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Linguistic Diversity and Workplace Productivity

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ISSN: 2365-9793

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ABSTRACT

Linguistic Diversity and Workplace Productivity*

We study the importance of linguistic diversity in the workplace for workplace productivity. While cultural diversity might improve productivity through new ideas and innovation, linguistic diversity might increase communication costs and thereby reduce productivity. We apply a new measure of languages' linguistic proximity to Norwegian linked employer-employee Manufacturing data from 2003-12, and find that higher workforce linguistic diversity decreases productivity. We find a negative effect also when we take into account the impact of cultural diversity. As expected proficiency in Norwegian of foreign workers improves since their time of arrival in Norway, the detrimental impact disappears.

JEL Classification: J15, D24, J24

Keywords: productivity, diversity, language diversity, GMM

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* We thank participants at ESPE 2019 in Bath and participants at the Institute for Social Research's Seminar Series for fruitful discussions and comments on earlier versions of the paper. We gratefully thank the Norwegian Research Council for funding (grant number No 255595).

1. Introduction

A key component in firms' production strategies is to put together a workforce with the optimal mix of skills. Hiring workers with complementary human capital will improve productivity and profits. The ability to speak several languages and knowledge about cultures and religions could thus be important human capital resources influencing firm performance. Workers might be different, however, along these dimensions as well, and this could also influence firm productivity (Lazear, 1999). Cultural diversity might introduce new ideas and innovation (Alesina, Spolaore, and Wacziarg 2000; Kerr and Lincoln, 2010; Peri, Shih and Sparber, 2015), since people with different backgrounds than the majority might see new solutions to problems that have been invisible for workers from the majority group. However, a firm with a workforce from several different cultures might have to spend resources to integrate the workers into well-functioning teams. For instance, cultural diversity will imply preference heterogeneity that might create tensions and conflicts (Easterly and Levine, 1997) unless the firm has institutions to handle such conflicts.[1]

In this paper, we study the importance of related costs and benefits of diversity, namely those associated with language diversity. In a workplace, language diversity will create costs of communication. These costs might slow down production as information spreads more slowly and because misunderstandings might occur. The potential costs are likely to increase with the distance between two languages. In contrast to cultural diversity, it is hard to think of positive effects of language diversity per se, at least unless the firm is exporting to a wide range of countries with different languages.[2] While language proficiency is a skill, the empirical evidence on the return is mixed. On one hand it appears that bilingualism is not paid very well by the labour market (Fry and Lowell, 2003), and even in a

[1] See Alesina and La Ferrara (2005) for a review of the literature on the economic effects of ethnic diversity.

[2] Isphording and Otten (2013) and Melitz and Toubal (2014) find that linguistic proximity is positively related to bilateral trade. For example, a common language increases trade by 200 percent (Melitz and Toubal, 2014). However, as Fidrmuc and Fidrmuc (2016) show, also knowledge of foreign languages matter, with English playing an especially important role.

dual language country as Canada, English-French bilingualism is not associated with economic rewards (Chiswick and Millar, 2015). On the other hand, US college graduates get a 2-3 per cent wage premium when mastering a second language (Saiz and Zoido, 2005), Williams (2011) reports significant earnings premia for foreign language usage at work in 12 European countries, while Toomet (2011) reports that among Estonian workers, English proficiency increased wages by 15 percent. Multilingualism during childhood is also thought to improve the ability to learn new languages (Kovacs and Mehler, 2009) and thus stimulate communicative skill. Furthermore, studies of immigrants' language proficiency (as surveyed by Chiswick and Millar, 2015) show that language proficiency in English-spoken countries is strongly related to pay, often as large as a premium of 20 percent, while the survey of Adserà and Pytliková (2016) reports that fluency in the host-country language increase earnings of immigrants in a range of 5-35 per cent.

Language and literacy skills are clearly also important for sorting (Bratsberg et al., 2013; Chiswick and Millar, 2015; Adserà and Pytliková, 2015, 2016), within and between countries. Several studies find that migration flows between countries increases as the language proximity between the countries increases. Adserà and Pytliková (2015) report that 1 s.d. increase in the linguistic proximity increases migration flows by roughly 0.02 s.d. However, linguistic proximity matters more for migration flows from countries with better-educated populations (Belot and Hatton, 2012; Adserà and Pytliková, 2015).

The empirical literature on the effects of linguistic diversity on productivity is surprisingly small. Some early studies rely on variation across U.S. cities to estimate the correlation between language fractionalization and average earnings (Ottaviano and Peri 2005, 2006). They find a positive correlation, which they interpret as a net positive effect of cultural diversity associated with linguistic fractionalization. More recently, Peri, Shih and Sparber (2015) find positive wage effects from STEM-migration and total factor productivity growth in U.S. cities.

We believe that cross-city variations are too coarse to capture the theoretical arguments related to linguistic diversity, and instead follow a more recent literature which relies on firm and workplace level data. Kahane, Longley, and Simmons (2013) relate NHL team performance to share of European players, and find that teams perform better when more of the European players come from the same country. While innovative, the external validity of the results is not clear, since it is not obvious that NHL teams are good comparisons to randomly picked workplaces. Ozgen et al, (2013), Böheim et al. (2014), and Trax et al. (2015) rely on more representative samples of firms, but they estimate the effect of different types of diversity indexes, rather than focusing specifically on linguistic diversity.[3] The paper most similar to ours is Parrotta et al. (2014a). They use employer-employee data from Denmark to group the workforce into language groups and then calculate Herfindahl indexes to measure language diversity. Allowing productivity to depend on type of labour, they use a regional diversity as their instrument to estimate the effect of language on productivity. They find negative effects of language when controlling for diversity in education levels and demography.

Our approach is similar in spirit to that of Parrotta et al. (2014), but we make three important contributions. First, we improve the measure of linguistic diversity. Instead of grouping together countries into language groups, we directly measure the linguistic proximity of languages using data of linguistic distances between 245 languages (Ginsburgh and Weber, 2016; Wichmann et al. 2018). Using this data set, we construct a measure of linguistic diversity within a firm's workforce based on Bossert et al. (2011) generalized index of fractionalization. We describe the approach in detail in Section 4. Second, we employ a more flexible production function than in the previous literature. More specifically, we use flexible Cobb-Douglas product functions that allow heterogeneous production technology and different labour immigrant-native skill groups, and even take into account fixed workplace effects. We simultaneously address endogeneity issues using the standard approach in the firm productivity literature. Third, we address the issue of language learning and proficiency in a foreign language. Fourth, we attempt to separate the impact of linguistic diversity from the correlated impact of cultural

[3] Ozgen et al. (2013) find a negative effect of cultural diversity on productivity, Böheim et al. (2014) find a positive effect of birthplace diversity, while Trax et al. (2015) find no significant effect of cultural diversity.

diversity. We do so by employing data on cultural differences between countries from the World Values Survey (WVS). These data allow us to construct measures of cultural diversity of firms and we can then examine how sensitive the estimates for linguistic diversity are to controls for cultural diversity.

Our results show productivity loss from language diversity. According to our estimates, we find that 10 percent increase in language diversity implies a loss in productivity of 1-3 percent. However, we identify heterogeneous effects: language diversity is clearly more detrimental for high-skilled workers than for low skilled-workers, and in some industries. The results are robust to controls for cultural value diversity, but the detrimental impact of language diversity are reduced by language assimilation over time. When all workers are proficient in Norwegian, then the detrimental impact of language diversity disappears.

2. Linguistic Diversity and Productivity

The literature typically considers language skills as a type of human capital. Knowing the local language has economic benefits in the labour market (Chiswick 1991, Fry, Carnivale and Lowell 2001; Bratsberg et al. 2013) and the decision to improve language skills can be considered as an investment decision (Lazear 1999). More relevant for this paper, however, are the effects at the aggregate level. Moretti (2004) identifies strong productivity spillover effects from co-workers education in plant-level production function analyses. Using Lazear's (1999) example, when two individuals want to negotiate a contract, they might need a translator if the parties speak the different languages. Acquiring a translator implies costs, which reduces the net benefits of the transaction specified by the contract. Language differences can increase uncertainty about the other parties' expectations, their interpretation of the contract, and their commitments to the contract. At the firm level, the flow of communication between co-workers will be slower if co-workers do not understand each other well, which can result in production problems and conflicts. Moreover, language differences can result in task differentiation, which might have negative effects on productivity if non-native language speakers do not have complementary skills. Obviously, language diversity can have positive effects as well, for instance if firms hire immigrants from the countries they trade with.

The empirical literature on the economic effects of language diversity at the firm-level is small, in particular in contrast to the vast literature on cultural diversity. Kahane et al. (2013) study team performance in the NHL, and find positive effects of buying hockey players from the same European origin country. They interpret this result as a positive effect of language proximity among the players (co-workers).

Parrotta et al. (2014) use administrative employer-employee data from Denmark to study the effects of various types of workforce heterogeneity, including language diversity, on firm productivity. They argue, as others (Guiso et al., 2009), that language diversity is a good proxy for cultural distance. Thus their language diversity measure implicitly contain cultural differences. Since Parrotta et al. (2014) share some similarities with our paper, we spend some time outlining their approach, while we spell out how we differ and improve on their approach in later sections. They group immigrants into different language groups based on what language tree the majority in the origin country speaks, at the third linguistic tree-level, with information based on the encyclopedia of languages (Lewis, 2009). As Ginsburgh and Weber (2016:138-39) note, the criteria used by Lewis (2009) to define a language is not solely within the realm of linguistic. Parrotta et al. use these language groups to construct an Herfindahl index of language diversity at the firm level. Then they estimate Cobb-Douglas production functions with heterogeneous labour to model firm's total factor productivity, which is estimated separately for sectors (1-digit level). Finally, they estimate the relationship between productivity and language diversity using OLS and 2SLS with a vector of controls. In the 2SLS models they instrument language diversity using a shift share/Bartik instrument with lagged diversity in the commuting area of the firm as the initial distribution. In their main OLS specifications, they find that a one standard deviation increase in diversity is associated with about 1.3 percent decrease in productivity, while the 2SLS estimates suggest that this negative effect is about double the OLS estimate.

3. Measuring Linguistic Diversity

The main contribution of our paper is that we use a more fine-tuned and precise measure of language diversity than in the previous literature. The usual approach, as followed by Parrotta et al. (2014) is to combine immigrants into groups depending on the language family the majority language in their country of origin belongs to. This coarse approach is unsatisfactory because it does not take into account variations within the groups, and, perhaps more importantly, do not attempt to measure how different the groups are from each other. Instead, we use data that measure the distances between languages, which allows us to construct a diversity index based on the aggregate, weighted language distances within each firm.

More specifically, we use the data from the Automated Similarity Judgment Program (ASJP) to measure the language proximity between all pairwise language combinations in our data (Brown et al. 2008). The ASJP is collaboration between linguistics and statisticians to quantify the differences between 245 languages. Lexicostatistical methods for language classification are based on one dimension only: the similarities and common roots of words in vocabularies of various languages (Ginsburgh and Weber, 2016: 143). ASJP-project adds typology to lexicostatistics. ASJP use a subset of 40 words from Swadesh's 100 word list (Swadesh, 1952; Ginsburgh and Weber, 2016) and use lexicostatistics together with 85 phonological, grammatical and lexical structures described in Dryer and Haspemath's (2013) World Atlas of Language Structures. ASJP then transcribes the meanings using Levenshtein distances. ASJP measures the lexical similarity of languages based on pairwise comparison of vocabulary from. Lexical similarity is simply the proportion of words that are judged to be phonologically similar. This proportion is adjusted for similarity by chance and normalized into a proximity score from 0 to 1. The proximity score is thus the share of words that are similar in the two languages.[4] For instance, the proximity score for the Norway-Sweden pair is .62, compared to .12 for the Norway-Poland score. These differences reflect that

[4] The AJSP program has been evaluated quantitatively and qualitatively by experts, and has been found to perform well, although qualitative expert classification of Austronesian has deviated slightly. However, Wichmann and Rama (2018) link this, at least partly, to expert inaccuracies under classification of Austronesian.

it is much easier for a Norwegian and a Swede to understand each other than for a Norwegian and a Pole.

[FIGURE 1 AROUND HERE]

Figures 1 a) and 1 b) illustrate the linguistic variance in our data of the Norwegian workforce. Figure a) shows that most immigrant languages have a low proximity to Norwegian, thus, transaction costs might be important. Figure b) plots linguistic proximity versus country group prevalence ranking in 2004 and 2012. The figure shows that over this period, country groups with less similar languages have grown in relative size. This is mainly due to labour immigration from Poland, Lithuania and other East European countries after the EEA expansion in 2004.[5]

4. Data and key measures

We use population-wide administrative register data provided by Statistics Norway, Statistics Norway's Structure Statistics and Statistics Norway's Capital Data Base (Raknerud et al., 2007). The administrative register data comprise the full Norwegian population of workers, workplaces, and firms during the years 2001-2012 (around 2,500,000 worker observations each year). The data include information on individuals and jobs including country of origin, work hours, education, occupation, and earnings. Unique identifying numbers exist for individual workers, workplaces, and firms, which allow us to track them over time.

The Structure Statistics provide workplace-level information on employment and total capital. The Capital Data Base includes firm data on value added, total capital, revenues, and inputs in production. This data set mainly comprises manufacturing firms, and for simplicity we restrict our analyses to manufacturing industries. Our unit of analysis is the workplace. For 85 percent of the firms they comprise a single workplace only. For the multi-workplace firms, we split firm-level information on value added and inputs in production by the workplaces share of the firm's total

[5] See Bratsberg et al. (2017) for an overview of the immigrant population in Norway and how it has changed over the period we study in this paper.

capital. Our analyses focus on workplaces with at least 3 employees, where we have been able to link The Capital Data Base, the Structure Statistics and the administrative worker data.

The key variables in our analysis are value added, the workplace linguistic diversity, the cultural diversity measures, Norwegian and English language proficiency.

Value added in our workplace productivity analyses is measured as the log of the operating revenues less operating costs, wage costs, depreciation and rental costs.

Linguistic diversity at the workplace is slightly more complex. We combine data on the language proximity between countries with the within-workplace distribution of workers across countries of birth. Then we calculate our diversity measure as the average linguistic distance between two randomly chosen employees at the workplace (Greenberg, 1956; Bossert et al., 2011; Ginsburgh and Weber, 2016), which can be interpreted as the expected dissimilarity between two individuals drawn at random.[6] More specifically, ignore the time indicator and just let n_f denote the number of employees at workplace f. Let J_{ij} denote the index of language proximity (AJSP) described above. Then our workplace index of linguistic diversity at the workplace can be expressed (i and j denote country number):

$$(1) \qquad \delta_f = 1 - (\tfrac{1}{n_f^2}) \textstyle\sum_{i=1}^{n} \sum_{j=1}^{n} J_{ij}.$$

Norwegian proficiency is measured as follows: First, based on the Norwegian Level of Living Immigrant Edition Survey of 2007 we conduct the auxiliary OLS regression:

I(Bad Norwegian proficiency)=α_0+α_1J+α_2Years since arrival+α_3J* Year since arrival + ε,

where ε expresses an error term, J denote the linguistic proximity index and I() denote an indicator function. We can then predict the average time (years) to when no worker report bad Norwegian proficiency as: $Y^*=[-\alpha_0-\alpha_1 J_{iN}]/[\alpha_2+\alpha_3 J_{iN}]$. Our estimates of the α's are: α_0=0.1838, α_1=-0.1579, α_2=-0.0006,α_3=-0.0439. Then we let Y_{iN}*/2 measure (admittedly) the time when time when the immigrant from

[6] If one instead focused on measuring the difference using dichotomous distances between distinct groups, the diversity measure would collapse to the Herfindahl index, applied by, for instance, Perrotta et al. (2015).

country i is able to communicate good in Norwegian. Then, for each immigrant from country i employed in workplace f, we measure the years since arrival and let a dummy for expected sufficiently good Norwegian take the value of 1 if years since arrival> Y_{iN}*/2, otherwise it is zero. All Norwegians are considered proficient in Norwegian. The workplace average of this dummy then measures the share of workers with expected sufficiently good Norwegian proficiency. If we exaggerate how quickly foreigners learn Norwegian, but we argue that from an economic perspective, foreigners do not have to be completely fluent in Norwegian before the communication costs drops to zero. We also incorporate the average years of living in some of the analyses.

English proficiency is measured as follows: Based on the ranking of 88 non-English speaking countries from EF EPI (https://www.ef.com/wwen/epi/), and where we have supplied missing countries with continent modal values, we create a dummy for good English proficiency, taking the value of 1 for those with EF EPI-scores less than 3 (3 corresponds to moderate English proficiency). We also give the dummy the value of 1 for English-speaking countries (UK, USA, Canada, Australia) and for Norwegians.

Finally, one might worry that the effect of language diversity conflates the impact of language and the impact of cultural diversity. Swedes do not only speak a more similar language (to Norwegian) than Poles, their cultural background is also more similar to Norwegians than Poles. Thus, any effect of language diversity instead reflect effects of cultural diversity (see Ozgen et al. 2013, but also Trax et al. 2015). To examine this possibility, we examine how sensitive the language proximity coefficient is to controls for workplace cultural diversity. We use data from the World Values Survey (WVS) to describe the cultural distance between countries on two value dimensions; traditional and self-expression values (Inglehart and Baker, 2000).[7] The traditional dimension is based on survey answers to questions about e.g. the importance of religion, parent-child ties, deference to authority, and traditional family values, while the self-expression dimension is based on questions about e.g. economic and physical security, tolerance of foreigners, gays and

[7] See Ashraf and Galor (2011) for an application in economics.

lesbians and gender equality, and rising demands for participation in decision-making in economic and political life. Figure 2 shows Inglehart and Welzel's (2005) "cultural map of the world" based on the two dimensions.

[FIGURE 2 AROUND HERE]

Cultural diversity related to traditional and to self-expression at the workplace are then based on these inputs to construct workplace-level indices of cultural diversity for both dimensions, using the same fractionalisation approach as for language diversity.[8]

As a backdrop to our productivity analyses, Figure 3 and Table 1 reveal the changing diversity among the Norwegian Manufacturing sector over time. We find that, on average, Norwegian firms are quite homogenous. The average score on the workplace language diversity across the years we study is .11 with a standard deviation of .14, but we have observations across the whole range of the index. Moreover, the average language diversity changes substantially across the years we study, from .08 in 2003 to .16 in 2012, a change which amount to 60 percent of the standard deviation in 2002.

Figure 3 plots the distribution (density) of the workplace language diversity across workplaces for years 2003, 2008 and 2012. Figure 3 reveals that the overall the distributions shift towards greater diversity.

[FIGURE 3 AROUND HERE]

However, it is not only language diversity that shifts towards greater diversity, the same is seen along several other dimensions. Table 1 shows yearly averages for several key characteristics, and the picture is clear: as the share of immigrants increases in Norway, diversity increases as well, while language proficiency and years of residence drop. Still, cultural diversity has to be defined as low, i.e., also

[8] The WVS do not cover all countries in our study. We replace missing country observations with the mean score for the respective continent.

with respect to cultural and secular diversity is Norwegian manufacturing workplaces quite homogeneous.

[TABLE 1 AROUND HERE]

The appendix includes a description of all variables used in the analysis (see Table A2) as well as descriptive statistics (see Table A1). Minor control variables will be explained in the text as they are introduced.

5. Empirical Approach

Consider the following simple Cobb-Douglas production function:

$$(2) \qquad Y_{it} = Ae^{\omega_i + u_{it} + \gamma_t + \beta^{\delta}\delta_{it}}(L_{lsit}^N + \beta^{Nhs}L_{hsit}^N + \beta^{Ils}L_{lsit}^I + \beta^{Ihs}L_{hsit}^I)^{\beta^L}K_{it}^{\beta^k},$$

where Y is value added for workplace i at time t, ω_{it} is a workplace specific productivity level known to the workplace as they choose the level of transitory inputs and make decisions on language diversity, but not observed by us, γ_t represents technological change, δ_{it} is language diversity of the workforce at workplace i at time t, ls represents low skill and hs high skill immigrant I and native N workers respectively, K is capital, and u is a stochastic term representing idiosyncratic shocks that are unknown to the firm when it makes its decisions. Note that we potentially allow high and low skilled native and immigrants to have different productivity. The coefficient β^{δ} captures the effect of language proximity on productivity.

We derive our empirical specifications in the following steps. First, we introduce a simple transformation. Let $L_{it} = L_{lsit}^N + L_{hsit}^N + L_{lsit}^I + L_{hsit}^I$. Then we can express

$$L_{lsit}^N + \beta^{Nhs}L_{hsit}^N + \beta^{Ils}L_{lsit}^I + \beta^{Ihs}L_{hsit}^I =$$

$$L_{it}[1 + (\beta^{Nhs} - 1)l_{hsit}^N + (\beta^{Ils} - 1)l_{lsit}^I + (\beta^{Ihs} - 1)l_{hsit}^I],$$

where $l_{nit}^m = \frac{L_{nit}^m}{L_{nit}^m}$ and m∈(N, I) and n∈(ls, hs), i.e., the low-case l denote the labour share. Furthermore, note that ln[1+$(\beta^{Nhs}-1)l_{hsit}^{N}+(\beta^{Ils}-1)l_{lsit}^{I}+(\beta^{Ihs}-1)l_{hsit}^{I}] \approx$

$(\beta^{Nhs}-1)l_{hsit}^{N}+(\beta^{Ils}-1)l_{lsit}^{I}+(\beta^{Ihs}-1)l_{hsit}^{I}$.

Thus we transform Equation 2) into its log-equivalent:

(3) $$lnY_{it} = lnA + \beta^{\delta}\delta_{it} + \beta^{L}lnL_{it} + \beta^{k}lnK_{it} + (\beta^{Nhs}-1)l_{hsit}^{N} + (\beta^{Ils}-1)\, l_{lsit}^{I} + (\beta^{Ihs}-1)l_{hsit}^{I} + \omega_{it} + u_{it} + \gamma_t \quad .$$

In Equation 3) β^{δ} expresses how language diversity impacts total factor productivity (TFP).

The classical estimation problem associated with 3) is the *endogeneity of transitory inputs*. We address this issue using Levinsohn and Petrin (2003) and Wooldridge's (Wooldridge, 2009) control function approach by including a proxy for time varying productivity, ω_{it} using lagged values of capital and materials and their interactions (third order polynomial) directly in the production function. We follow Wooldridge (2009) and estimate 3) using GMM as described by Rovigatti and Mollisi (2018). Note that Wooldridge's GMM-framework consistently estimates 3) even if labour, language diversity and materials are allocated simultaneously at time t, after the productivity shock, and thus is not sensitive to the criticism of Ackerberg, Caves and Frazer (2015). Implicitly we assume that firms observe their productivity shock and adjust intermediate inputs such as materials according to optimal demand conditional on the productivity shock and the state variable(s). In our main specification, capital is the only state variable, and evolve following an investment policy, determined at time t-1. Time varying productivity, ω_{it}, evolves following a first-order Markov process: ω_{it} = E(ω_{it} $|\Omega_{it-1}$) + ξ_{it} = E(ω_{it}, $/\omega_{it-1}$) + ξ_{it} = g(ω_{it-1}) + ξ_{it}. However, we also estimate the relationship using the Ackerberg, Caves and Frazer (2015)-framework. This implies that we let labour be determined before intermediate inputs and the realization of the productivity shock. We assume that neither labour, language diversity nor materials affect future profits.

We also face an identification problem if *workers who sort into workplaces with immigrants differ in their productivity* from those who do not: This might induce a correlation between language diversity and productivity. We know that literacy skills are particularly important for immigrants when determining their labour market careers (Bratsberg et al., 2013; Chiswick and Millar, 2015; Adserà and Pytliková, 2015, 2016). First, our key specification differentiate between high and low educated immigrant and native workers. However, we also estimate the specification only differentiating between high and low educated workers. Second, we also include a set of controls to account for workers' productivity and the composition at the workplace. Based on all observations of log hourly wages in the Norwegian labour market (i.e., not just restricted to those workplaces in our productivity analysis), we estimate fixed occupation effects (4-digit code) while controlling for age vignitile dummies and year effects. Then, based on the first year of observation for the workplaces in our analyses, we calculate the average workplace occupational wage based on the occupational fixed effects for the observed occupational mix. Across all firms, we then split the occupational productivity into deciles and make a linear trend for each decile.

Finally, another difficult estimation problem we address is the *potential endogeneity of language diversity*, which, as discussed above, may occur for a variety of reasons, with different implications for the direction of any bias when making causal inferences. Our key worry is that our language measure picks up the effects of confounding factors. On one hand, language is inherently linked to nationality, and immigrants may for some reasons have different productivity than natives. Our factors might also vary across nationality, e.g., cultural and religious values might translate into productivity differences. If employers optimize on the confounding factors, this yields biased estimates when estimating Equation 2) by OLS. We address these issues by three approaches.

First, in one specification we measure all variables as deviations from workplace mean. This transformation, the within-transformation, effectively clear away all fixed workplace effects. Second, in one specification we treat our workplace language diversity measure as an endogenous variable, and let this be instrumented or determined by lagged regional language diversity.[9] This approach is similar to Parrotta et al. (2014), which uses lagged language diversity within commuting zones as instrument for firm language diversity. While our strategy is similar, we do not rest on predetermined fixed commuting zones, but take each workplace and define the labour supply facing this workplace as all workers located within a 100 km radius of the workplace.[10] Third, as described in Section 4, we use data from the World Values Survey (WVS) to describe the cultural distance between countries on two value dimensions; traditional and self-expression values (Inglehart and Baker, 2000), and add equivalent cultural diversity measures in addition to our workplace language diversity measure.

In all specifications, the reported standard errors are adjusted for clustering at the workplace level.

6. Empirical Results

Our key question is how workplace productivity is affected by workplace language diversity. To descriptively shed light on this issue, we start by averaging 20 equal-sized binned observations of the log language diversity and log value added. A priori we have residualized the data by applying a regression controlling for year dummies and log workforce size, thus measuring the relationships while taking into account variation across years and workforce size. Figure 4 presents this relationship. We see that even this rough non-parametrical test reveals that increased diversity implies lower value added, i.e., it is indicating a negative relationship between productivity and language diversity.

[FIGURE 4 AROUND HERE]

[9] This implies that the first-order Markov process can be written: ω_{it} = g(ω_{it-1}, δ_{it-1}) + ξ_{it}, and thus takes into account firms updating their expectation of the productivity level and adjust their investments based on the optimal level of the language diversity.

[10] The choice of radius rests on the notion that Statistics Norway has shown that close to nobody commute more than 90 minutes (Høydahl, 2017).

Tables 2 presents our main results, while Tables 3 and 4 explore different explanations for our results and act as robustness tests.

In Table 2, we assume homogenous production technology across industries. For completeness, the first two columns present the correlation between log language proximity and log value added when we only control for year dummies, log capital, log labour, the shares of immigrants and of natives with high and low educational qualification (Model 1) and fixed workplace effects (Model 2). In both these specifications, the correlations are negative. Increasing the language diversity index by 10 percent, reduces value added by 1.2-1.3 percent.

In the remaining columns we report the results when we apply the Levinsohn-Petrin-Wooldridge (LPW)- and Ackerman-Caves-Frazer(ACF)- control function approaches. Models 3-4 only differ with respect to estimation method. Model 5 is identical to Model 3, except that all variables are measured as deviation from workplace mean. Model 7 deviates slightly since we here do not take into account that immigrant and natives might have different levels of educational qualifications. However, the results are remarkable robust across these models. Increased language diversity implies reduced value added, in the range of 1-1.6 percent for a ten percent increase in language diversity. In Model 6 we let language diversity acts as an additional state variable, and let this be determined by lagged language diversity within the workplace's region of labour supply. In this case, we still see a negative impact on value added from increased language diversity, but the negative impact becomes thrice as strong as the previous results.[11]

[TABLE 2 AROUND HERE]

Thus, all our results indicate that increased language diversity implies reduced productivity and value added. However, so far we have implicitly assumed that immigrants do not learn Norwegian with years since arrival. This assumption is obviously false and might introduce measurement errors that biases our estimate.

[11] Note we have also estimated models were we treat all labour related variables, e.g. log workforce size and the different labour shares, as endogenous variables and let these be instrumented by their lagged values. This causes the estimated parameter associated with language diversity to be qualitatively unchanged, always significant, ranging from -0.14 to -0.22.

If people quickly learn Norwegian, our estimate will reflect confounding unobserved factors such as skills and ability that is correlated with language diversity and productivity. Next, a related measurement problem arises if communication in Norwegian is not necessary in Norway. In general, Norwegians have good English foreign language skills, and many studies (see Section 1 and 2) treat English as a Lingua Franca. English is particularly important in business and science.

To tackle this issue we conduct three robustness checks. First, we use administrative data on year of birth and year of arrival to include controls for workplace composition with respect to immigrants' time of residence (for natives year of arrival is equal to year of birth). The workplace average difference between age and time of residence in Norway then expresses how much shorter time immigrants have been exposed to Norwegian than natives. Second, as is described in Section 4, we estimate based on the time of residence the share of the workplace's workforce expected to having learnt good Norwegian language proficiency. These two measures ignore the possibility that Norwegians learn immigrants' foreign languages, but we argue that Norwegians have very weak incentives to learn the language of immigrants since the share of the population with a Norwegian background is so large (Lazear 1999). Neither do we take into account the possibility that immigrant also might learn each other language as time goes by, and only focus on this with respect to Norwegian. Third, using the ranking based on the EF EPI-index and the workers' country of origin, we measure the share of the workplace expected to have good English proficiency. These three variables, measured as deviation from global mean, are then interacted with our language diversity measure in a regression equivalent to Model 3 of Table 2.

[TABLE 3 AROUND HERE]

Furthermore, to take into account that our language diversity measure just pick up trends associated with workforce composition, we add ten linear trends based on the workforce occupational productivity the first year of observation. As discussed previously, we might also worry that our results regarding language diversity in reality is just a reflection of cultural diversity. Thus, we add as controls in our analysis, two measures of cultural diversity based on the World Value Surveys. Table 3 reports the results from our regressions.

In Model 1, we just control for workplace age, the difference between age and time of residence, the linear productivity time trends and the diversity measures for cultural values. We see that the estimated effect associated with language diversity is virtually unchanged compare the estimate in Model 3 of Table 2. Thus we can ignore time of residence, the linear productivity time trends and the cultural value diversity as important explanations for why language diversity has a detrimental impact on productivity.

In Model 2 we interact the difference between age and time of residence with language diversity. Model 2 show that the shorter time the workforce has been exposed to Norwegian, the more detrimental impact language diversity has on productivity.

Models 3 and 4 interact language diversity with expected good Norwegian and good English proficiency, respectively, while Model 5 adds both interactions. As the share of the workforce expected to have good language proficiency increases, the detrimental impact of language diversity is reduced. When all workers are expected to be proficient in Norwegian, language diversity no longer matter negatively for productivity. Similarly, as workers are expected to be more proficient in English, the detrimental impact of language diversity is clearly reduced, but even when we estimate the impact when all workers are expected to be proficient in English, we find that the impact is still -0.13 (at a p-value of 0.07).

Table 3 has shown that residence time matter, in that respect that as time goes by, most immigrants learn the native language, and language diversity as measured by the immigrants' country of origin becomes less relevant. In that respect, our analyses of Table 2 exaggerates the negative impact of language diversity. However, even the analyses of Table 3 clearly shows that language diversity has a negative impact on productivity.

In the analyses so far, we have assumed that language diversity has the same importance for low and high-skilled workers. This might not be the case. Thus, we estimate the language diversity separately for low- and high-skilled workers. Then we repeat several of the analyses of Table 2. The results are presented in Table 4. In Model 1 we just add the language diversity measures for low- and high-skilled workers. In Model 2 we treat these language diversity measures as endogenous, and instrument these by the lagged regional language diversity measures (similar to Model 6 in Table 2). In Model 3, we add linear productivity time trends and diversity measures for cultural diversity.

[TABLE 4 AROUND HERE]

All the models reveal the same pattern: when it comes to productivity, language diversity is more detrimental for high skilled workers than for low-skilled workers. Increasing the language diversity for high-skilled workers by 10 per cent reduces the workplace productivity by 1.5-2.7 percent. Similarly, increasing the language diversity for low-skilled workers by 10 per cent reduces the workplace productivity by 0.7-1.1 percent. Thus even for this latter group language diversity should not be ignored.

Finally, since high- and low-skilled workers are employed to a different degree in different industries, we ask whether the language diversity has different impact depending on the industries. Therefore, we repeat the analysis in Model 3 of Table 4 separately for the 2-digit Manufacturing industries. Figure 5 presents the results in the form of elasticities.[12] We see that for the low-skilled workers close to all estimates are small and non-significant. However, for the high-skilled workers the elasticities of language diversity on productivity are, with one exception, all negative and mostly significant.

[FIGURE 5 AROUND HERE]

[12] Details on the regressions, e.g., parameter estimates, are available from the authors upon request.

7. Conclusion

A key component in firms' production strategies is to put together a workforce with the optimal mix of skills. In modern societies communication skills have become more important. Proficiency of languages is one such skill. To be able to communicate, precisely and swiftly, is crucial in many occupations. At the same time, changing flows of workers and people across countries has increased the number of migrant workers in many countries. Diversity has thus increased. In many labour markets the prevalence of different languages has also increased as a consequence of migration. In this paper, we study the importance of related costs of diversity, namely those associated with language diversity, and studied how such diversity influence productivity. In a workplace, language diversity might create costs of communication, but it will also be a pool of language resources.

We utilize a new measure of language proximity, the ASJP-index, which measures the rate of how many words are similar when comparing two languages. Applying this index to Norwegian linked employer-employee Manufacturing data from 2003-13, we have constructed a measure of the average workplace language diversity at the workplace. We find that higher workforce linguistic diversity decreases productivity. The results are fairly robust.

Our estimates are slightly smaller than what other researcher have found, when measuring the impact of language diversity on productivity, but our language diversity index measures truly language dissimilarity and not cultural or country differences. Furthermore, our results survive even when we take into account cultural diversity and expected English proficiency. However, we clearly find evidence supporting the notion that the improvement of proficiency in Norwegian of foreign workers since their time of arrival in Norway is important. Language diversity does no longer matter when the expected proficiency in Norwegian is good. This clearly indicates that when we find language diversity as detrimental to productivity, this is because of communication costs. Similarly, we find less detrimental impact of language diversity as the share of workers expected to speak

English well, increases.[13] The policy implication is that it is important to improve the language skills of immigrants.

However, another lesson might be drawn from our results. First, we do find a differential language proximity impact for less skilled workers, i.e., for these workers language diversity acts less detrimental for productivity, but it still matters. This implies that language skills and communication is more important and costly for high skilled workers than low skilled workers, but even for the latter group of workers, language skills and communication should not be ignored.

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[13] Admittedly we do not observe each workers proficiency in English or in Norwegian, but use information on average country language skills in home country (for English) and in Norway (for Norwegian) as a measure of expected language skills.

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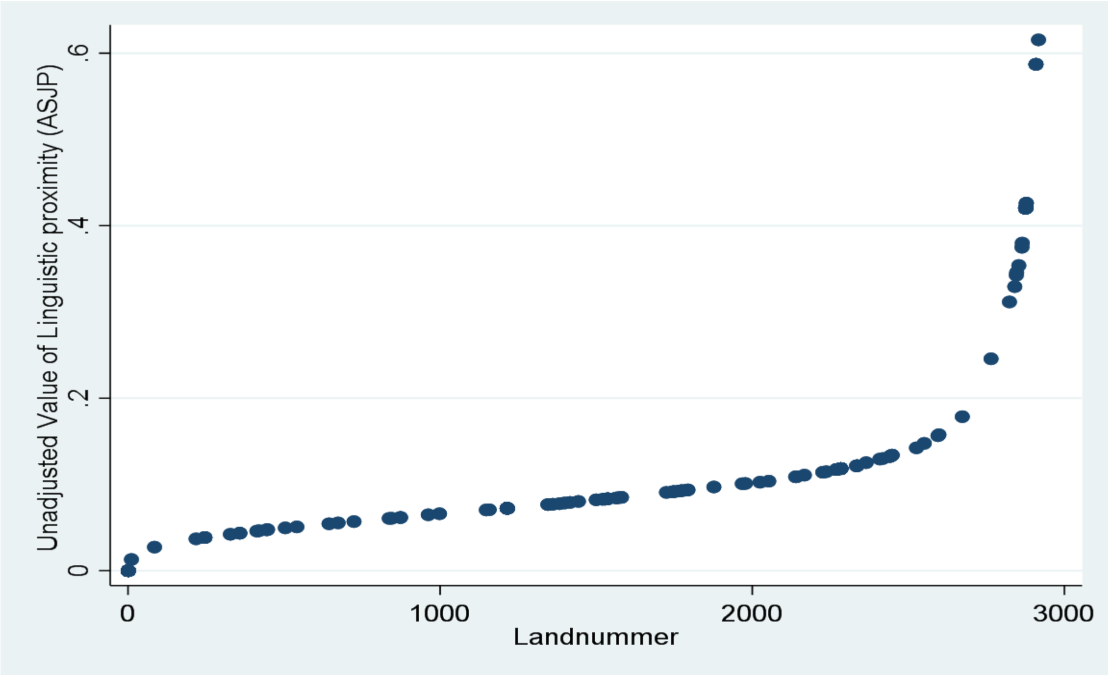
APPENDIX

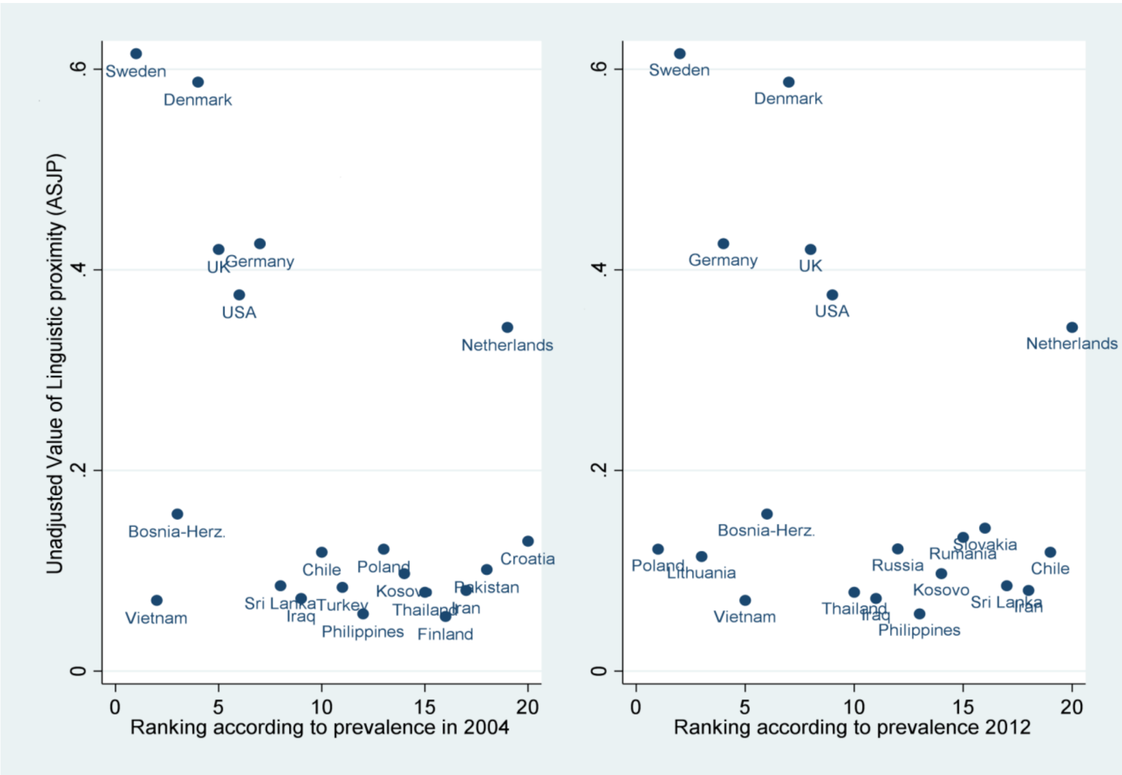
[TABLE A1 AROUND HERE]

[TABLE A2 AROUND HERE]

Figure 1. Linguistic proximity in the Norwegian workforce

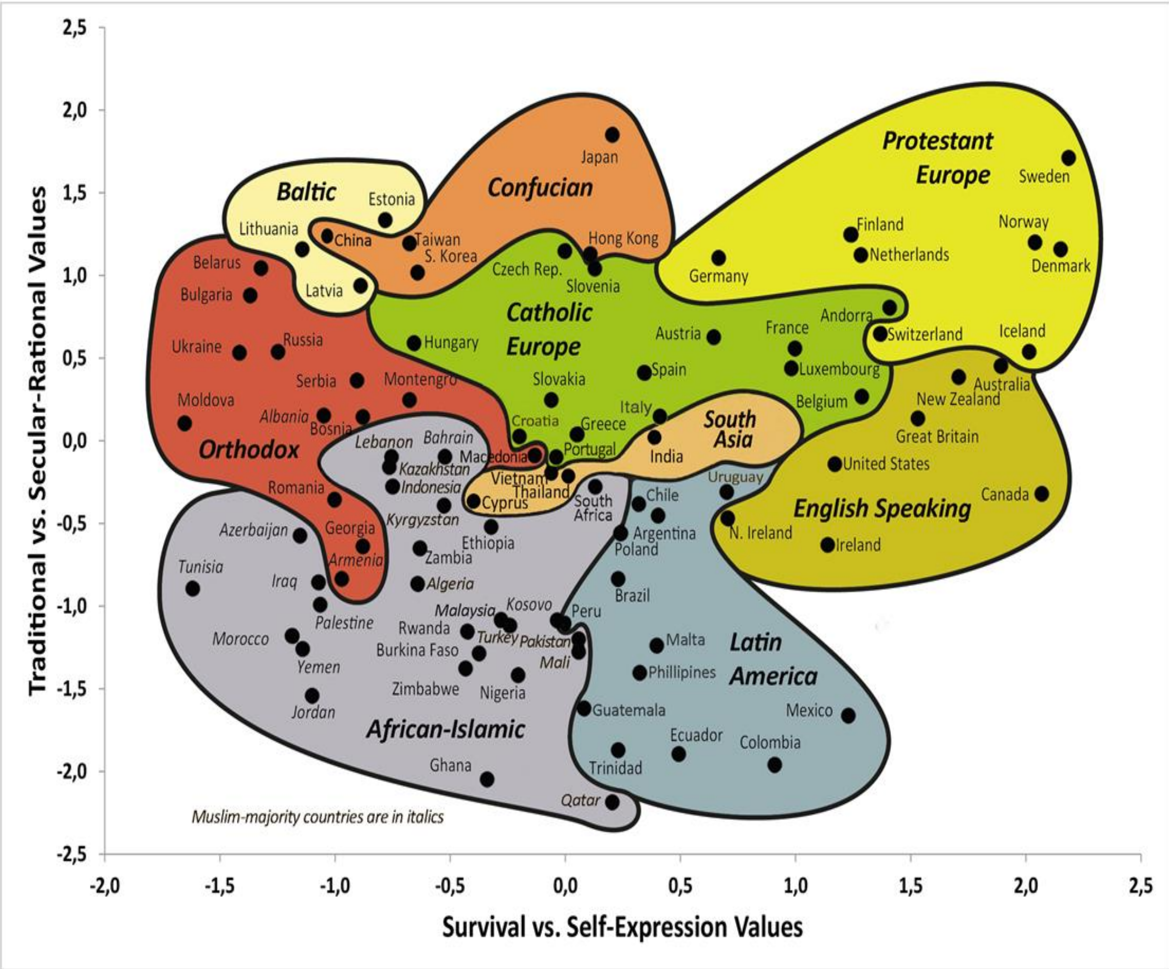


a) Distribution of linguistic proximity



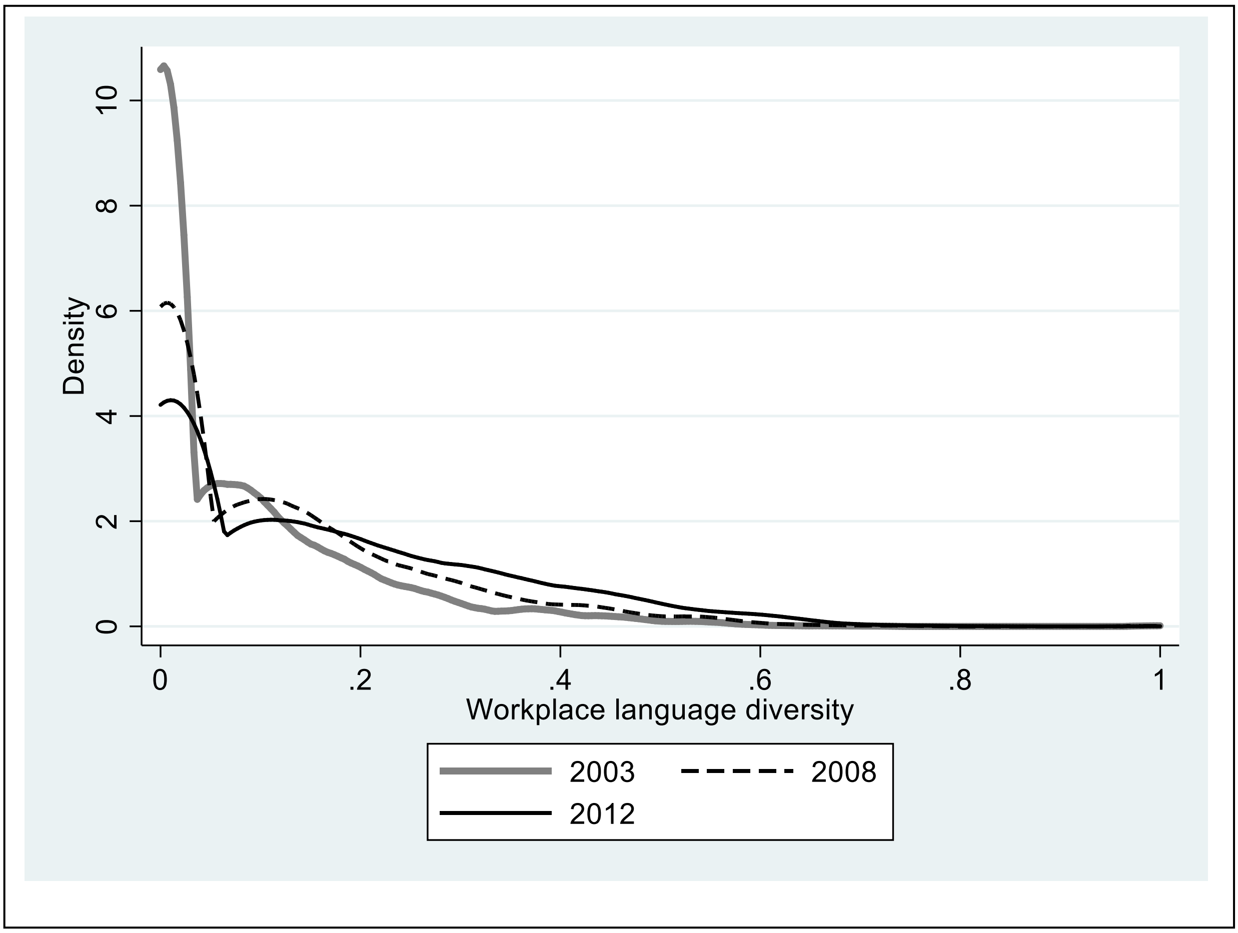
b) Linguistic proximity and ranking according to prevalence.

Figure 2. Two dimensions of cultural diversity.



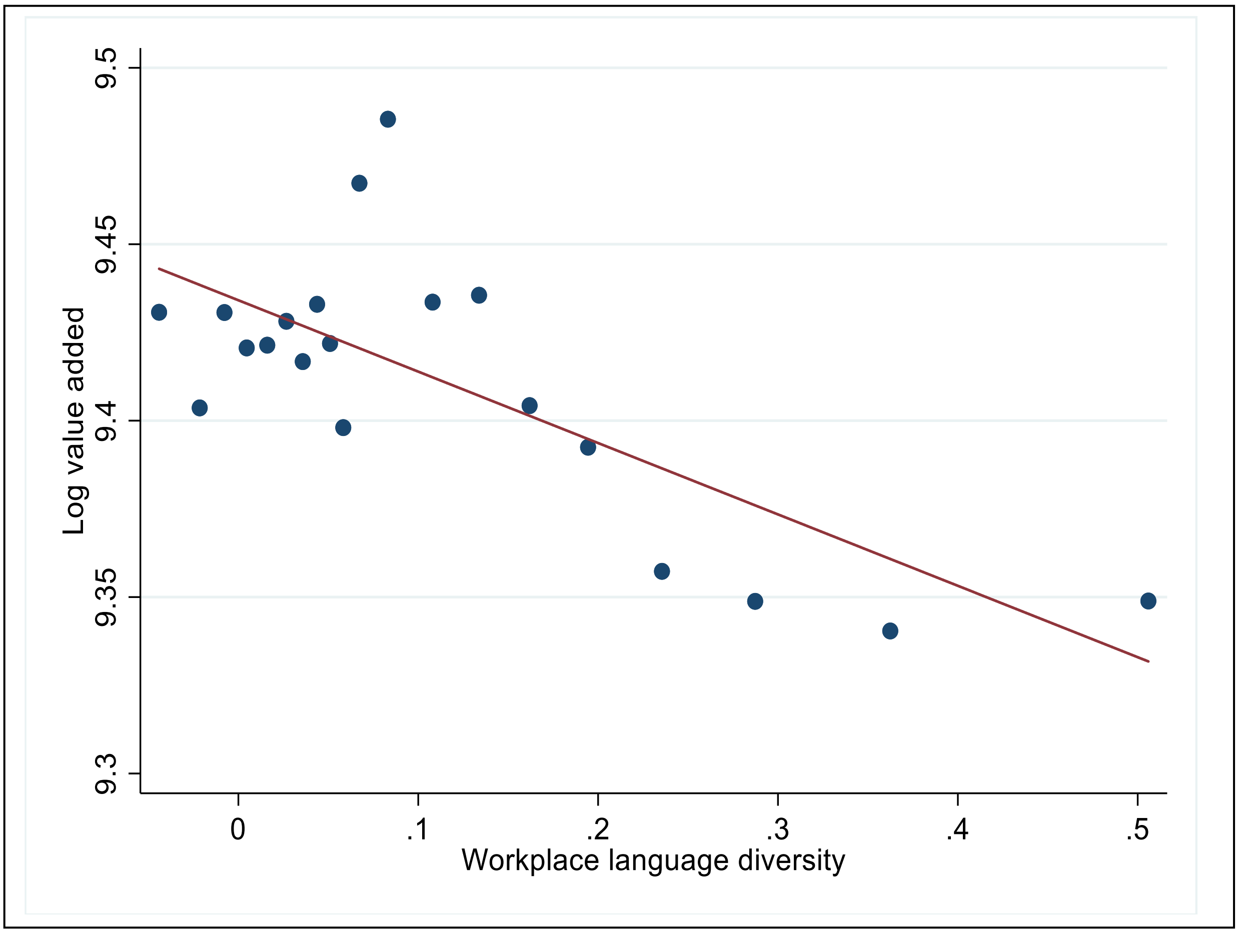
Note: Source: Inglehart and Welzel (2005)

Figure 3. The development of workplace language diversity over time



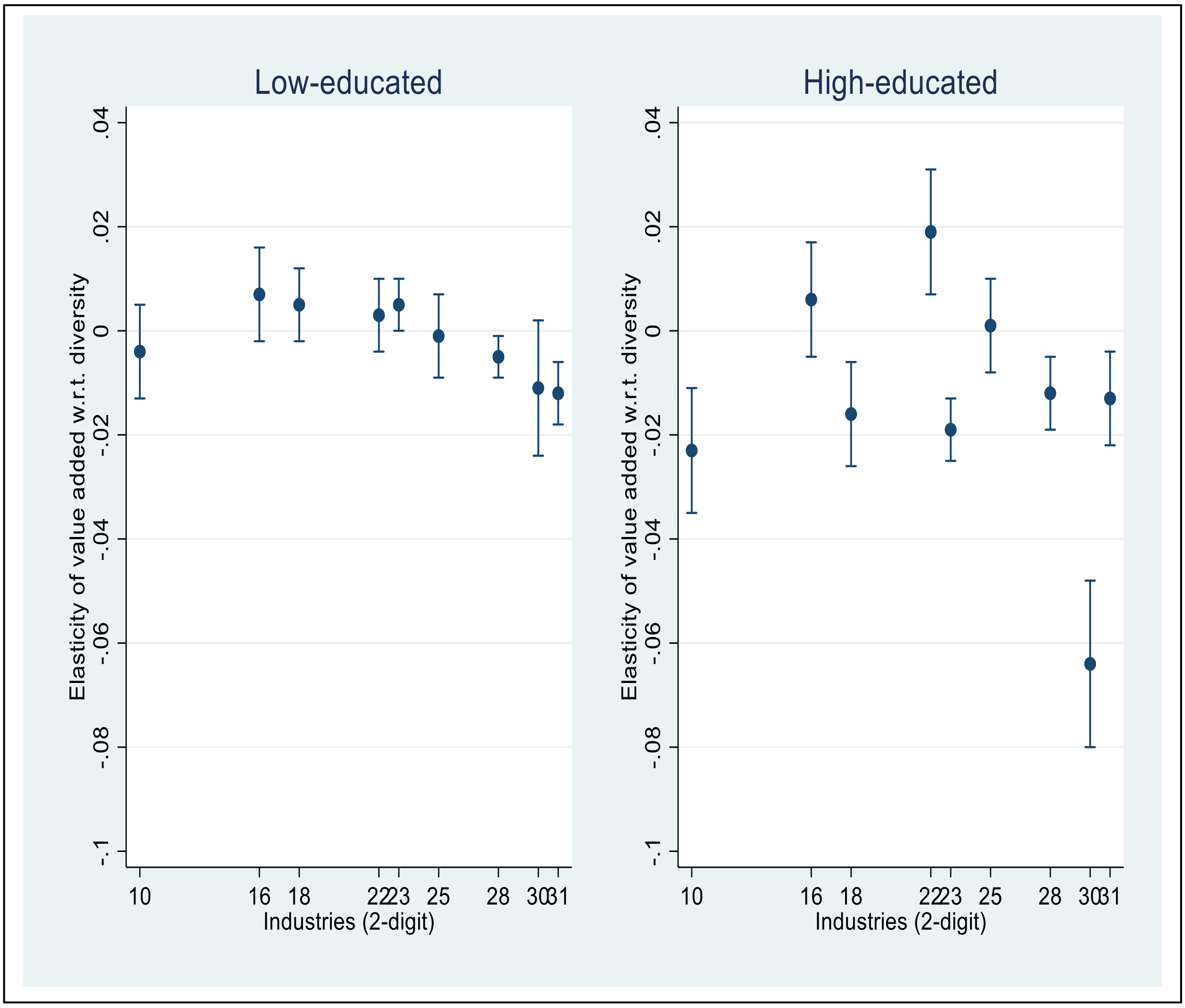
Note: Kernel density plots of yearly distributions of the workplace language diversity.

Figure 4. The correlation between productivity and language diversity



Note: The figures are based on averages of 20 equal-sized binned observations of the language diversity and log value added, where one a priori has residualized data applying a regression controlling for year dummies and log workforce size, thus measuring the relationships while taking into account variation across years and workforce size.

Figure 5 The impact of language diversity on productivity for selected industries



Note: The reported estimates and standard errors are from industry-specific regressions similar to Model 3 of Table 2, but where we measure language diversity indices separately for low- and high-educated workers. The regressions are conducted only for workplaces within industries with at least 1000 observations. See Table A3 for further details on regressions (e.g., the parameter estimates).

Table 1: The impact of language diversity on total factor productivity. Basic.

Year	LnValue added	LDI_all	LDI-low	LDI-high	Share Norw. proficiency	Share Eng. proficiency	CDI	RDI
2003	9.18	0.080	0.059	0.078	0.212	0.498	0.037	0.037
	(1.29)	(0.116)	(0.117)	(0.128)	(0.355)	(0.479)	(0.054)	(0.057)
2004	9.25	0.077	0.056	0.078	0.204	0.481	0.036	0.035
	(1.28)	(0.115)	(0.115)	(0.125)	(0.350)	(0.479)	(0.053)	(0.059)
2005	9.30	0.078	0.057	0.076	0.205	0.486	0.037	0.036
	(1.29)	(0.115)	(0.116)	(0.125)	(0.350)	(0.480)	(0.054)	(0.056)
2006	9.39	0.087	0.063	0.084	0.206	0.508	0.040	0.040
	(1.31)	(0.124)	(0.125)	(0.132)	(0.349)	(0.478)	(0.057)	(0.060)
2007	9.50	0.098	0.073	0.094	0.203	0.540	0.046	0.045
	(1.32)	(0.130)	(0.133)	(0.139)	(0.340)	(0.474)	(0.059)	(0.062)
2008	9.47	0.113	0.084	0.111	0.186	0.568	0.054	0.052
	(1.29)	(0.137)	(0.141)	(0.151)	(0.322)	(0.467)	(0.064)	(0.067)
2009	9.40	0.126	0.089	0.125	0.180	0.589	0.060	0.057
	(1.28)	(0.147)	(0.146)	(0.160)	(0.316)	(0.464)	(0.069)	(0.070)
2010	9.41	0.137	0.091	0.136	0.173	0.601	0.065	0.061
	(1.32)	(0.156)	(0.151)	(0.169)	(0.310)	(0.461)	(0.073)	(0.073)
2011	9.45	0.147	0.096	0.145	0.171	0.612	0.070	0.065
	(1.30)	(0.162	(0.156)	(0.175)	(0.307)	(0.458)	(0.076)	(0.075)
2012	9.49	0.158	0.104	0.154	0.170	0.633	0.075	0.069
	(1.32)	(0.166)	(0.164)	(0.177)	(0.306)	(0.452)	(0.079)	(0.076)
2013	9.51	0.168	0.111	0.164	0.169	0.648	0.080	0.073
	(1.36)	(0.171)	(0.170)	(0.180)	(0.297)	(0.445)	(0.081)	(0.079)

Note: Population: Workplaces in Capital Data Base Manufacturing firms with never less than three employees and residuals within +/- 5*mrse from an auxiliary log value added linear regression with 2-digit industry and year dummies as controls. LDI-all, LDI-low and LDI-high express workplace language diversity for all workers and separately for low- and high-skilled workers, respectively. Share Norwegian profiency and share English proficiency express share of immigrant workforce estimated to have good proficiency in these languages. Norwegian proficiency is estimated based on time of residence. English proficiency is estimated based on immigrants' country of origin and EF EPI-index of English proficiency across countries. CDI and RDI express cultural and religious diversity as measured by the World Values Surveys according to Inglehart and Welzel's (2005) definitions.

Table 2: The impact of language diversity on total factor productivity. Basic.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
LD-index (LDI)	-0.118**	-0.132***	-0.159***	-0.095***	-0.168***	-0.303***	-0.097***
	(0.049)	(0.049)	(0.048)	(0.007)	(0.051)	(0.057)	(0.049)
Share low-educated imm.	0.022	0.246***	0.116**	0.046***	0.162***	0.171***	
	(0.056)	(0.061)	(0.057)	(0.003)	(0.060)	(0.062)	
Share high-educated imm.	0.535***	0.506***	0.424***	0.565***	0.338***	0.476***	
	(0.080)	(0.092)	(0.073)	(0.008)	(0.084)	(0.076)	
Share high-educated natives	0.752***	-0.094***	0.521***	0.769***	-0.029	0.510***	
	(0.023)	(0.035)	(0.021)	(0.003)	(0.033)	(0.021)	
Log employment	0.952***	0.797***	0.684***	0.974***	0.601***	0.676***	0.684***
	(0.006)	(0.011)	(0.005)	(0.018)	(0.011)	(0.005)	(0.005)
Log capital	0.088***	0.032***	0.060***	0.109***	0.025***	0.060***	0.060***
	(0.005)	(0.003)	(0.004)	(0.042)	(0.003)	(0.004)	(0.004)
Share high-educated							0.500***
							(0.020)
Method	OLS	OLS	WRDG	ACF	WRDG	WRDG	WRDG
Within (FE) workplace		Yes			Yes		
State			LnCapital	LnCapital	LnCapital	LnCapital+LDI	LnCapital
Proxy			Ln materials	Ln materials	Ln materials	Ln materials	Ln materials
Polynomial			3	3	3	3	3
Excluded instrument						Lagged regional LDI	
Workplaces(F)	3995	3995	3995	3995	3995	3995	3995
Observations(FXT)	29991	29991	25837	29943	25837	25837	25837

Note: Population: Workplaces in Capital Data Base Manufacturing firms with never less than three employees and residuals within +/- 5*mrse from an auxiliary log value added linear regression with 2-digit industry and year dummies as controls. Dependent variable: the residuals from the auxiliary regression. Within: Denotes that the observations are measured as deviation from workplace mean (within-workplace transformed observations). OLS denotes ordinary least square regressions. WRDG denotes Wooldridge GMM-approach (Wooldridge, 2009). ACF denotes the approach of Ackerman, Caves and Frazer (2005). In Model 6, lagged regional language diversity is excluded in the second step and thus act as an instrument. See text for details. Robust standard errors adjusted for workplace-level clustering are reported in parentheses. ***, ** and * denote significant at the 1, 5 and 10 percent level of significance, respectively.

Table 3: Language diversity and productivity: the importance of confounding factors

	Model 1	Model 2	Model 3	Model 4	Model 5
LD-index(LDI)	-0.159***	-0.160***	-0.145***	-0.199***	-0.161**
	(0.048)	(0.072)	(0.073)	(0.105)	(0.072)
LDI X Diff. age-time of residence		-0.026***			
		(0.004)			
LDI X Share good Norw. language proficiency			0.606***		0.572***
			(0.059)		(0.063)
LDI X Share good English language proficiency				1.462***	1.025***
				(0.266)	(0.294)
Difference age-time of residence	-0.017***	-0.008***			
	(0.002)	(0.002)			
Share good Norw. language proficiency			0.049***		0.058***
			(0.008)		(0.008)
Share good English language proficiency				-0.553***	-0.500***
				(0.098)	(0.103)
Share low-educated imm.	0.472***	0.522***	0.006	0.135**	0.058
	(0.081)	(0.081)	(0.068)	(0.063)	(0.064)
Share high-educated imm.	0.828***	0.913***	0.375***	0.492***	0.429***
	(0.100)	(0.099)	(0.078)	(0.077)	(0.062)
Share high-educated natives	0.500***	0.548***	0.548***	0.558***	0.543***
	(0.021)	(0.021)	(0.021)	(0.021)	(0.011)
Log employment	0.684***	0.671***	0.670***	0.672***	0.670***
	(0.005)	(0.005)	(0.005)	(0.006)	(0.003)
Log capital	0.058***	0.066***	0.066***	0.066***	0.066***
	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)
Method	WRDG	WRDG	WRDG	WRDG	WRDG
State	LnCapital	LnCapital	LnCapital	LnCapital	LnCapital
Proxy	Lnmaterials	Lnmaterials	Lnmaterials	Lnmaterials	Lnmaterials
Polynomial	3	3	3	3	3
Other controls					
Age	Yes	Yes	Yes	Yes	Yes
Cultural and religious diversity	Yes	Yes	Yes	Yes	Yes
Compositional prod. trend	Yes	Yes	Yes	Yes	Yes
Workplaces(F)	3995	3995	3995	3995	3995
Observations(FXT)	25837	25837	25837	25837	25837

Note: Population: Workplaces in Capital Data Base Manufacturing firms with never less than three employees and residuals within +/- 5*mrse from an auxiliary log value added linear regression with 2-digit industry and year dummies as controls. Dependent variable: the residuals from the auxiliary regression. Within: Denotes that the observations are measured as deviation from workplace mean (within-workplace transformed observations). WRDG denotes Wooldridge GMM-approach (Wooldridge, 2009). Compositional trend is based on the average occupational wage effects for the first observational year, and which is split in ten groups and then linearly trended, where the effects are calculated from the estimated fixed worker effect from a worker-level population-wide log hourly wage regression on year dummies (10) and age vigintile (19) dummies. Cultural and religious diversity are measured by Inglehart and Welzel's (2005) two measures as reported in the World Value Surveys. Age expresses the workplace average age of the workforce. The difference between workforce age and workforce time of residence expresses the reduction in the potential time spent practicing Norwegian. The share of workers with good Norwegian language proficiency is estimated based on an auxiliary regression. Share of workers with good English proficiency based on workers country of origin and EF EPI-ranking of countries. See text for details. Robust standard errors adjusted for workplace-level clustering are reported in parentheses. ***, ** and * denote significant at the 1, 5 and 10 percent level of significance, respectively.

Table 4: The impact of language diversity on productivity: skill-dependent effects

	Model 1	**Model 2**	**Model 3**
LD-index low educated (LDI-L)	-0.067***	-0.080***	-0.110
	(0.024)	(0.033)	(0.073)
LD-index high educated (LDI-H)	-0.149***	-0.203***	-0.271***
	(0.028)	(0.034)	(0.072)
Share low-educated imm.	0.124***	0.136***	0.061
	(0.042)	(0.045)	(0.043)
Share high-educated imm.	0.478***	0.441***	0.451***
	(0.066)	(0.061)	(0.067)
Share high-educated natives	0.515***	0.501***	0.517***
	(0.022)	(0.022)	(0.021)
Log employment	0.687***	0.676***	0.676***
	(0.005)	(0.005)	(0.005)
Log capital	0.059***	0.058***	0.057***
	(0.004)	(0.004)	(0.004)
Method	WRDG	WRDG	WRDG
State	LnCapital	LnCapital, LDI-L, LDI-H	LnCapital
Proxy	Lnmaterials	Lnmaterials	Lnmaterials
Polynomial	3	3	3
Excluded instruments		Lagged regional LDI-L/LDI-H	
Other controls			
Cultural and religious diversity			Yes
Compositional prod. Trend			Yes
Workplaces(F)	3995	3995	3995
Observations(FXT)	25837	25837	25837

Note: Population: Workplaces in Capital Data Base Manufacturing firms with never less than three employees and residuals within +/- 5*mrse from an auxiliary log value added linear regression with 2-digit industry and year dummies as controls. Dependent variable: the residuals from the auxiliary regression. Within: Denotes that the observations are measured as deviation from workplace mean (within-workplace transformed observations). WRDG denotes Wooldridge GMM-approach (Wooldridge, 2009). In Model 2, lagged regional language diversity indices for low-educated and for high–educated workers are excluded in the second step and thus act as an instruments for the workplace-specific language diversity indices for low-educated and for high–educated workers. Compositional trend is based on the average occupational wage effects for the first observational year, and which is split in ten groups and then linearly trended, where the effects are calculated from the estimated fixed worker effect from a worker-level population-wide log hourly wage regression on year dummies (10) and age vigintile (19) dummies. Cultural and religious diversity are measured by Inglehart and Welzel's (2005) two measures as reported in the World Value Surveys. Age expresses the workplace average age of the workforce. The difference between workforce age and workforce time of residence expresses the reduction in the potential time spent practicing Norwegian. See text for details. Robust standard errors adjusted for workplace-level clustering are reported in parentheses. ***, ** and * denote significant at the 1, 5 and 10 percent level of significance, respectively.

Table A1 Descriptive statistics. N=39885.

	Mean	Standard deviation	Name	Mean	Standard deviation
Log value added	9.418	1.297	Language diversity	0.115	0.145
Log total capital	7.963	2.177	Language diversity –low	0.081	0.142
Log intermediates	9.824	1.614	Language diversity-high	0.113	0.156
Log workforce size	2.895	1.091	Diversity Secular	0.052	0.068
Share immigrants	0.089	0.144	Diversity Self-expression	0.034	0.125
Share low-skill immigr.	0.069	0.108	Diff Age-Years since arrival	2.448	3.859
Share high-skill immigr.	0.024	0.052	Good Norwegian proficien.	0.588	0.441
Share high-skill natives	0.151	0.167	Good Norw. prof. centered	0.000	0.441
Workforce age	43.449	4.761	Good English proficiency	0.968	0.071
			Good English prof.centered	0.000	0.071

Note: Population: Workplaces in Capital Data Base Manufacturing firms with never less than three employees and residuals within +/- 5*mrse from an auxiliary log value added linear regression with 2-digit industry and year dummies as controls. Shares of good language proficiency (Norwegian, English) is for both the immigrant and native population. Measured for the immigrant population only, good Norwegian proficiency and good English proficiency are 0.18 and 0.54 respectively. The centered variables are measured as deviation from global mean.

Table A2 List and description of variables

Log value added: log of the operating revenues less operating costs, wage costs, depreciation and rental costs.

Log total capital: Log total capital

Log intermediaties: Log total value of intermediates factors

Log workforce size: Log number of workers

Share immigrants: Share of immigrants in the workforce.

Share low-skilled immigrants: Share of workforce being immigrants and not being educated at college or university level.

Share high-skilled immigrants: Share of workforce being immigrants and educated at college or university level.

Share high-skilled natives: Share of workforce being natives and educated at college or university level.

Workplace language diversity: average linguistic distance between two randomly chosen employees at the workplace, constructed as a generalized fractionalization index based on the ASJP-language proximity index.

Diversity secular: The secular/traditional dimension is based on survey answers to questions about e.g. the importance of religion, parent-child ties, deference to authority, and traditional family values (Inglehart and Baker, 2000). Workers from countries with missing information has been imputed with continent average values. Distance secular then measures the average secular distance between two randomly chosen employees at the workplace, constructed as a generalized fractionalization index based on the secular/traditional index.

Diversity self-expression: The self-expression dimension is based on questions about e.g. economic and physical security, tolerance of foreigners, gays and lesbians and gender equality, and rising demands for participation in decision-making in economic and political life (Inglehart and Baker, 2000). Workers from countries with missing information has been imputed with continent average values. Distance self-expression then measures average self-expression distance between two randomly chosen employees at the workplace, constructed as a generalized fractionalization index based on the self-expression index

Years since arrival: Years since immigrant arrival to Norway, years since birth for those born in Norway.

Workforce age: Average age of workers across the workplace

Difference age-years since arrival: Increasing values measure average difference between natives and immigrants in being exposed to Norwegian language (in Norway).

Share workers with good Norwegian proficiency: Using survey data of immigrants to Norway we estimate the relationship between self-reported proficiency in Norway and time since arrival, language proximity and the interaction between these variables. This makes us able to estimate linearly when workers from different countries of origin achieve perfect proficiency of Norwegian. We define that immigrant workers have sufficiently good Norwegian language proficiency after half this time so communication between natives and immigrants is costless. Let this be denoted by a dummy taking the value 1 if worker has good Norwegian proficiency, 0 otherwise. Workplace average then expresses the share of workers with good Norwegian proficiency.

Share workers with good English proficiency: Based on the country ranking of Education First (EF.com), we define a dummy taking the value of 1 for immigrant workers from countries having very good and good (values 1 and 2) English proficiency and workers from English-spoken countries, zero otherwise. Workplace average then expresses the share of workers with good English proficiency. Norwegians are supposed to be proficient in English.

Composition trends: Linear trends for workforce productivity deciles conditional on composition, where composition is defined as the average occupational wage effects across the workplace at the first year of observation. The occupational wage effects are estimated as the fixed occupational effects from a worker-level population-wide log hourly wage regression on year dummies (10) dn age vignitile dummies (19).