameter $\lambda\bar{F}(w)$. Together with unemployment durations ending in a transition to a job with wage w these identify the remaining parameters λ and θ. Since the reservation wage is unobservable, the marginal unemployment durations are mixtures of exponentials, $\Pr\{T_u \leq t | b \leq w\} = 1 - \int_{-\infty}^{w} \exp(-\lambda\bar{F}(b)t) dH_u(b;\theta | b \leq w)$.

Absent such mixing, when H is degenerate and all agents accept all wage offers above the common reservation wage, transitions to a new job from each labour market state would permit separate identification of the job offer arrival rates, and thus would give rise to testable overidentification restrictions. In the presence of unobservable heterogeneity captured by H, overidentification restrictions only arise with additional data that would permit, for instance, an independent estimation of the wage offer distribution (see e.g. Christensen et al. (2005) for such an approach).

2.3. Maximum Likelihood Contributions for Labour Market Segments

The preceding constructive identification argument suggests that we can estimate the structural parameters using maximum likelihood on our data on unemployment and employment durations and wages. The likelihood contributions we consider in detail next differ slightly from those in Bontemps et al. (1999) since our data are flow and not stock samples. The validation exercise reported in Appendix B verifies the good performance of our estimation procedure on artificial data. The density of accepted wages, and thus G, is estimated using kernel methods, and enters all likelihoods as a nuisance parameter.

[8] Eckstein and van den Berg (2007) discuss identification issues in empirical search models more generally.

Consider first the likelihood contributions of unemployed agents. Since the unemployment rate is a function of the model parameters, it needs to enter the sampling plan. In equilibrium, the probability of encountering an unemployed individual is given by (4). Since the reservation wage b is unobservable, it needs to be integrated out. We distinguish between individuals for whom $b \leq \underline{w}$ as they accept all job offers, a mass of $H(\underline{w})$, and those for whom $b > \underline{w}$ as they reject offers below b. Recall that $F(\underline{w}) = 0$, and we assume that all individuals included in our sample would accept at least one wage offer $w \in [\underline{w}, \overline{w}]$. This implies that the sup of H is lower than the sup of F, $\overline{b} \leq \overline{w}$, so this specification does not take into account cases of permanently unemployed individuals. Conditional on b, the distribution of unemployment durations in our flow sample is exponential with parameter $\lambda\overline{F}(b)$. The accepted wage, w, is a realisation of the wage offer distribution truncated at b: $f(w)/\overline{F}(b)$. The likelihood contribution of an unemployed L_u is thus, having substituted out u,

$$L_u(\lambda, \delta, \theta) = \lambda^{(1-d_r)} \exp(-\lambda t) \frac{H(\underline{w})}{1+k} [f(w)]^{(1-d_r)} +$$

$$+ \int_{\underline{w}}^{w} \left\{ \left[\lambda\overline{F}(b)\right]^{(1-d_r)} \exp[-\lambda\overline{F}(b)\, t] \left[\frac{f(w)}{\overline{F}(b)}\right]^{(1-d_r)} \frac{1}{\left[1 + k\overline{F}(b)\right]} \right\} dH(b), \qquad (7)$$

where d_r is a dummy variable equal to one if the spell is right-censored (the only relevant censoring in our data). In this case it is only known that the unemployment duration exceeds t.

We turn to the likelihood contributions of employed workers, denoted by L_e. The probability of sampling an employed individual receiving a wage w is $(1-u)\, g(w)$. We have further data on the job duration and the exit state. Let v be a dummy variable equal to one if the destination of an employment spell is unemployment, and zero if the destination is another job. We have two competing risks: Exits to unemployment occur with probability $\delta / \left[\delta + \lambda\overline{F}(w)\right]$ and exits to higher paying jobs occur with probability $\lambda\overline{F}(w) / \left[\delta + \lambda\overline{F}(w)\right]$. Conditional on being employed with wage w, the job duration has an exponential distribution with parameter $\left[\delta + \lambda\overline{F}(w)\right]$. If a transit to unemployment is observed at duration t, this implies that the duration of the other latent risk factor exceeds t, the joint density factorises, and we have $\delta \exp(-\delta t) \exp(-\lambda\overline{F}(w))$. Therefore

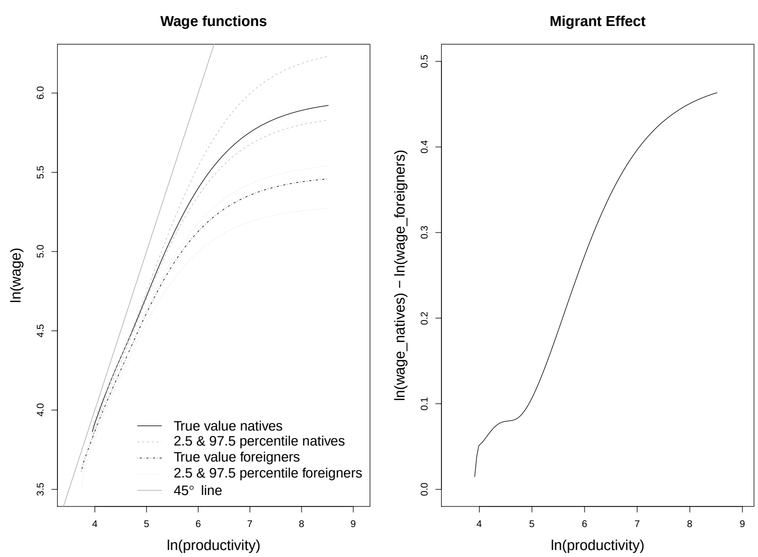
$$L_e(\lambda, \delta, \theta) = (1-u)\, g(w) \exp\left\{-\left[\delta + \lambda\overline{F}(w)\right] t\right\} \times \left\{\delta^v \left[\lambda\overline{F}(w)\right]^{(1-v)}\right\}^{(1-d_r)}, \quad (8)$$

where $(1-u)$ is given by equation (4). If an employment spell is right-censored, indicated by d_r, we only know that the job duration exceeds t.

2.4. Migrants, Natives, Wage Differentials and the Migrant Effect: Concepts and Simulated Data

We develop an illustrative example in order to introduce our key concepts. Consider two labour market segments, one occupied by natives (N) and the other by immigrants (F). Workers in either segment exhibit the same observable characteristics (in our empirical application below we consider the same skill and age group). We calibrate the two segments (in line with the empirical results) as follows: the job turnover parameters of migrants are assumed to be higher than those of natives, $\delta_F = .016 > .005 = \delta_N$ and $\lambda_F = .13 > .07 = \lambda_N$, while natives have higher mean reservation wages, $\mu_F = 45 < 60 = \mu_N$. The productivity distribution in the segment for natives is assumed to first order stochastically dominates that of migrants: $\Gamma_F(p) = 1 - (\underline{p}_F/p)^\alpha$ and $\Gamma_N(p) = 1 - (\underline{p}_N/p)^\alpha$ with $\alpha = 2.1$, $\underline{p}_F = 40$, and $\underline{p}_N = 50$. The validation exercise reported in Appendix B discusses the estimation results.

Figure 1: Wage offer curves for natives and migrants, and the "migrant effect".



For this economy, the aggregate wage gap is substantial (equal to 32.02), but differences in the productivity distributions are likely to play an important role (recall the discussion in the Introduction). Figure 1 Panel A depicts the resulting wage offers given by (3) as functions of productivity. These enable us to consider a component of the wage gap which we label "migrant effect", depicted in Panel B, being the difference in wage offers between similar native and immigrant workers in firms of the same productivity: $w_N(p) - w_F(p)$. This effect is of interest since we thus control for firm-level differences as measured by their productivities.

This concept of the migrant effect suggests to decompose the aggregate wage differential[9] between migrants and natives, $\int_A w_N(p)d\Gamma_N(p) - \int_A w_F(p)d\Gamma_F(p)$, into the aggregate migrant effect and a weighted difference between firm productivities (where A denotes the intersection of the supports of the productivity distributions). Solving for the aggregate migrant effect, we thus have

$$\begin{aligned} \int_A [w_N(p) - w_F(p)]\, d\Gamma_N(p) &= \int_A w_N(p)d\Gamma_N(p) - \int_A w_F(p)d\Gamma_F(p) \\ &- \int_A w_F(p)d\left[\Gamma_N(p) - \Gamma_F(p)\right]. \end{aligned} \tag{9}$$

We briefly comment on the relationship between the migrant effect and the concept of monopsonistic discrimination, as examined in e.g. Hirsch and Jahn (2012). The latter is measured by these authors indirectly from a search-model inspired decomposition of the long run wage elasticity of labour supply using reduced-form job separation models that are estimated separately on data for migrants and natives. In our model, greater monopsony power of firms (measured by the absolute or relative distance between productivity, i.e. the 45 degree line, and wages as illustrated in Figure 1.A) in the migrant segment gives rise to the migrant effect. Our approach enables us to go beyond measuring the migrant effect, as we explain it within a common framework in terms of the relative importance of differences in the job turnover parameters and behavioural differences induced by differences in reservation wages. In particular, a closer inspection of (3) shows that the wage offers are complicated functions of these structural parameters, $w_i(p|\underline{p}_i, \alpha_i, \mu_i, \sigma_i, \lambda_i, \delta_i)$ for $i \in \{N, F\}$.

2.4.1. Counterfactual Wage Decompositions

In order to identify the principal drivers of the migrant effect, and to conduct policy experiments, we consider next a second decomposition of the wage gap based on counterfactuals. In particular, we ask: what would be the migrant effect and the wage differential if one group is imputed counterfactually parameter values of the other group? For instance, choosing natives as the reference group and equalising counterfactually the reservation wage distribution parameters (μ, σ), the counterfac-

[9] For a decomposition of wage differentials in a reduced form setting, see Dustmann and Theodoropoulos (2010). Note that their decomposition considers, as we do, the wage offer function, but their empirical approach does not recover it from the data.

Table 1: Counterfactual decompositions of the wage differential using natives as the reference group.

	Counterfactually equalised para.	Remaining differing para.	Wage differential	Migrant effect
(1)		$\underline{p}, \alpha, \mu, \sigma, \lambda, \delta$	32.022	6.825
(2)	μ, σ	$\underline{p}, \alpha, \lambda, \delta$	30.096	3.747
(3)	δ	$\underline{p}, \alpha, \mu, \sigma, \lambda$	28.973	1.954
(4)	λ	$\underline{p}, \alpha, \mu, \sigma, \delta$	34.029	10.032
(5)	μ, σ, δ	$\underline{p}, \alpha, \lambda$	27.423	-0.524
(6)	α, μ, λ	$\underline{p}, \alpha, \delta$	31.694	6.300
(7)	λ, δ	$\underline{p}, \alpha, \mu, \sigma$	30.459	4.328
(8)	$\mu, \sigma, \lambda, \delta$	$\underline{p}, \alpha$	28.758	1.610
(9)	$\underline{p}, \alpha$	$\mu, \sigma, \lambda, \delta$		4.904
(10)	$\underline{p}, \alpha, \mu, \sigma$	λ, δ		1.932
(11)	$\underline{p}, \alpha, \delta$	μ, σ, λ		0.750
(12)	$\underline{p}, \alpha, \lambda$	μ, σ, δ		7.814
(13)	$\underline{p}, \alpha, \mu, \sigma, \delta$	λ		-1.842
(14)	$\underline{p}, \alpha, \mu, \sigma, \lambda$	δ		4.400
(15)	$\underline{p}, \alpha, \lambda, \delta$	μ, σ		2.741

Notes: Based on the DGP given in Appendix Table B.16, and the decomposition of equation (10). Rows 9+: the wage differential equals the migrant effect because the productivity distributions are the same.

tual migrant effect is, using (9),

$$\begin{aligned} & \int_A [w_N(p|\underline{p}_N, \alpha_N, \mu_N, \sigma_N, \lambda_N, \delta_N) - w_F(p|\underline{p}_F, \alpha_F, \mu_N, \sigma_N, \lambda_F, \delta_F)] d\Gamma_N(p) \qquad (10) \\ = & \int_A w_N(p|\underline{p}_N, \alpha_N, \mu_N, \sigma_N, \lambda_N, \delta_N) d\Gamma_N(p) - \int_A w_F(p|\underline{p}_F, \alpha_F, \mu_N, \sigma_N, \lambda_F, \delta_F) d\Gamma_F(p) \\ - & \int_A w_F(p|\underline{p}_F, \alpha_F, \mu_N, \sigma_N, \lambda_F, \delta_F) d[\Gamma_N(p) - \Gamma_F(p)] \end{aligned}$$

with $\Gamma_i(p) = \Gamma_i(p|\underline{p}_i, \alpha_i)$ for $i \in \{N, F\}$.

Table 1 collects the exhaustive list of possible counterfactual experiments, and the resulting quantifications of both the counterfactual migrant effect and wage differential (the first term on the right hand-side of (10)). The reference group consists of natives. In column 1 we list the parameters we counterfactually equalise, so (μ, σ)

in row and experiment 2 is a shorthand for $\mu_F = \mu_N$ and $\sigma_F = \sigma_N$. The residual parameters enumerated in column 2 constitute thus the sources of the remaining wage differences. In the first experiment, reported in row 1, no parameters are equalised, hence the reported results are based on actual wages (i.e. we use the actual wage decomposition (9)). In experiment 9 and later, we equalise the two parameters of the productivity distribution, $\underline{p}$ and α (Bartolucci (2013a) labels such differences in the productivity distribution parameters "segregation"). This nils the last term in equation (10), so migrant effect and wage differential are equalised. In all experiments we use simulated data based on the DGP of Appendix Table B.16 but the results reported next are in line with our data-based empirical results for the comparative statics and policy experiments reported in Section 5.2.

The actual migrant effect of 6.8, reported in experiment 1, is substantial, about 21% of the wage differential. At the same time this implies that the largest contribution to the native-migrant wage gap is made by the differences between the productivity distributions. Turning to the drivers of the migrant effect, experiments 13-15 consider the marginal roles of δ, λ, and (μ, σ). Recalling that $\lambda_F > \lambda_N$ explains the negative sign in experiment 13. Also note that $\delta_F > \delta_N$, and $\mu_F < \mu_N$ while $\sigma_F = \sigma_N$. Experiment 14 suggests that the difference in the separation rates plays a large quantitative role in the determination of the migrant effect, the latter being 4.4; the complementary insight is that, by experiment 3, equalising the job separation rates reduces the migrant effect to 29% of its former size. The differences in mean reservation wages, considered in experiment 15, leads to a smaller migrant effect of 2.7. The joint effect of δ and (μ, σ), reported in experiment 12, equals 7.8, and is slightly larger than the sum of the two marginal effects. We defer discussing the policy implications of these results to Section 5.2 as these are similar to those based on our empirical results.

3. The Data

The empirical analysis is based on the 2% subsample of the German employment register provided by the Institute of Employment Research, known as IABS (75-04 distribution). For a detailed description of the dataset, see Bender et al. (2000). This large administrative dataset for Germany, covering the period 1975-2004 consists of mandatory notifications made by employers to social security agencies. These notifications are made on behalf of workers, employees, and trainees who pay social security contributions. This means that self-employed individuals, civil servants, and workers in marginal employment are not included. Notifications are made at the beginning and at the end of an employment or unemployment spell. Information on individuals not experiencing transitions during a calendar year is updated by means of an annual report. Hence, we are able to use a flow sample in our empirical analysis.

Apart from wages, transfer payments, and spell markers, the dataset contains some standard demographic measures, including nationality, as well as occupation and firm markers. The education variable is not used since its problems, particularly in the migrant context, are well-known and skills are better measured by the occupation (see Fitzenberger et al. (2006) for a detailed discussion; we do not use the suggested imputations since the education variable for migrants, when observed, is likely to be of poor quality, as discussed in Brücker and Jahn (2011, p. 296 point (ix)) and Lehmer and Ludsteck (2011, p. 900)). Wage records in the IABS are top coded at the social security contribution ceiling. However, this ceiling is not binding for our population of interest, namely individuals (natives and foreigners) in low and middle skill occupations. We use real wages in 1995 prices. The occupational information is provided in extensive (three digit codes) but non-standard form. We therefore map this coding into 10 major groups based on the International Standard Classification of Occupations (ISCO-88). The Data Appendix provides some details. Since immigration is known to be predominantly low skilled, we select from these 10 groups 3 low and middle skilled occupations, namely (1) unskilled blue-collar workers, (2) clerks and low-service workers, and (3) skilled blue-collar workers.

The data allows us to distinguish between three labour market states: employed, recipient of transfer payments (i.e. unemployment benefits, unemployment assistance and income maintenance during participation in training programs) and out of sample. Unfortunately, none of the two last categories corresponds exactly to the economic concept of unemployment. This issue is discussed in several studies, see e.g. Fitzenberger and Wilke (2010). For example, participants in a training program are transfer payment recipients despite being in employment (they are considered unemployed from an administrative point of view), while individuals that are registered unemployed but are no longer entitled to receive benefits appear to be out of the labour force. Therefore, the dataset provides a representative sample of those employed and covered by the social security system, but somewhat mis-represents those in the state of unemployment. For our purposes, all individuals who are out of sample between two different spells are classified as unemployed, so only two labour market states are considered: unemployment and employment. The definition of unemployment used in our analysis is therefore somewhat broad: we assume that unemployment is proxied by non-employment, strictly speaking non-employment is an upper-bound for unemployment.

Nationality is included as a binary variable indicating whether an individual is German or a foreign national. German nationality is usually conferred by descent, and not by place of birth. The data set does not report place of birth. Given this coding practice, some young foreign nationals might be born and raised in Germany. At the same time, ethnic Germans who immigrated from the former Soviet Union after the fall of the Berlin Wall will be classified as German, although they usually speak little German and have low skills. However, Dustmann et al. (2010) have argued that the former issue is ignorable, and we address the second by repeating the estimation using the subsample of individuals that were present in the data before the fall of the Berlin Wall, see the analysis in Section 4.5.3.

3.1. The Sample

The data used in our empirical analysis is restricted to male full-time workers aged 25 to 55 years old residing in West-Germany (East Germany is excluded because of the peculiar transition processes taking place in the wake of unification). This sample is grouped into cells by occupation, nationality, and age. We define three age groups (25-30, 30-40, and 40-55) to proxy for potential experience. The aim of the grouping is to arrive at cells in which individuals are fairly homogeneous, and which are sufficiently large for the subsequent econometric investigation.

Table 2: Occupational Immobility: Share of Stayers by Segment

	Age group	Natives		Foreigners	
Unskilled		89.52%		88.27%	
	Twenties		85.72%		85.45%
	Thirties		88.03%		88.56%
	Fourtyplus		92.54%		92.38%
Clerks		90.06%		88.52%	
	Twenties		88.03%		87.33%
	Thirties		87.44%		89.00%
	Fourtyplus		91.82%		91.89%
Skilled		92.48%		92.56%	
	Twenties		90.35%		91.03%
	Thirties		90.22%		92.43%
	Fourtyplus		94.26%		95.25%

The model is estimated using a *flow sample* of employed and unemployed individuals, who experienced a transition from their original state within the period 1995-2000. We consider the first such transition, and any subsequent transitions are ignored. For all these individuals we can determine the beginning of their original state, so that all durations are complete. The only exception is constituted by a small number of individuals who disappear from the dataset in the period 1995-2000, in which case their durations are considered censored. We note that the period 1995-2000 was a period of fairly stable growth (around 2%, with SD=.007) and unemployment (around 8%, with SD=.007). Focussing on this stable period reduces the scope for biases arising from asymmetric responses of natives and foreigners to the business cycle.

Foreigners in our sample are predominantly low skilled: 94% of the population of foreigners are included in our three occupational groups, while the corresponding number for natives is approximately 86%. The remainder occupational category is the highly skilled, which we have excluded because of their small share in the population of migrants (moreover, their earnings are excessively top-coded). Table 2 considers the occupational immobility by labour market segment. It is evident that occupational mobility is small, as most workers remain in the same class. This gives further support to our segmentation hypothesis, and such occupational immobility has also been found for other countries (e.g. by de Matos (2012) for Portugal).

Table 3 summarises the labour market transitions for all nationality-age-occupation cells observed in our flow data. For both natives and foreigners, we observe many more transitions from employment than from unemployment. However, for natives, the majority of transitions from employment are to another job, whereas for the majority of foreigners the destination is unemployment. Hence, in terms of the structural parameters, we expect higher separation rates for foreigners, $\delta_F > \delta_N$. The duration data for the unemployed, examined briefly in the next subsection, suggests that foreigners exit more quickly, so that we expect $\lambda_F > \lambda_N$ at least for this group.

Turning to the wage data, Table 4 reports for each labour market segment the mean and standard deviation of wages (measured by daily gross wages in 1995 DM), as well as the average log wage gap, $\Delta \log(w) \equiv \log(w_N) - \log(w_F)$. Natives receive substantially higher mean wages than foreigners across all occupation groups. The segment-specific raw average log wage gaps in our data range from .09 to .45. The overall log wage gap of .22 is in line with reports in the literature for Germany (e.g. Dustmann et al. (2010) report an unconditional average log wage gap of .23, Hirsch and Jahn (2012) report a gap of .2, while Lehmer and Ludsteck (2011) report predicted wage gaps ranging from .08 to .44). The three occupational groups can be partially ordered in terms of mean wages: mean wages for the skilled exceed those for the unskilled for all age groups and across nationalities. Foreign clerks and low-service workers assume an intermediate position, but mean wages of natives in this group can exceed those for skilled workers.

Rather than only restricting attention to the mean wage, Figure 2 depicts the

Table 3: Descriptives for the transition data.

Age	Transitions	Natives Services	Natives Unskilled	Natives Skilled	Foreigners Services	Foreigners Unskilled	Foreigners Skilled
25-30	All	8060	5097	11939	1887	2347	3023
	from E	6088	3085	8450	1438	1670	2155
	E→ U	2132	1764	4418	718	997	1225
	E→ E	3432	1037	3562	373	351	550
	from U	1972	2012	3489	449	677	868
	U→ E	1879	1932	3275	431	637	795
	$E_{censored}$	524	284	470	347	322	380
	$U_{censored}$	93	80	214	18	40	73
30-40	All	12800	7748	15381	2074	2752	3681
	from E	10723	5506	12448	1637	2067	2830
	E→ U	2988	2644	5284	735	1128	1451
	E→ E	6717	2400	6157	453	477	795
	from U	2077	2242	2933	437	685	851
	U→ E	1853	2055	2601	393	619	749
	$E_{censored}$	1018	462	1007	449	462	584
	$U_{censored}$	224	187	332	44	66	102
40-55	All	16900	12770	24530	1494	2938	5004
	from E	13912	9399	19127	1146	2090	3726
	E→ U	4538	4467	8973	505	1101	2019
	E→ E	6671	3206	6848	329	513	1024
	from U	2988	3371	5403	348	848	1278
	U→ E	1554	2013	2130	244	540	582
	$E_{censored}$	2703	1726	3306	312	476	683
	$U_{censored}$	1434	1358	3273	104	308	696

Notes: “Censoring” refers to a drop out from the administrative register.

Table 4: The average wage gap in the transition data by labour market segment.

		Services		Unskilled		Skilled	
Age	Wages	Native	Migrant	Native	Migrant	Native	Migrant
25-30	mean	122.36	88.94	107.77	92.54	124.74	111.07
	sd	41.86	44.15	37.68	36.09	29.94	35.21
	$\Delta\log(w)$	.32		.15		.11	
30-40	mean	156.35	99.38	120.94	97.99	135.79	116.65
	sd	51.22	55.02	38.24	36.61	32.04	36.22
	$\Delta\log(w)$	.45		.21		.15	
40-55	mean	158.17	112.74	125.05	107.49	138.29	126.20
	sd	48.09	56.81	36.71	36.89	33.29	33.50
	$\Delta\log(w)$	.33		.15		.09	

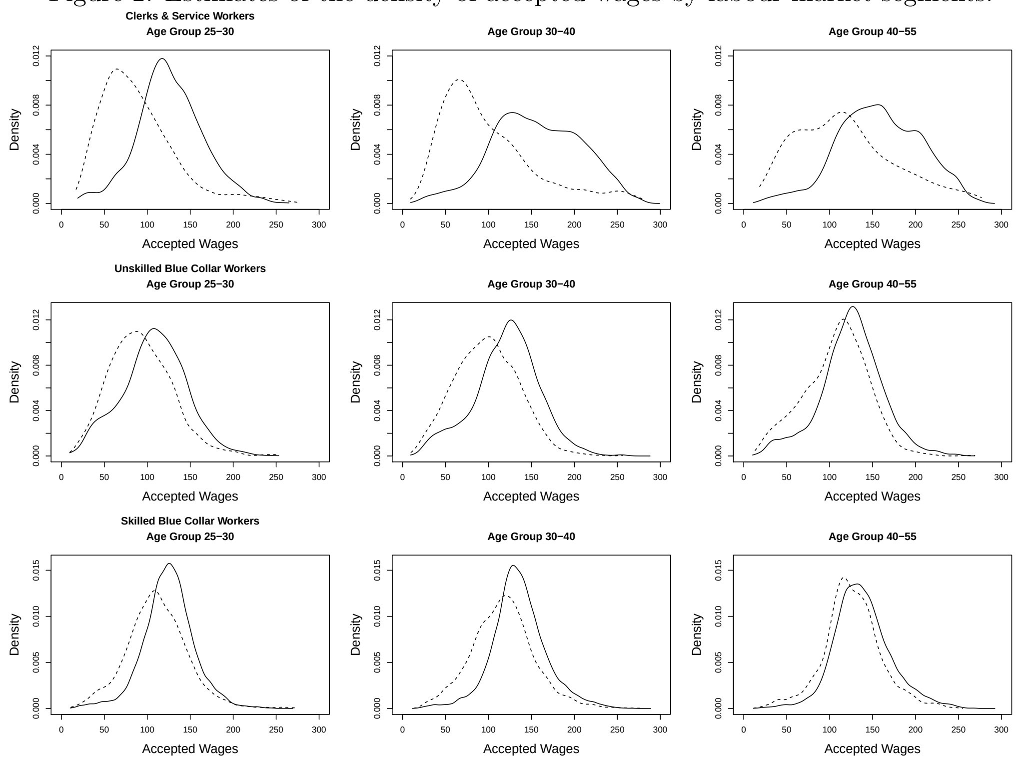
Notes: $\Delta\log(w) \equiv \log(w_N) - \log(w_F)$. The overall log wage gap is .22. Wage dating: for transitions from employment (E$\rightarrow$ {U,E}), these are the last earned wages in this state, for transition out of unemployment (U$\rightarrow$ E) these are the first wages earned in the new job.

kernel estimates of the realised wage densities (the solid lines refer to natives). The most pronounced distributional difference exist for the semi-skilled workers (clerks and service workers), and the differences persist across age groups. By contrast, for all other occupations, the differences decrease in age. The density estimates also exhibit "blips" in the far left tails of the wage densities. This bimodality leads to problems in the estimation of the model, manifesting themselves by the occurrence of spikes in the estimated productivity density. We overcome this issue by truncating the wage distributions at the 5% percentile, which is a common cut-off in the literature (see e.g. Bowlus (1997) or Flabbi (2010)). The estimation of the reservation wage distribution is, of coure, likely to be sensitive to the choice of the cut-off point. We therefore explore the robustness of our parameter estimates below in Section 4.5, and find that the frictional parameters are fairly stable, while μ increases usually somewhat as the truncation increases from 3% to 7%.

3.1.1. Reduced Form Estimates: The Importance of Unobservable Heterogeneity

Before embarking on the estimation of the model, we first explore descriptively whether there is scope for unobserved heterogeneity to play a role in explaining unemployment durations. To this end, we estimate standard reduced-form proportional hazard (PH) and mixed proportional hazard (MPH) models for the unemployed, controlling incrementally for duration dependence and unobserved heterogeneity. Since

Figure 2: Estimates of the density of accepted wages by labour market segments.



Notes: Natives (solid lines) v. foreigners (dashed lines).

the conditional unemployment durations in the structural model are exponential with parameter $\lambda\bar{F}(b)$ and the marginal durations are a mixture of such exponentials, we first estimate an exponential PH model, and then allow for duration dependence by estimating a Weibull specification. As the latter confounds dynamic sorting driven by unobservable heterogeneity and genuine duration dependence (see e.g. van den Berg (2001)), we then estimate MPH models using the common gamma frailty (assumed to be independent of the covariates). Note, however, that these reduced-form parameters do not identify the parameters of the structural model as the former are complicated functions of the latter. In all models we condition on interactions between age and occupational groups in order to mirror our subsequent structural analysis of the corresponding labour market segments.

Table 5 reports the results. Across all models the migrant dummy is positive throughout, so that their job offer arrival rates exceed those of natives. The Weibull PH model suggests the presence of duration dependence, but the MPH reveals this to be caused by dynamic sorting: once unobservable heterogeneity is controlled for, the Weibull parameter does not differ statistically from 1. Hence Weibull and exponential MPH models yield similar coefficient estimates. This inferred absence of duration dependence is consistent with the structural model, as it cannot generate genuine duration dependence but does yield dynamic sorting through unobserved heterogeneity in reservation wages.

Table 5: Reduced-form unemployment duration models

		(1) Exponential	(2) Weibull	(3) Weibull§	(4) Exponential§
Migrant		.087***	.069***	.049*	0.046*
		(.020)	(.020)	(.027)	(.027)
Clerks × Twenties		1.368***	1.212***	1.409***	1.431***
		(.035)	(.036)	(.047)	(.047)
Clerks × Thirties		1.059***	.984***	1.197***	1.217***
		(.034)	(.035)	(.047)	(.046)
Clerks × Fourtyplus		.037	.011	-0.005	-0.006
		(.037)	(.037)	(.045)	(.046)
Skilled × Twenties		1.500***	1.327***	1.602***	1.631***
		(.031)	(.031)	(.043)	(.041)
Skilled × Thirties		.914***	.867***	1.155***	1.182***
		(.032)	(.033)	(.045)	(.044)
Skilled× Fourtyplus		-0.429***	-0.451***	-0.531***	-0.539***
		(.034)	(.034)	(.041)	(.042)
Unskilled× Twenties		1.297***	1.153***	1.392***	1.417***
		(.035)	(.035)	(.047)	(.046)
Unskilled × Thirties		.864***	.828***	1.062***	1.083***
		(.035)	(.034)	(.046)	(.046)
duration dependence	$ln(\alpha)$		-.222***	-.023*	
			(.006)	(.012)	
unobserved heterogeneity	θ			.702***	.770***
				(.042)	(.024)

Notes. Standard errors in parentheses, *($p < 0.1$), ***($p < 0.001$). Reference groups: Unskilled × Fourtyplus. §Frailty is Gamma distributed.

4. Estimation Results

We proceed to estimate the structural parameters of the model, i.e. the job offer arrival rate, λ, the match destruction rate, δ, and the parameters of the distribution of workers' reservation values, (μ, σ), as well as the density of firms' productivity in each segment. Each occupation group is considered in turn, and we segment for each occupation the labour market further by age and nationality. The average migrant effects and the wage decompositions are then quantified in detail in Section 5 below.

Table 6: Structural parameter estimates: Unskilled blue collar workers

Age	Nation.	μ	σ	λ	δ	$k = \lambda/\delta$
25-30	N	53.76	11.10	.0666	.0257	2.59
		[51.74-56.02]	[9.67-14.06]	[.0487-.0891]	[.0241-.0268]	
	F	50.15	17.47	.1705	.0339	5.03
		[46.91-52.04]	[14.86-20.34]	[.1447-.1932]	[.0307-.0358]	
30-40	N	50.97	8.76	.0416	.0098	4.24
		[49.06-53.77]	[6.95-11.10]	[.0356-.0583]	[.0092-.0106]	
	F	49.35	15.86	.1071	.0167	6.41
		[46.33-50.78]	[13.14-20.2]	[.0762-.1261]	[.0162-.0178]	
40-55	N	54.05	10.10	.0355	.0051	6.96
		[51.81-55.98]	[8.56-11.87]	[.0281-.0412]	[.0048-.0056]	
	F	50.44	8.12	.0353	.0072	4.90
		[47.62-52.88]	[6.40-11.92]	[.0221-.0501]	[.0067-.0075]	

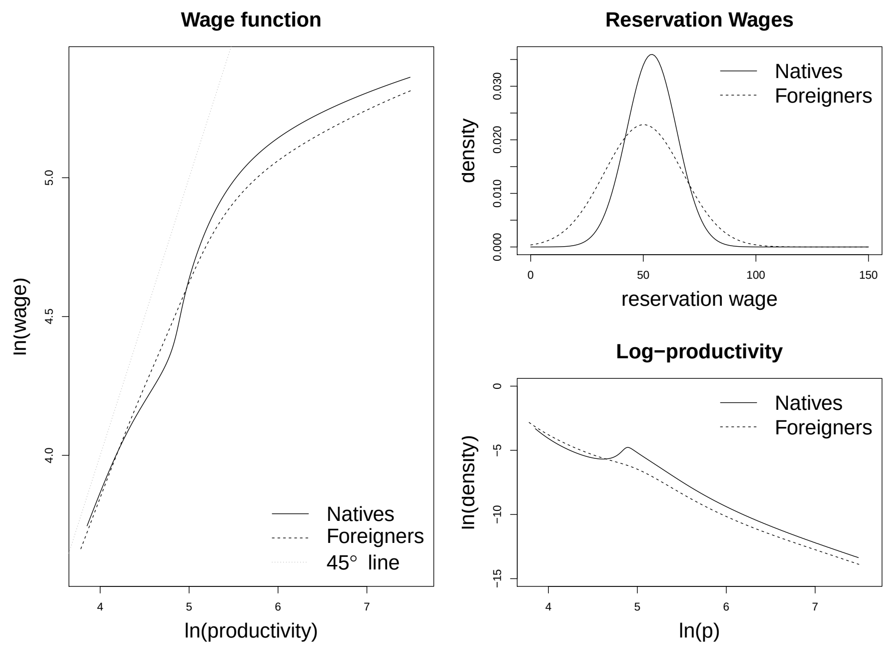
Notes: In brackets: the 2.5% and 97.5% percentiles of the bootstrap distribution.

4.1. Unskilled Blue Collar Workers

Table 6 reports the results. Across all three age groups, the labour turnover parameters of migrants exceed those of natives, $\hat{\delta}_F > \hat{\delta}_N$ and $\hat{\lambda}_F > \hat{\lambda}_N$. Migrants experience job separations more often, but this is partially compensated by them also finding new jobs more quickly. All job turnover parameters fall in age. Across age groups and nationality, transitions into new jobs happen more quickly than transitions into unemployment, $\hat{\lambda} > \hat{\delta}$. Foreigners have slightly lower mean reservation wages, $\hat{\mu}_F < \hat{\mu}_N$, but confidence intervals overlap. The estimates are fairly stable across age. The estimates for the reservation wage distribution for both groups imply that not all new job offers are accepted: there are some workers with high reservation wages who would and do turn down new job offers with insufficiently high wages.

In Figure 3 we consider some implications of the estimated model for the young. Panel A plots the wage offer functions, panel B the reservation wage density, whilst panel C plots the estimated productivity densities[10]. It is evident that the productivity densities for both groups are well approximated by a Pareto density. The slopes for sufficiently high productivities are very similar. Turning to wage offers (panel A), for low productivities foreigners do not do worse than natives, while for log productivities above 5 natives receive better wage offers. Overall, the figure suggests a positive but small migrant effect, and this is confirmed by our quantifications reported in Section 5.

Figure 3: Unskilled blue collar workers aged 25-30.



4.2. Clerks and Low-Service Workers

Table 7 reports the results for this occupational group, for which we observed in Table 4 the largest average wage gap. As before, job separation rates for foreigners exceed those of natives, decline in age, and are smaller than job offer arrival rates.

[10]These are obtained as follows. Given the parameter estimates and kernel estimate of the realised wage density, the unemployment rate u is estimated using equation (4), and the wage offer distribution F follows from (5); the productivity distribution is then estimable from equation (6).

Table 7: Structural parameter estimates: Clerks & service workers

Age	Nation.	μ	σ	λ	δ	$k = \lambda/\delta$
25-30	N	65.60	14.39	.0984	.0194	5.07
		[61.92-66.53]	[11.61-15.8]	[.0697-.0836]	[.0189-.0199]	
	F	36.09	13.65	.0701	.0272	2.58
		[30.88-41.69]	[8.6-17.17]	[.0624-.0886]	[.0259-.0284]	
30-40	N	72.66	9.42	.0423	.0073	5.79
		[68.41-75.12]	[7.54-10.39]	[.0355-.0530]	[.0071-.0076]	
	F	43.27	7.40	.0593	.0157	3.77
		[40.88-45.62]	[6.41-9.57]	[.0478-.0703]	[.0151-.0162]	
40-55	N	73.07	7.92	.0698	.0035	19.94
		[70.51-75.12]	[7.07-9.16]	[.0603-.0841]	[.0031-.0037]	
	F	49.04	6.86	.0759	.0077	9.86
		[46.38-51.94]	[5.22-8.41]	[.0565-.0911]	[.0072-.0081]	

Notes: As for Table 6.

Except for the young, the transition rates of foreigners exceed those of natives. But unlike the case of the unskilled, differences in mean reservation wages are substantial: foreigners are substantially less demanding, on average, than natives. These means increase in age. Figure 4 panel C suggests that productivities are again well approximated by a Pareto form, and panel A suggests that the maximal migrant effect is substantial.

4.3. Skilled Blue-Collar Workers

For the skilled blue-collar workers, the by now familiar pattern emerges too, as is evident from Table 8: both turnover parameters are higher for migrants, and decline in age. As regards mean reservation wages, foreigners are less demanding than natives, but the gap is not as wide as for clerks and service workers, and it declines in age. Focussing on the young in Figure 5, productivities are Pareto like. The migrant effect, captured in Panel A, is modest.

4.4. General Discussion

Comparing the results across occupations, we observe similar patterns. Migrants experience job separations more often than natives but also typically find jobs more quickly, and job turnover parameters tend to decline in age. These findings are in line with differences in employment protection observed in Sa (2011), who reports

Figure 4: Clerks and service workers aged 25-30.

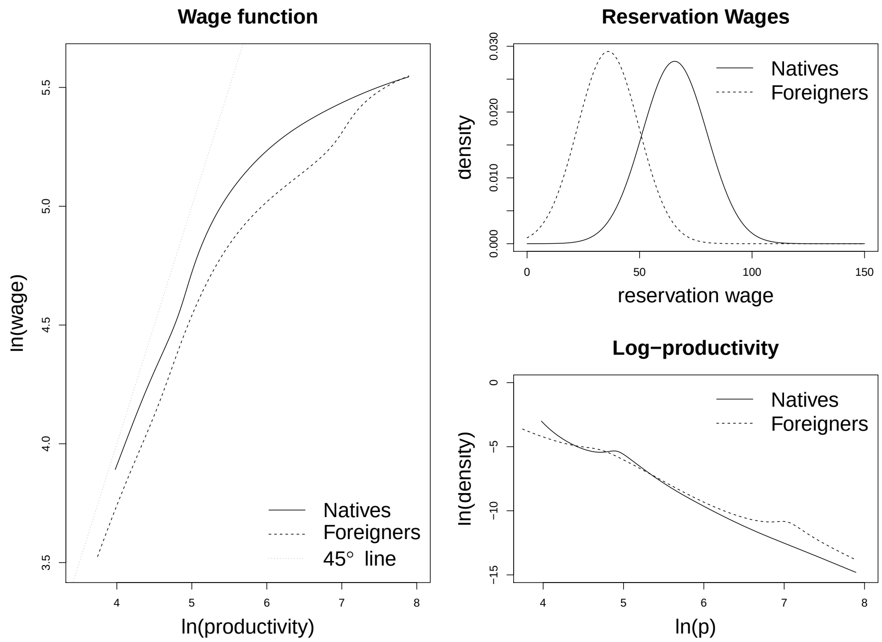
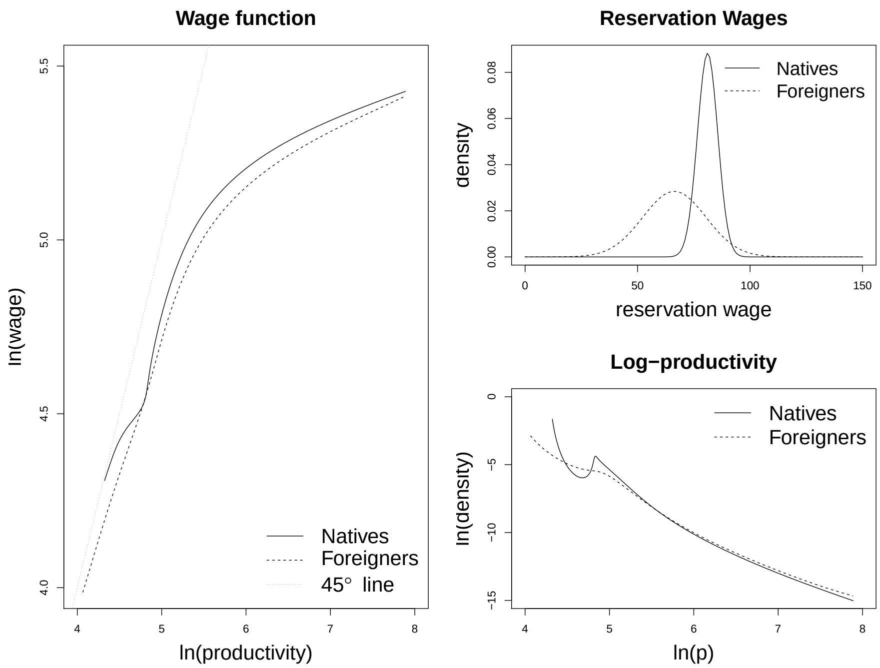


Table 8: Structural parameter estimates: Skilled blue collar workers

Age	Nation.	μ	σ	λ	δ	$k = \lambda/\delta$
25-30	N	81.15	4.52	.0801	.0158	5.07
		[77.64-83.97]	[3.81-6.59]	[.0684-.0911]	[.0121-.0179]	
	F	66.38	14.05	.1067	.0225	4.74
		[62.88-69.04]	[11.88-17.32]	[0.955-0.1182]	[.0170-.0268]	
30-40	N	76.68	8.85	.0698	.0068	10.26
		[73.82-77.90]	[7.69-9.71]	[.0621-.0760]	[.0063-.0071]	
	F	69.30	8.06	.0866	.0124	6.98
		[65.57-72.05]	[7.34-9.16]	[.0681-.0946]	[.0119-.0127]	
40-55	N	79.71	6.44	.0408	.0035	11.66
		[77.18-80.94]	[5.62-7.01]	[.0343-.0478]	[.0033-.0036]	
	F	75.05	7.33	.0449	.0049	9.16
		[71.48-78.24]	[6.51-8.70]	[.0325-.0512]	[.0045-.0051]	

Notes: As for Table 6.

Figure 5: Skilled blue collar workers aged 25-30.



that migrants in Germany are much more likely than natives to work on temporary contracts. The findings are also consistent with the other dimensions of segregation extensively documented in Glitz (2012). Across all segments and nationality, transitions into new jobs happen more quickly than transitions into unemployment. Overall, search frictions, as measured by $(\lambda/\delta)^{-1}$, are of the same order of magnitude across all occupational groups, decrease in age (except for unskilled foreigners in which case they are stable), and are larger for foreigners than for natives for the skilled and clerks and service workers. Thus, the higher job offer arrival rate for foreigners cannot compensate for their higher job separation rates. As regards the reservation wage distribution, across all segments there are some workers with high reservation wages who turn down new job offers when wage offers are too low.[11] Migrant workers are on average less demanding than natives. Firm productivities are well approximated by Pareto forms. However, migrants receive wage offers that are lower than for natives who have the same productivity. This migrant effect is the largest for clerks and service workers, and small for unskilled workers. The drivers of the migrant effect are the subject of Section 5.

4.5. Robustness Checks

4.5.1. Return Migration

A concern for our estimates in the migrant segments might be the effect of return migration, when such returnees leave Germany out of employment. In order to investigate the sensitivity of our estimates to this issue, we consider restricted samples of migrants who should, in principle, be available for work after their employment transition, by requiring foreigners to be observable in the data 6 months after their transition. This restriction leads to a net dropout of foreigners (relative to that of

[11] These results differ from estimates for Netherlands (van den Berg and Ridder (1998)) and France (Bontemps et al. (1999)) since both countries have a binding legal minimum wage. Similar to these studies, however, we observe that job separation parameter δ is approximately one order of magnitude smaller than the estimated job offer arrival rate λ. Our results are comparable to those reported by Bartolucci (2013a) for Germany obtained from a different empirical search model applied to a different market segmentation. For low qualified male workers in the manufacturing sector he reports a job separation rate of .03 and a job offer arrival rate of .3. Our estimates of δ range from .004 to .03, and the job offer arrival rate ranges from .04 to .17. Our result regarding the mean reservation wage, the lack of a statistically significant difference between natives and migrants for most groups, is also consistent with external evidence reported in Bergemann et al. (2011, Table 2) who use the IZA evaluation sample of individuals who entered unemployment in late 2007 and early 2008: the means of the self-reported reservation wages are not statistically significantly different between natives and migrants, and their levels are comparable to ours.

natives) across segments between 7.7% and 15.3%.[12] Table 9 juxtaposes the estimates for these restricted samples (labelled noRetMig) to our unrestricted estimates. We find that most parameter estimates remain relatively stable (the occasional fall in $\hat{\sigma}$ reflects the extent to which the sample restriction increases the homogeneity of the group; the more homogeneous the sample, the smaller the estimated reservation wage dispersion).

Table 9: Sensitivity analysis - the effect of excluding return migrants

Occupation	Age	Group	μ	σ	λ	δ
Unskilled	25-30	full	50.15	17.47	0.1705	0.0339
		noRetMig	49.88	10.14	0.1207	0.0433
	30-40	full	49.35	15.86	0.1071	0.0167
		noRetMig	50.65	8.53	0.0588	0.0219
	40-55	full	50.44	8.12	0.0353	0.0072
		noRetMig	48.53	3.28	0.0495	0.0087
Skilled	25-30	full	66.38	14.05	0.1067	0.0225
		noRetMig	65.00	9.05	0.0871	0.0281
	30-40	full	69.30	8.06	0.0866	0.0124
		noRetMig	68.72	5.86	0.0660	0.0142
	40-55	full	75.05	7.33	0.0449	0.0049
		noRetMig	62.74	7.44	0.0379	0.0058
Clerks & Services	25-30	full	36.09	13.65	0.0701	0.0272
		noRetMig	37.84	11.37	0.0749	0.0344
	30-40	full	43.27	7.40	0.0593	0.0157
		noRetMig	45.11	9.09	0.0689	0.0201
	40-55	full	49.04	6.86	0.0759	0.0077
		noRetMig	48.23	5.39	0.1036	0.0098

4.5.2. The effect of truncating the wage distribution

Our samples have been truncated at 5% at the left tail of the wage distribution, a common cut-off in the literature. Here, we examine the sensitivity of our estimates to varying the cut-off from 3% to 7%. Table 10 reports the results. Across all segments,

[12]These rates are consistent with Gundel and Peters (2008, Table 1) who, using GSOEP data for the period 1984-2005, suggest that among male immigrants aged less than 60 the return rate is 10%

Table 10: Sensitivity analysis - the effects of truncation

Occupation	Age	Trunc.	Foreigners				Natives			
			μ	σ	λ	δ	μ	σ	λ	δ
Unskilled	25-30	3%	45.31	19.68	.1698	.0344	42.77	15.85	.0603	.0256
		5%	50.15	17.47	.1705	.0339	53.76	11.10	.0666	.0257
		7%	54.47	15.18	.1593	.0333	56.72	9.53	.0783	.0254
	30-40	3%	47.89	16.51	.1215	.0167	38.62	11.64	.0321	.0099
		5%	49.35	15.86	.1071	.0167	50.97	8.76	.0416	.0098
		7%	55.62	12.56	.1000	.0162	57.53	9.10	.0306	.0095
	40-55	3%	40.18	3.86	.0435	.0074	38.62	11.64	.0321	.0099
		5%	50.44	8.12	.0353	.0072	54.05	10.10	.0355	.0051
		7%	52.83	7.64	.0298	.0071	53.87	14.73	.0276	.0049
Skilled	25-30	3%	57.41	18.69	.0915	.0229	72.78	9.66	.0611	.0162
		5%	66.38	14.05	.1067	.0225	81.15	4.52	.0801	.0158
		7%	71.79	10.38	.1061	.0219	82.65	3.72	.0729	.0154
	30-40	3%	63.53	12.14	.0695	.0127	73.51	9.44	.0798	.0069
		5%	69.30	8.06	.0866	.0124	76.68	8.85	.0698	.0068
		7%	72.36	6.56	.0579	.0121	87.08	4.58	.0612	.0064
	40-55	3%	67.90	7.57	.0557	.0045	69.17	8.12	.0407	.0036
		5%	75.05	7.33	.0449	.0049	79.71	6.44	.0408	.0035
		7%	77.32	5.81	.0392	.0045	83.31	5.40	.0583	.0035
Clerks & Services	25-30	3%	35.43	14.04	.0628	.0269	58.30	18.68	.1113	.0198
		5%	36.09	13.65	.0701	.0272	65.60	14.39	.0984	.0194
		7%	35.44	14.04	.0628	.0269	68.11	13.14	.0953	.0191
	30-40	3%	41.98	7.83	.0608	.0156	62.80	15.13	.0555	.0075
		5%	43.27	7.40	.0593	.0157	72.66	9.42	.0423	.0073
		7%	47.34	5.79	.0464	.0154	78.16	5.92	.0490	.0072
	40-55	3%	47.89	8.88	.0534	.0078	66.87	10.03	.0452	.0035
		5%	49.04	6.86	.0759	.0077	73.07	7.92	.0698	.0035
		7%	48.59	5.09	.0635	.0076	78.09	6.47	.0709	.0034

the frictional parameters δ and λ are very stable. An increase in the truncation is expected to lead to an increase in the estimated mean reservation wage. This increase, however, turns out to be typically very modest. We conclude that our estimates are robust.

4.5.3. Ethnic German Immigrants

Table 11: Native workers: full and restricted sample results

Occupation	Age	Group	μ	σ	λ	δ
Unskilled	30-40	all	50.97	8.76	.0416	.0098
		pre '88	48.46	5.22	.0362	.0090
	40-55	all	54.05	10.10	.0355	.0051
		pre '88	51.95	6.66	.0203	.0046
Skilled	30-40	all	76.68	8.85	.0698	.0068
		pre '88	88.53	2.78	.0700	.0060
	40-55	all	79.71	6.44	.0408	.0035
		pre '88	81.34	7.51	.0407	.0032
Clerks & Services	30-40	all	72.66	9.42	.0423	.0073
		pre '88	71.11	9.12	.0496	.0067
	40-55	all	73.07	7.92	.0698	.0035
		pre '88	72.66	8.93	.0413	.0033

Notes: "all" refers to the full sample of native workers, "pre '88" to the sample of natives observed before 1988.

The inflow of foreign-born ethnic Germans in the late 1980's and early 1990's changed the composition of the group of natives. While qualifying for a German passport by descent, many did not speak German and were more similar to the group of foreign nationals considered above. However, these ethnic German immigrants are not directly identifiable in our data and thus latent in the group of natives. This arguable misclassification could lead to biases in our estimates for native workers. To check the robustness of our results to such changes in the population of German citizens, we estimate the model using the subsample of native workers that are also present in the data set before 1988 (labelled pre'88), the year before the inflow of ethnic Germans occurred. Table 11 reports our estimates, and for ease of comparison, juxtaposes these to our earlier results for the unrestricted sample (labelled all). The young age group is excluded from this exercise since many in this group would be too young to be employed pre 1988. The estimates are fairly similar in the full sample and the subsample, which suggests that the presence of ethnic Germans has only little effect on the estimates of the structural parameters for natives.

5. Migrant Effects and Wage Decompositions

We proceed to examine actual and counterfactual decompositions of the wage differential by considering the scenarios of Section 2.4.1. The discussion there has highlighted the importance of the productivity distribution, and we operationalise the decomposition as follows.

5.1. Calibration Details

Our estimation has yielded, given the (estimate of the) actual wage distribution G, the estimated wage offer functions $w_i^e(p|\hat{\lambda}, \hat{\delta}, \hat{\mu}, \hat{\sigma})$. Given the Pareto-like productivity distributions, we calibrate wage offer functions $w_i(p|\hat{\lambda}, \hat{\delta}, \hat{\mu}, \hat{\sigma}, \underline{p}, \alpha)$ based on Pareto productivity distributions by minimising the integrated absolute deviations between $w_i^e(p|.)$ and $w_i(p|., \underline{p}, \alpha)$. Table 12 reports the calibrated parameters.[13]

Table 12: Calibrated parameters of the Pareto productivity distribution.

Age Group	Nationality	Unskilled		Skilled		Clerks	
		$\underline{p}$	α	$\underline{p}$	α	$\underline{p}$	α
25-30	Natives	79.789	2.511	81.282	3.172	67.677	2.449
	Foreigners	47.632	2.205	51.010	2.146	43.053	1.468
30-40	Natives	84.343	2.894	71.212	3.076	104.849	3.096
	Foreigners	57.071	2.611	61.414	2.661	41.818	1.463
40-55	Natives	70.263	2.842	69.293	3.045	72.222	3.197
	Foreigners	70.202	2.833	63.838	2.896	34.545	1.738

Figure 6 illustrates these calibrations for young workers in the three occupations, as well as the counterfactual experiment of improving the job turnover situation of foreigners by lowering their job separation rate to those of natives, $\delta_F \equiv \delta_N$. The first two columns of the figure show the close match between $w^e(p)$ (which we have seen before in Figure 3) and $w(p)$. Column three depicts the calibrated wage offers $w_N(p)$ (solid line) and $w_F(p)$ (dashed line), as well as the counterfactual $w_F(p|., \hat{\delta}_N)$ (dotted

[13] These are also consistent with alternative estimates based on the shapes of Figures 3 - 5. The approximate linearity in the productivity plots suggests a simple (graphical) estimator of the shape parameter of the Pareto distributions: use OLS to estimate the regression of log density on log productivity (and add 1).

line). The reduction in the separation rate for foreigners from $\hat{\delta}_F$ to $\hat{\delta}_N$ 'rotates' the wage offer curve up: for lower productivities, the improvement is negligible, but for very high productivities foreigners receive wage offers equal to or better than those for natives. This results in the improvement in the density of accepted wages depicted in the fourth column of the figure.

5.2. Results

Tables 13 to 15 report by age group the average migrant effect (row 1), as well as the results of the counterfactual experiments which follow the structure of Table 1. We can anticipate the qualitative results of these experiments based on numerical comparative statics exercises which show (for the set of parameters considered) that wage offers increase in the job offer arrival rate λ as search frictions decrease, and, contrariwise, decrease in the job separation rate δ as search frictions increase. Of course, as $k = \lambda/\delta \to \infty$ and search frictions disappear, by eq. (3), wage offers converge to the competitive wage. Wage offers increase in the mean reservation wage μ, since by the reservation wage property of job search only sufficiently high wage offers are accepted out of unemployment, but the effect of σ is ambiguous. Since we found that job separation rates for foreigners always exceed those of natives, setting $\delta_F = \delta_N$ increases their wage offers, which implies a reduction both of the wage gap and the migrant effect. Similarly, we found that $\lambda_F > \lambda_N$ (except for young clerks and service workers), so reducing the foreigners' job offer arrival rate to that of natives reduces their wage offers, which implies an increase both in the wage gap and the migrant effect. As regards reservation wages, we found that foreigners are on average less demanding than natives, but the overall effect of the joint experiment involving (μ, σ) is ambiguous given the ambiguous effect of σ. All these qualitative effects are observed in the results tables (experiments (1)-(4)). The principal objective of the tables is then to quantify the impacts in order to understand the principal drivers of the migrant effect.

We comment first on the level of the average migrant effect. Across all age groups, the absolute migrant effect is the largest for clerks and service workers, followed by the skilled, and is negligible for the unskilled. In relative terms, the migrant effect of the skilled accounts for 12-15% of the average wage gap, and for clerks and service workers for 23-39%, the average effect being 19.6 %. Expressed in terms of the average segment-specific wage of natives (see Table 4), the migrant effect amounts to 9.2-18.3% for clerks and service workers, 1.6-7.7% for skilled workers, 0.7-2.6% for unskilled workers, and 5.6% for the full sample. The latter estimates are consistent with estimates of "unexplained wage differences" reported in the literature for Germany based on standard Oaxaca-Blinder decompositions (for instance, Lehmer and

Ludsteck (2011) report a range from 4 to 17%) or complementary approaches (Hirsch and Jahn (2012) report 6% while Bartolucci (2013b) suggests discrimination effects ranging between 7 and 17%). The observed difference between the wage differential and the migrant effect also implies that the largest part of the native-migrant wage gap is explained by differences in the productivity distribution, which is confirmed in experiment (9) by the drop in the wage gap (which now equals the migrant effect by construction). Policy interventions that seek to reduce the productivity gap will thus reduce the wage gap. We turn to the various experiments, highlighting the role of search frictions.

Consider first the role of the mean reservation wage μ (experiment (2)). The gap in mean reservation wages is the largest for clerks and service workers whilst the dispersion parameters are fairly similar. Raising then the foreigners' mean reservation wages shows that the substantial migrant effect for this occupational group is reduced to between 41% and 61% of its former level. For the skilled, we only observe a significant gap in mean reservation wages for the young, and an equalisation of (μ, σ) reduces the migrant effect to 48% of its former level. For the other age groups, and for the unskilled, differences in μ between natives and foreigners are either small or negligible, so equalisations have little effect. Once productivity differences have been eliminated, a comparison between experiments (9) and (10) shows that for clerks and service workers, the relative improvement in the migrant effect due to the additional equalisation of (μ, σ) is slightly larger (the migrant effect is now between 20% and 30% of the level generated in experiment (9)). Turning to the policy implications, although foreigners are on average less demanding than natives, we believe that foreigners' reservation wages should be less a concern for policy interventions which are migrant-centred (as emphasised by recent policy debates in the EU, e.g. EUCommission (2012, p. 28)) and seek to reduce the migrant effect. Nor would any migrant-targeted benefit increase be politically feasible in the light of the debate about welfare magnets.

By the same token, job arrival rates for foreigners typically exceed those of natives, and thus should equally be of little policy concern. In fact, the experiments (4) show that reducing this rate to that of natives only substantially increases the migrant effect for the unskilled in the two first age groups; for all other groups the induced increase in the migrant effect is fairly small. This is also in line with the observation that λ falls in age for the unskilled and skilled.

We turn to the remaining frictional parameter, the job separation rate δ. Recall that foreigners' job separation rates are larger than those for natives, and sometimes substantially so, and that search frictions experienced by them are typically larger than those of natives as a higher λ cannot compensate for the higher δ. Hence there is scope for migrant-centred policy interventions that seek to reduce their search frictions, such as improving migrants' employment protection. This scope, however, decreases in age, as δ falls in age across all occupational groups. Reducing the foreigners' job separation rates to that of natives has the largest absolute impact for clerks and service workers, followed by the skilled. For the unskilled, the migrant effect is already fairly small, and an equalisation of δ reduces the remainder further.

6. Conclusion

The use of the structural empirical general equilibrium search model with on-the-job search has enabled us to disentangle the role of various unobservables for the explanation of wage differentials between migrants and natives. In particular, we have examined differences in search frictions, reservation wages, and productivities in segments of the labour market defined by occupation, age, and nationality using a large scale German administrative dataset. The resulting decompositions of the actual and counterfactual wage differential quantify the marginal and joint roles of the various factors.

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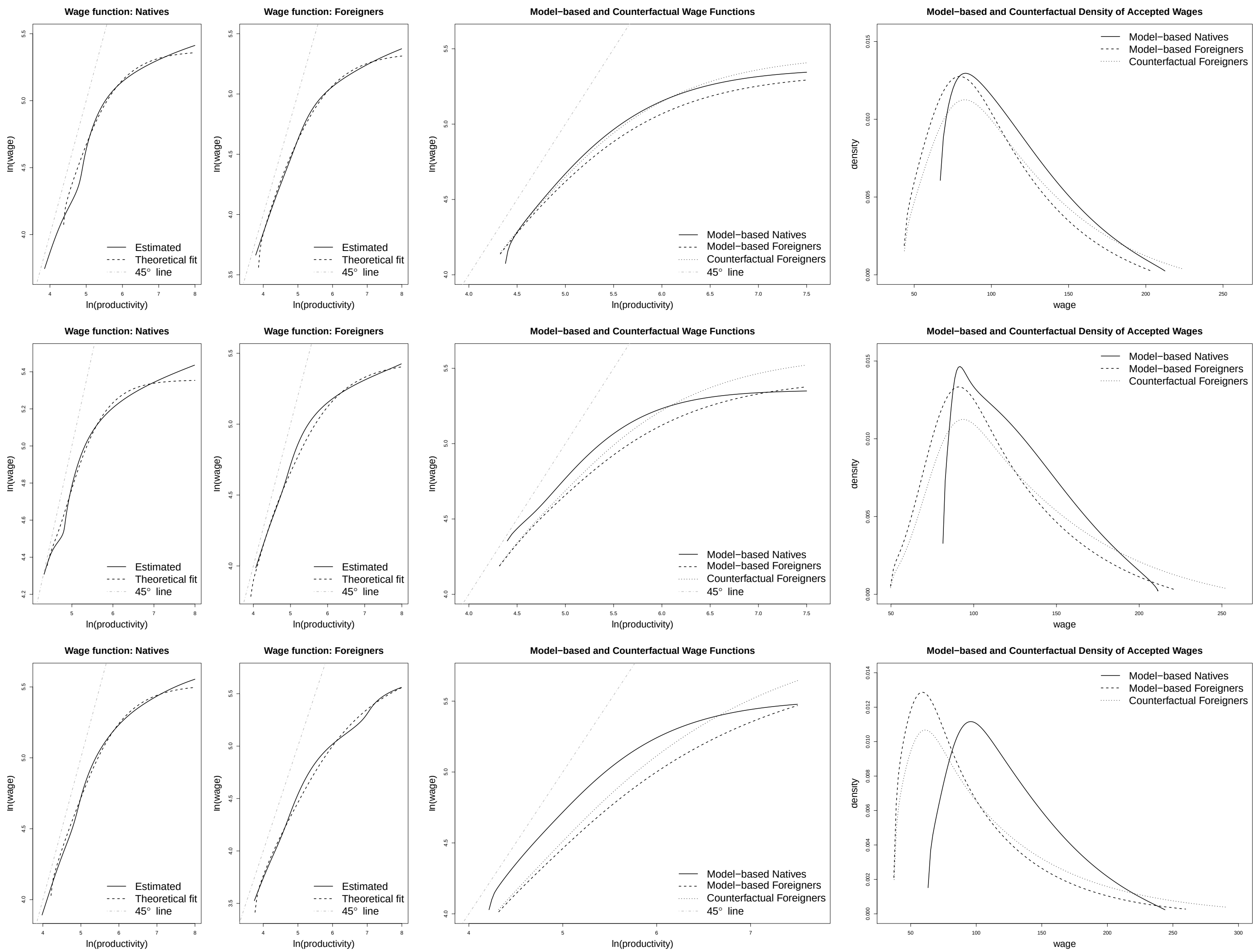
This study uses the factually anonymous regional file of the IAB Employment Sample (IABS) 1975-2004. Data access was provided via a Scientific Use File supplied by the Research Data Centre (FDZ) of the German Federal Employment Agency (BA) at the Institute for Employment Research (IAB).

Figure 6: Calibration, migrant effects, and wage densities for young workers.



Notes. Row 1: unskilled blue collar workers. Row 2: skilled blue collar workers. Row 3: clerks and lower service workers.

Table 13: Wage differential decomposition and average migrant effects: Ages 25-30.

	Counterfactually equalised para.	Remaining differing para.	Unskilled Wage differential	Unskilled Migrant effect	Skilled Wage differential	Skilled Migrant effect	Clerks Wage differential	Clerks Migrant effect
(1)		$\underline{p}, \alpha, \mu, \sigma, \lambda, \delta$	61.717	2.779	62.463	9.560	43.426	16.929
(2)	μ, σ	$\underline{p}, \alpha, \lambda, \delta$	61.740	2.793	60.964	4.609	38.357	6.995
(3)	δ	$\underline{p}, \alpha, \mu, \sigma, \lambda$	60.806	0.349	61.260	7.691	40.637	14.205
(4)	λ	$\underline{p}, \alpha, \mu, \sigma, \delta$	64.804	11.272	63.437	11.146	40.639	14.206
(5)	μ, σ, δ	$\underline{p}, \alpha, \lambda$	60.828	0.373	59.900	3.150	36.253	5.321
(6)	μ, σ, λ	$\underline{p}, \alpha, \delta$	64.803	11.134	61.804	5.798	36.254	5.322
(7)	λ, δ	$\underline{p}, \alpha, \mu, \sigma$	63.917	8.793	62.237	9.201	37.861	11.681
(8)	$\mu, \sigma, \lambda, \delta$	$\underline{p}, \alpha$	63.930	8.729	60.766	4.334	34.028	3.660
(9)	$\underline{p}, \alpha$	$\mu, \sigma, \lambda, \delta$		-4.336		4.142		11.569
(10)	$\underline{p}, \alpha, \mu, \sigma$	λ, δ		-4.962		0.264		3.501
(11)	$\underline{p}, \alpha, \delta$	μ, σ, λ		-6.137		2.610		9.065
(12)	$\underline{p}, \alpha, \lambda$	μ, σ, δ		2.989		5.529		9.066
(13)	$\underline{p}, \alpha, \mu, \sigma, \delta$	λ		-6.756		-1.088		1.710
(14)	$\underline{p}, \alpha, \mu, \sigma, \lambda$	δ		2.330		1.458		1.711
(15)	$\underline{p}, \alpha, \lambda, \delta$	μ, σ		0.647		3.840		6.812

Notes: Based on the decomposition of equation (10). Rows 9+: the wage differential equals the migrant effect because the productivity distributions are the same. The parameter estimates are reported in Tables 6- 8.

Table 14: Wage differential decomposition and average migrant effects: Ages 30-40.

	Counterfactually equalised para.	Remaining differing para.	Unskilled: Wage differential	Unskilled: Migrant effect	Skilled: Wage differential	Skilled: Migrant effect	Clerks: Wage differential	Clerks: Migrant effect
(1)		$\underline{p}, \alpha, \mu, \sigma, \lambda, \delta$	59.484	0.854	29.662	3.904	89.489	28.642
(2)	μ, σ	$\underline{p}, \alpha, \lambda, \delta$	59.699	1.456	28.539	2.228	87.086	17.559
(3)	δ	$\underline{p}, \alpha, \mu, \sigma, \lambda$	57.916	-2.964	27.915	1.956	84.023	19.278
(4)	λ	$\underline{p}, \alpha, \mu, \sigma, \delta$	62.756	9.059	30.355	4.696	91.897	33.358
(5)	μ, σ, δ	$\underline{p}, \alpha, \lambda$	58.089	-2.472	26.937	0.476	82.447	11.304
(6)	μ, σ, λ	$\underline{p}, \alpha, \delta$	63.106	10.004	29.159	2.922	88.962	20.378
(7)	λ, δ	$\underline{p}, \alpha, \mu, \sigma$	60.872	4.298	28.503	2.603	86.404	23.116
(8)	$\mu, \sigma, \lambda, \delta$	$\underline{p}, \alpha$	61.136	5.027	27.482	1.065	84.526	13.974
(9)	$\underline{p}, \alpha$	$\mu, \sigma, \lambda, \delta$		-3.091		2.547		14.515
(10)	$\underline{p}, \alpha, \mu, \sigma$	λ, δ		-2.585		1.097		3.011
(11)	$\underline{p}, \alpha, \delta$	μ, σ, λ		-5.709		0.758		8.259
(12)	$\underline{p}, \alpha, \lambda$	μ, σ, δ		3.264		3.286		18.087
(13)	$\underline{p}, \alpha, \mu, \sigma, \delta$	λ		-5.249		-0.549		-2.022
(14)	$\underline{p}, \alpha, \mu, \sigma, \lambda$	δ		3.938		1.763		5.737
(15)	$\underline{p}, \alpha, \lambda, \delta$	μ, σ		-0.563		1.349		10.719

Notes: As for Table 13.

Table 15: Wage differential decomposition and average migrant effects: Ages 40-55.

	Counterfactually equalised para.	Remaining differing para.	Unskilled Wage differential	Unskilled Migrant effect	Skilled Wage differential	Skilled Migrant effect	Clerks Wage differential	Clerks Migrant effect
(1)		$\underline{p}, \alpha, \mu, \sigma, \lambda, \delta$	2.817	2.723	19.784	2.327	64.712	14.591
(2)	μ, σ	$\underline{p}, \alpha, \lambda, \delta$	1.728	1.631	18.883	1.172	62.721	6.298
(3)	δ	$\underline{p}, \alpha, \mu, \sigma, \lambda$	1.145	1.056	18.971	1.404	62.127	11.248
(4)	λ	$\underline{p}, \alpha, \mu, \sigma, \delta$	2.788	2.694	20.030	2.608	65.002	15.012
(5)	μ, σ, δ	$\underline{p}, \alpha, \lambda$	0.125	0.032	18.114	0.304	60.519	4.125
(6)	μ, σ, λ	$\underline{p}, \alpha, \delta$	1.700	1.603	19.113	1.433	62.954	6.553
(7)	λ, δ	$\underline{p}, \alpha, \mu, \sigma$	1.120	1.030	19.193	1.655	62.374	11.533
(8)	$\mu, \sigma, \lambda, \delta$	$\underline{p}, \alpha$	0.100	0.008	18.325	0.541	60.737	4.321
(9)	$\underline{p}, \alpha$	$\mu, \sigma, \lambda, \delta$		2.716		1.699		7.375
(10)	$\underline{p}, \alpha, \mu, \sigma$	λ, δ		1.623		0.601		1.676
(11)	$\underline{p}, \alpha, \delta$	μ, σ, λ		1.049		0.828		5.173
(12)	$\underline{p}, \alpha, \lambda$	μ, σ, δ		2.687		1.966		7.660
(13)	$\underline{p}, \alpha, \mu, \sigma, \delta$	λ		0.025		-0.225		-0.160
(14)	$\underline{p}, \alpha, \mu, \sigma, \lambda$	δ		1.595		0.851		1.905
(15)	$\underline{p}, \alpha, \lambda, \delta$	μ, σ		1.023		1.064		5.359

Notes: As for Table 13.

Appendix A. Data Appendix: Variable Description

Our sample only includes full-time working men aged 25-55 years old residing in West Germany. In what follows, we describe how we construct the key variables used in our empirical analysis.

Age: The age variable is constructed using information on the date of birth and the year in which the spell took place. Date of birth is not available for individuals who were under 16 years old at their first observed spell or over 65 years old at their last observed spell. In such cases, we assume that workers were 15 years old at their first spell and 67 years old at their last spell.

Labour Market Status: The information provided in the data set are sufficient to distinguish between three labour market states: employed, recipient of transfer payments, and out of sample. In our analysis, we employ the broad definition of unemployment, as proposed by Fitzenberger and Wilke (2010), and assume that unemployment is proxied by non-employment. Using this definition of unemployment, we only consider two labour market states (employment and unemployment) since being out of sample is equivalent to being unemployed. However, this strategy may lead to the mis-classification of non-participants as unemployed: for example, an individual that had an employment spell in her late teens, subsequently went to university, and reappeared in the sample in her late twenties would be classified as unemployed despite the fact that she was not in the labour market. To correct for this problem, individuals that are out of sample are only classified as unemployed if their out of sample duration does not exceed the average duration of transfer payment recipients' spells.

Spells: Due to the annual reporting system, all spells have a maximum duration of one year. We merge all consecutive annual spells during which the individual does not experience a change in her labour market status, i.e. she either remains unemployed or employed with the same employer. We use firm-identifiers included in the dataset to determine when a worker changes employers. The new merged spells record the start date, the end date, the duration of the spell, the employment status, the average wage under the same employer, and the transition experienced by the individual (job-to-unemployment, job-to-job, unemployment-to-job).

Wages: The dataset reports gross daily wages and does not provide information on hours worked. We therefore exclude part-time employees, trainees, interns, and at-home workers from the sample since the wage information is not comparable for these groups. Wages are truncated at the social security contributions threshold (DM10) and censored at the social security contributions ceiling (DM300). For workers with wages below the social security contribution threshold, we use wages of adjacent employment spells. Wage censoring is not pronounced as the social security contributions ceiling is not binding in our sample as we focus on low-wage workers who are not likely to earn wages in excess of this upper bound.

Since the focus of our analysis is the transitions experienced by workers in the early 1990s, all wages are reported in DM and adjusted to real 1995 prices using the German Consumer Price Index. For all individuals who experience wage variation during employment spells, we compute the average per period wage of each worker under the same employer.

Occupation: The dataset includes extensive information on occupations (three-digit codes), which is used to classify individuals to 10 major groups based on the International Standard Classification of Occupations (ISCO-88). Exploiting the detailed index of occupational titles of the ISCO-88, we are able to map the code list from the Federal Employment Service of Germany included in the IABS into the following ISCO-88 major groups: (1) Legislators, Senior Officials, and Managers; (2) Professionals; (3) Technicians and Associate Professionals; (4) Clerks; (5) Service Workers and Shop & Market Sales Workers; (6) Skilled Agricultural and Fishery Workers; (7) Craft and Related Trades Workers; (8) Plant and Machine Operators and Assemblers; (9) Elementary Occupations; (10) Armed Forces.

We restrict attention to low- and middle-skill occupations, where the concentration of foreigners is higher. Specifically, we consider three occupational groups that are defined as follows: (1) Unskilled blue-collar workers, which includes individuals classified in the ISCO-88 major groups 8 and 9; (2) Skilled blue-collar workers, which includes individuals classified in the ISCO-88 major group 7; (3) Clerks & low-service workers, which includes individuals classified in the ISCO-88 major groups 4 and 5.

Appendix B. Estimation: A Validation Exercise

Given the complexity of both the model and the estimating equations, it is of interest to test their performance in a simulation exercise. In this appendix, we carry out such a validation exercise.

The data generating process uses the parametrisations discussed above: arrival of job offers and separations follow Poisson processes, and the reservation wage distribution is normal. The particular calibration, given in Table B.16, distinguishes between the segments for natives (subscripted N) and immigrants (subscripted F), and uses values similar to those encountered in our data. We also need to stipulate either a realised wage distribution G, or a productivity distribution Γ. Since we observe wages but not productivities in our data, we specify a productivity distribution here in order to verify that the model-implied wage distributions "look realistic" (i.e. share the principal features of real wage distributions). Since the empirical results suggest that productivities are Pareto-like, we assume this explicitly here: $\Gamma_F(p) = 1 - (\underline{p}_F/p)^\alpha$ and $\Gamma_N(p) = 1 - (\underline{p}_N/p)^\alpha$ with $\alpha = 2.1$, $\underline{p}_F = 40$, and $\underline{p}_N = 50$. Hence the productivity distribution in the segment for natives first order stochastically dominates that of migrants. We also compute the model-implied unemployment rate u. Using this Data Generating Process (DGP), we draw 400 samples of 2000 observations each and estimate the model by maximum likelihood.

Table B.16: Natives and immigrants: DGP and parameter estimates.

	μ_N	μ_F	σ_N	σ_F	λ_N	λ_F	δ_N	δ_F	u_N	u_F
True Value	60	45	10	10	.07	.13	.005	.016	.1214	.1838
Mean	56.23	40.88	8.61	10.18	.0887	.1181	.0050	.0173	.1145	.1822
Median	56.33	40.96	8.43	10.17	.0835	.1136	.0050	.0173	.1142	.1819
2.5 perc.	53.46	36.62	5.63	6.86	.0566	.0939	.0047	.0164	.1053	.1711
97.5 perc.	59.88	45.21	12.38	13.62	.1403	.1671	.0053	.0181	.1246	.1935

Section 2.4 has considered the economic implications of the estimation results. Here, the main focus is on the quality of the estimates. Table B.16 reports the results. All structural parameters are estimated well as the true values are included in the 95% bootstrap confidence intervals (the table reports the 2.5 and 97.5 % confidence limits). The means of the job turnover parameters are particularly well estimated. The mean of the reservation wage distribution H is somewhat below the true value; this underestimate is perhaps not too surprising since the model effectively only considers the right tail of H (i.e. reservation wages b that satisfy $b > \underline{\mathrm{w}}$). The predicted unemployment rate is also very close to the theoretical value.

Figure 1 above has depicted the implied wage offers as a function of productivities[14] while Figure 6 has depicted the skewed densities of realised wages, which do have a shape often encountered in empirical work (see e.g. Figure 2).

[14] The computation of the wage offer curves for the validation exercise based on a given productivity distribution Γ is more involved than in our empirical analysis below. In the latter case, given the estimates of the structural parameters and the wage density, $F(w)$ follows straightforwardly from equation (5) and the productivity values follow from (6). In the former case, $F(w) = \Gamma\left(K^{-1}(w)\right)$, and $K(p)$ in (3), defined implicitly, is estimated progressively: starting from $\underline{p}$, p is incremented by a small step ε_p, and $K(p+\varepsilon_p)$ is found through a local search based on (3), whence $p + 2\varepsilon_p$ is considered. The confidence bands are computed pointwise, and simply determined by the relevant tail quantiles of the bootstrap distribution.

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