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Linguistic diversity and workplace productivity

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ABSTRACT

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 control for the impact of cultural diversity. The detrimental impact disappears over time as immigrant workers' expected proficiency in Norwegian improves since their time of arrival.

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 differ along these dimensions too, and this could influence firm productivity (Lazear, 1999). Cultural diversity might introduce new ideas and innovation (Alesina et al., 2000; Kerr and Lincoln, 2010; Peri et al., 2015), since people with different backgrounds than the majority might see new solutions to problems. 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 implies preference heterogeneity that might create tensions and conflicts (Easterly and Levine, 1997) unless the firm has institutions to handle conflicts.[1]

In this paper, we study the importance of the related costs and benefits of linguistic diversity on productivity. 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. Language differences can result in task differentiation, which might have negative effects on productivity if non-native language speakers do not have complementary skills. 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, except if the firm is exporting to a wide range of countries with different languages.[2]

The empirical literature on the effects of linguistic diversity on productivity is surprisingly small (see Section 2). The paper most similar to ours is Parrotta et al. (2014). They use employer-employee data from Denmark to group the workforce into language groups (based on Ethnologue, 2009) and then calculate Herfindahl indexes to measure linguistic diversity. In their main OLS specifications, they find that a one standard deviation increase in diversity is associated with about 1.3% decrease in productivity, while the 2SLS estimates are twice this size.

We make four important contributions to the previous literature on how linguistic diversity affects productivity. 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).[3] Using this data

[2] See review in Section 2.

[3] We are not the first to use this measure in economics (see e.g. Isphording 2014; Isphording and Otten, 2013, 2014; Adserà and Pytliková, 2015; Bredtmann et al., (2018), Frattini, T. and Meschi, 2019), but it has not been applied in productivity analyses. We thank one of the anonymous referees for pointing out this.

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

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set, we construct a measure of linguistic diversity within a firm's workforce based on Bossert et al. (2011) generalized index of fractionalization. Second, we employ a flexible production function, where we allow heterogeneous production technology and different labour immigrant-native skill groups, and even take into account fixed workplace effects. We simultaneously address different endogeneity issues using the standard approach in the firm productivity literature. Third, we address the issue of language learning and proficiency in a foreign universal language. Fourth, we attempt to separate the impact of linguistic diversity from the correlated impact of cultural diversity. We do so by employing data on cultural, religious and genetic differences between countries from the World Values Survey (WVS) and from Spolaore and Wacziarg (2016, 2018).[4] These data allow us to construct measures of cultural, religious and genetic diversity of workplaces and we can then examine how sensitive the estimates for linguistic diversity are to controls for potentially confounding cultural diversities. Since Becker (1957), we know that both employer and co-worker discrimination might affect workplace productivity.[5] While we cannot exclude the possibility that discrimination occur due to language preferences, discrimination can clearly also be attributed to genetic, religious and cultural differences. Since linguistic distance is positively correlated with genetic, religious and cultural distance (Spolaore and Wacziarg, 2016), controls for genetic, religious and cultural distance are important also from a discrimination perspective.

In Section 2, we review the previous literature. Section 3 discusses how to measure linguistic diversity. Data and key measures are defined in Section 4. Section 5 presents the empirical approach. Section 6 studies the relationship between workplace linguistic diversity and the linguistic diversity of the lagged labour supply facing a workplace. Our main results are presented in Section 7, while Section 8 briefly concludes.

2. Language, linguistic diversity and the labour market

Language has for decades been recognized as important the labour market, either directly or indirectly. Linguistic proximity is positively related to bilateral trade (Isphording and Otten, 2013; Melitz and Toubal, 2014), and common language increases trade (Melitz and Toubal, 2014). Knowledge of foreign languages also matters for trade (Fidrmuc and Fidrmuc, 2016).

While language proficiency is a skill, the empirical evidence on the return is mixed. On one hand, some find that bilingualism is not paid very well by the labour market (Fry and Lowell, 2003), even in a dual language country as Canada (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), and a significant earnings premium for foreign language proficiency has been found in Europe (Williams, 2011; Toomet, 2011; Isphording 2013).[6] Studies of immigrants' language proficiency find that fluency in the host-country language increase earnings of immigrants in a range of 5–35% (Chiswick and Millar, 2015; Adserà and Pytliková, 2016). Language and literacy skills are also important for sorting (Bratsberg et al., 2013; Chiswick and Millar, 2015; Adserà and Pytliková, 2015, 2016), within and between countries (Adserà and Pytliková, 2015; Belot and Hatton, 2012). For example, Adserà and Pytliková (2015) find that migration rates increase with linguistic proximity, but linguistic proximity matters less when local linguistic networks are larger. Isphording and Otten (2014) also point to linguistic barriers in the destination language acquisition of immigrants.

Return to language proficiency for ethnic or immigrant groups could be reduced if language, referring to all aspects of verbal and non-verbal communication, is related to discrimination (Lang, 1986). Variation is, however, an intrinsic feature of a spoken language (Lippi-Green, 1997), making it possible for employers to discriminate on accent, even for native groups. Heblich et al. (2015) links similar behaviour to individuals, but attribute the perceptions of regional accents to the social rating of the linguistic distance. In several countries one also observes evidence of homophilous hiring discrimination related to language, ethnicity or religion, for example France (Edo et al., 2019), UK (Larsen and Di Stasio, 2019), and Norway (Midtbøen, 2016; Larsen and Di Stasio, 2019).

Linguistic distance might be related to the spread of technological and institutional innovations. Several studies have explored how a society's ancestral population might influence its current level of development (Spolaore and Wacziarg, 2009; Ashraf and Galor, 2013), i.e., ancestry matters since populations interact more and learn more easily from closely related populations. Thus technological and institutional innovations move first amongst closely related communities and ancestral distance acts as a temporary barrier to the diffusion of development (Spolaore and Wacziarg, 2018). Similarly, Krieger et al. (2018) finds that long-term relatedness measured by genetic variance is important for educational migrant selection. These mechanisms could also be at play within a workplace, affecting the interaction between immigrant groups and natives, and the sorting to workplaces.

However, as stated in the introduction, 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 positive correlations between language fractionalization and average earnings (Ottaviano and Peri, 2005, 2006; see also Peri et al., 2015). We believe that cross-city variations are too coarse to capture the theoretical arguments, and instead follow a more recent literature that relies on firm and workplace level data. Kahane et al. (2013) find that NHL 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. Ozgen et al. (2013), Böheim et al. (2014), and Trax et al. (2015) rely on more representative samples of firms, but they do not focus specifically on linguistic diversity.[7]

Finally, Parrotta et al. (2014) apply employer-employee data from Denmark to group the workforce into language groups and then calculate Herfindahl indexes to measure linguistic diversity. Allowing productivity to depend on type of labour, they use regional linguistic diversity as their instrument to estimate the effect of language on productivity. Like others (Guisoet al., 2009), they argue that linguistic diversity is a good proxy for cultural distance. Thus, their linguistic diversity measure implicitly contain cultural differences. In their main OLS specifications, they find that a one standard deviation increase in diversity is associated with about 1.3% decrease in productivity, while the 2SLS estimates are twice this size.

3. Measuring linguistic diversity

The main contribution of our paper is that we use a more fine-tuned and precise measure of linguistic 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

[4] These measures are influenced by Pemberton et al.'s (2013) work on microsatelite variation, which differs from measures based on classic genetic markers such as Cavalli-Sforza (1994).

[5] In Becker's theory employer-discrimination is costly and detrimental to productivity, and over time these employers are forced out of business. With search frictions employers' profits from discrimination (Rosén 2003). The same is found in Lang (1986), where the transaction costs induced by language diversity is born by the minority group, while employers reap profits as compensation for hiring minority workers. As Bodvarsson and Partridge (2001) show, the interaction of employer, co-worker and customer discrimination is complex.

[6] Fry et al (2001) argue that understanding the spoken word is crucial, because reading, writing and speaking ability is not significant predictors of immigrant wages in the U.S.

[7] 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.

majority language in their country of origin belongs to, and then link this to a diversity measure (e.g., the Herfindahl index as in Parrotta et al.). 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 Judgement Program (ASJP) to measure the language proximity between all pairwise language combinations in our data (Brown et al., 2008; Wickmann et al., 2018). 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.[8] For instance, the proximity score for the Norway-Sweden pair is 0.62, compared to 0.12 for the Norway-Poland score. These differences reflect that it is much easier for a Norwegian and a Swede to understand each other than for a Norwegian and a Pole.

Fig. 1a) and 1 b) illustrate the linguistic variance in our data of the Norwegian workforce. Figure a) shows that both in 2004 and 2012 many immigrant languages have a low proximity to Norwegian, thus, transaction costs might be important, but that some large immigrant groups have close proximity to Norwegian (the size of circles expresses the relative prevalence of a group within year). 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.[9]

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 made available to us comprise the full Norwegian population of workers, workplaces, and firms during the years 2001–2012 (around 2500,000 worker observations each year, recent years available today). 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% 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 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 the majority language of 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 we interpret as the expected dissimilarity between two individuals drawn at random.[10] More specifically, ignore the time indicator and just let n_f denote the number of employees at workplace f. Let J_{CD} denote the index of language proximity (AJSP) described above, where C and D denote workers' language groups C and D. When $C = D$ then $J_{CD} = 1$. Then our workplace index of linguistic diversity at the workplace can be expressed (i(C) and j(D) denote workers employed by workplace f):

$$\delta_f = 1 - \left(\frac{1}{n_f^2}\right)\sum_{i=1}^{n}\sum_{j=1}^{n} J_{i(C)j(D)}. \qquad (1)$$

On one hand, this measure implies a certain substitutability. Potentially one might get the same value for a combination of workers speaking a language slightly different from Norwegian as a combination of one worker speaking a language very different from Norwegian and several Norwegians. On the other hand, one does not have impose artificial limitation laws, arguing that certain combinations or mixtures of languages perform differently than others.

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) = $\alpha_0 + \alpha_1 J_{iN} + \alpha_2$Years since arrival$+\alpha_3 J_{iN}{}^*$ Year since arrival $+ \varepsilon$, where ε expresses an error term, J_{iN} denote the linguistic proximity index between country i and Norwegian, and I() denote an indicator function.

We can then predict the average time (years) to when no worker report bad Norwegian proficiency as: $Y_i{}^0 = [-\alpha_0 - \alpha_1 J_{iN}]/[\alpha_2 + \alpha_3 J_{iN}]$. Our estimates of the α's are: $\alpha_0 = 0.1838$, $\alpha_1 = -0.1579$, $\alpha_2 = -0.0006, \alpha_3 = -0.0439$.[11] Thus $Y_i{}^0$ varies between immigrants' country of origin.

However, the time no worker reports bad Norwegian proficiency and the time when an immigrant from country i is able to communicate well in Norwegian (costless in productivity terms) are not necessary the same. Thus we define the time an immigrant from country i is able to communicate well in Norwegian (costless in productivity terms) as $Y_i{}^* = gY_i{}^0$, where $g \in \frac{1}{4}, \frac{1}{2}, \frac{3}{4}, 1$. For languages closest to Norwegian, this means that an immigrant speaks sufficiently good Norwegian (costless in productivity terms) in 1–3 years. For languages most different to

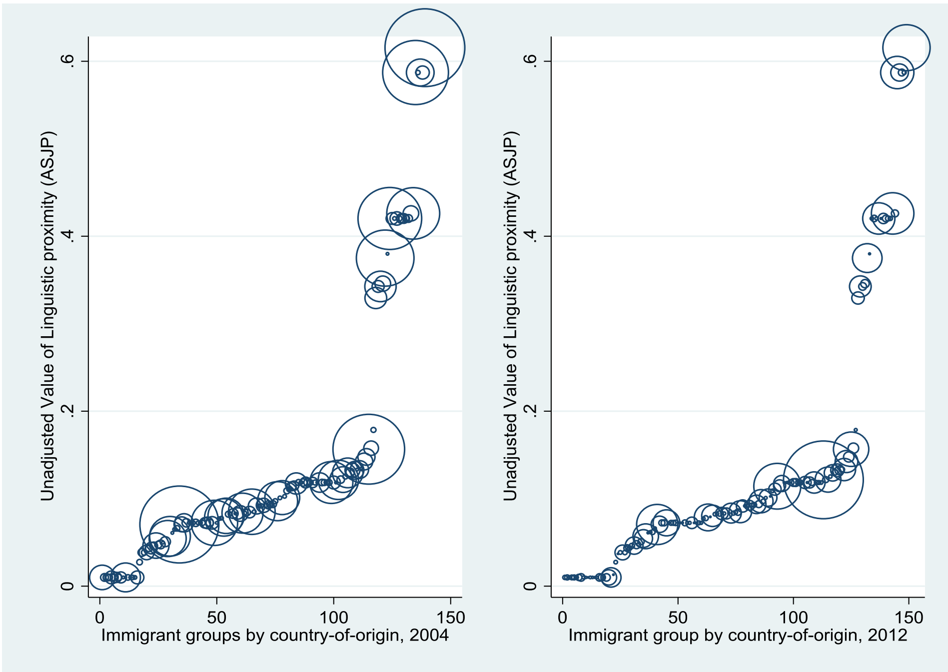
[8] For multilingual countries, the index assigns the most prevalent native language, excluding lingua francas. The AJSP program has been evaluated quantitatively and qualitatively by experts, and has been found to perform well, although qualitative expert classification of Austronesian has deviated slightly. However, Wichmann and Rama (2018) link this, at least partly, to expert inaccuracies under classification of Austronesian.

[9] 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.

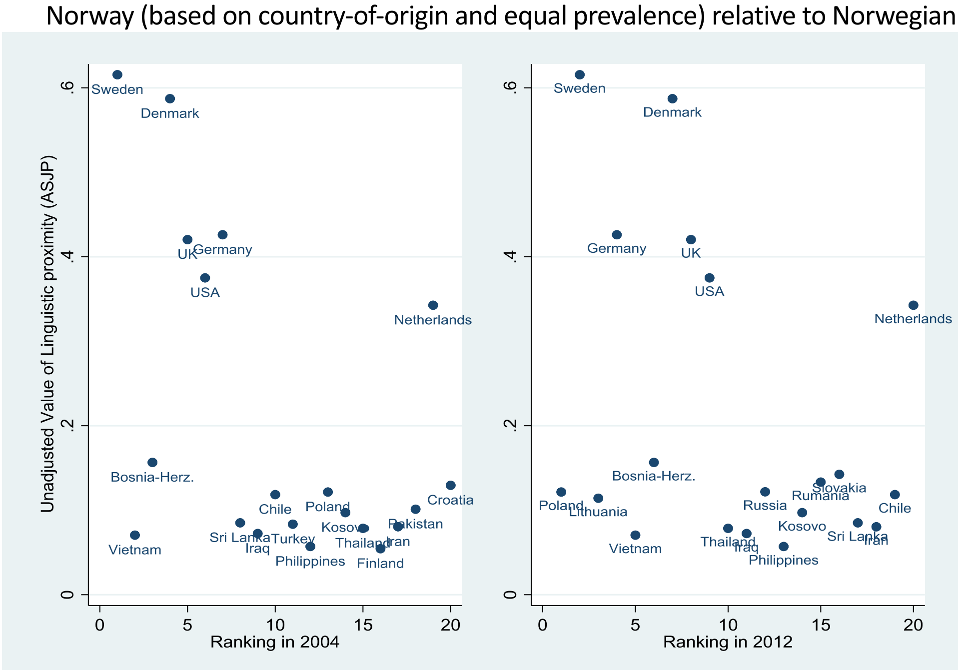
[10] If one instead focused on measuring the difference using dichotomous distances between distinct groups, the diversity measure would collapse to the Herfindahl index, as applied by, for instance, Parrotta et al. (2014).

[11] Unfortunately, this regression has a rather low R^2 of 0.02, but this is partly caused by few explanatory variables.

Fig. 1. Linguistic proximity of country-of-origin groups present in the Norwegian workforce. (a) Distribution of the linguistic proximity of the languages of immigrants group in Norway (based on country-of-origin and equal prevalence) relative to Norwegian. (b) Linguistic proximity and ranking according to the size of immigrant groups defined by country-of-origin in the Norwegian economy.



a) Distribution of the linguistic proximity of the languages of immigrants group in Norway (based on country-of-origin and equal prevalence) relative to Norwegian.



b) Linguistic proximity and ranking according to the size of immigrant groups defined by country-of-origin in the Norwegian economy.

Norwegian, depending on the choice of g, this then vary between 5 and 35 years.

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_i^*, otherwise it is zero. We consider all Norwegians as proficient in Norwegian. The workplace average of this dummy then measures the share of workers with expected sufficiently good Norwegian proficiency.

Admittedly, neither do we observe how quickly each immigrant learns Norwegian, nor do we observe when immigrants are sufficiently fluent in Norwegian so the communication costs drops to zero. However, by studying this at the group-level (country-of-origin) for different

Table 1
Descriptive statistics on key variables over time.

Year	LnValue added	LDI_all	LDI-low	LDI-high	Share Norw. proficiency	Share Eng. Proficiency	CDI	RDI	GEN	REL
2003	9.18	0.080	0.059	0.078	0.212	0.498	0.037	0.037	0.033	0.085
	(1.29)	(0.116)	(0.117)	(0.128)	(0.355)	(0.479)	(0.054)	(0.057)	(0.135)	(0.213)
2004	9.25	0.077	0.056	0.078	0.204	0.481	0.036	0.035	0.031	0.080
	(1.28)	(0.115)	(0.115)	(0.125)	(0.350)	(0.479)	(0.053)	(0.059)	(0.131)	(0.203)
2005	9.30	0.078	0.057	0.076	0.205	0.486	0.037	0.036	0.032	0.084
	(1.29)	(0.115)	(0.116)	(0.125)	(0.350)	(0.480)	(0.054)	(0.056)	(0.131)	(0.209)
2006	9.39	0.087	0.063	0.084	0.206	0.508	0.040	0.040	0.034	0.096
	(1.31)	(0.124)	(0.125)	(0.132)	(0.349)	(0.478)	(0.057)	(0.060)	(0.135)	(0.223)
2007	9.50	0.098	0.073	0.094	0.203	0.540	0.046	0.045	0.032	0.101
	(1.32)	(0.130)	(0.133)	(0.139)	(0.340)	(0.474)	(0.059)	(0.062)	(0.118)	(0.220)
2008	9.47	0.113	0.084	0.111	0.186	0.568	0.054	0.052	0.036	0.118
	(1.29)	(0.137)	(0.141)	(0.151)	(0.322)	(0.467)	(0.064)	(0.067)	(0.118)	(0.226)
2009	9.40	0.126	0.089	0.125	0.180	0.589	0.060	0.057	0.038	0.136
	(1.28)	(0.147)	(0.146)	(0.160)	(0.316)	(0.464)	(0.069)	(0.070)	(0.121)	(0.242)
2010	9.41	0.137	0.091	0.136	0.173	0.601	0.065	0.061	0.040	0.141
	(1.32)	(0.156)	(0.151)	(0.169)	(0.310)	(0.461)	(0.073)	(0.073)	(0.123)	(0.240)
2011	9.45	0.147	0.096	0.145	0.171	0.612	0.070	0.065	0.046	0.153
	(1.30)	(0.162	(0.156)	(0.175)	(0.307)	(0.458)	(0.076)	(0.075)	(0.134)	(0.247)
2012	9.49	0.158	0.104	0.154	0.170	0.633	0.075	0.069	0.045	0.153
	(1.32)	(0.166)	(0.164)	(0.177)	(0.306)	(0.452)	(0.079)	(0.076)	(0.124)	(0.242)
2013	9.51	0.168	0.111	0.164	0.169	0.648	0.080	0.073	0.048	0.165
	(1.36)	(0.171)	(0.170)	(0.180)	(0.297)	(0.445)	(0.081)	(0.079)	(0.124)	(0.242)

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 (alt. $\frac{1}{2}$, see text). 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 Baker's (2000)' definitions. GEN and REL express indices of weighted genetic and religious diversity as measured by the measures of Spolaore and Wacziarg (2016, 2018).

assumptions, we can analyse the issue of varying Norwegian proficiency over time in Norway.

We also incorporate the average years of living in Norway 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 linguistic 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, Spolaore and Wacziarg, 2016, 2018). To examine this possibility, we examine how sensitive the linguistic diversity coefficient is to controls for workplace cultural diversity.

We use two sets of measures. First, we apply 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).[12] 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 lesbians and gender equality, and rising demands for participation in decision-making in economic and political life. Second, we use data from Spolaore and Wacziarg (2016, 2018), which measures are influenced by Cavalli-Sforza et al. (1994) and Pemberton et al. (2013). First, we use the weighted F_{st} genetic distance measure expressing the expected genetic distance between two randomly selected individuals, one from each country. This measure, on the country-level, takes into account that many countries are made up of sub-populations that are genetically distant. Second, following Spolaore and Wacziarg (2015), we use the weighted religious distance measure from Mecham et al. (2006), which expresses the expected religious distance between two randomly selected individuals, one from each country. Note that our primary interest is not in how these measures of diversity and cultural distance influence productivity, but we add these measures as control variables to avoid the potential confounding impact from these when we study the impact of lingustic diversity on productivity. Such confounding impacts could be caused directly by genetic, religious and cultural diversity, but also indirectly through employer, co-worker and customer discrimination on these features. We also recognize that some immigrant groups might have cultural values that differ from a random person from their country of origin.

Cultural diversity related to 1) traditional, 2) to self-expression, 3) to genetic variation, and 4) religion at the workplace are based on these four inputs, to construct workplace-level indices of cultural diversity for both dimensions, using the same fractionalisation approach as for linguistic diversity.[13]

As a backdrop to our productivity analyses, Fig. 3 and Table 1 reveal the changing diversity amongst the Norwegian Manufacturing sector over time. We find that, on average, Norwegian firms are quite homogenous. The average score on the workplace linguistic diversity across the years we study is 0.11 with a standard deviation of 0.14, but we have

[12] See Ashraf and Galor (2013) for an application in economics.

[13] The WVS do not cover all countries in our study. We replace missing country observations with the mean score for the respective continent. The two WVS-mesaures are highly correlated with our linguistic diversity index (correlation coefficients of 0.9). Also the Spolaore and Wacziarg (2015)-measures are positively correlated with linguistic diversity, but less (correlation coefficients of 0.4-0.5). These four cultural diversity measures are also strongly correlated (correlation coefficients of 0.4-0.5).

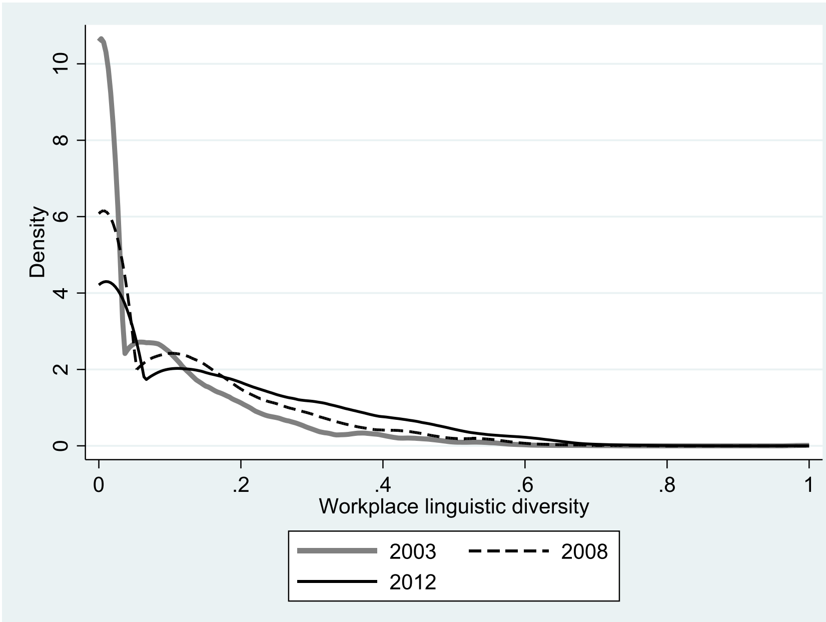


Fig. 2. The development of workplace linguistic diversity over time
Note: Kernel density plots of yearly distributions of the workplace linguistic diversity.

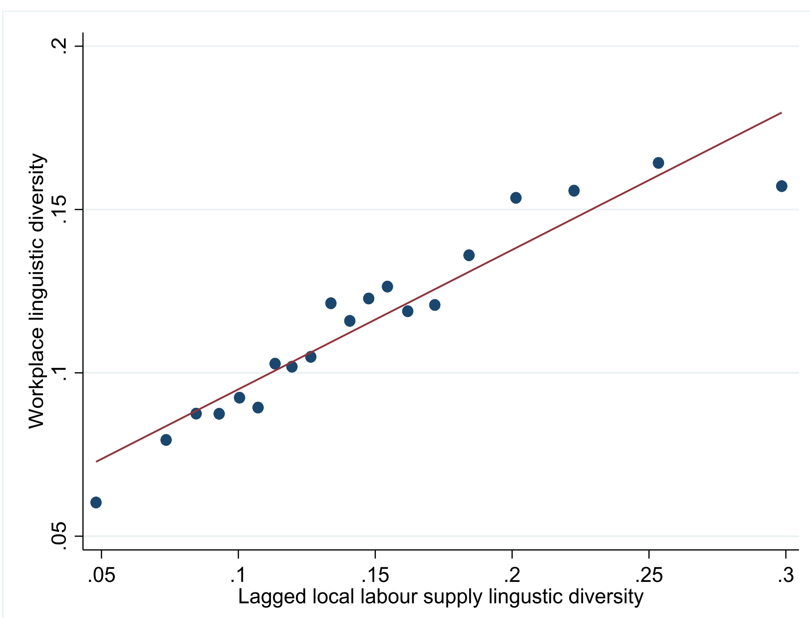


Fig. 3. The correlation between workplace linguistic diversity and lagged local labour supply linguistic diversity
Note: The figures are based on averages of 20 equal-sized binned observations of the workplace linguistic diversity and lagged labour supply linguistic diversity (labour supply within a 100 km radius of the workplace), 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.

observations across the whole range of the index. Moreover, the average linguistic diversity changes substantially across the years we study, from 0.08 in 2003 to 0.16 in 2012, a change that amounts to 60% of the standard deviation in 2002 Fig. 2.

Fig. 2 plots the distribution (density) of the workplace linguistic diversity across workplaces for years 2003, 2008 and 2012. Fig. 2 reveals that the overall the distributions shift towards greater diversity.

However, it is not only linguistic 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 with respect to cultural and secular diversity is Norwegian manufacturing workplaces quite homogeneous.

The appendix includes a description of all variables used in the analysis (see Table A3) as well as descriptive statistics (see Table A1). Control variables of minor importance are explained in the text as they are introduced.

5. Empirical approach

Consider the following simple Cobb-Douglas production function:

$$Y_{it} = Ae^{\omega_i + u_{it} + \gamma_t + \beta^{\delta}\delta_{it}}\left(L^N_{lsit} + \beta^{Nhs}L^N_{hsit} + \beta^{Ils}L^I_{lsit} + \beta^{Ihs}L^I_{hsit}\right)^{\beta^L} K_{it}^{\beta^k}, \quad (2)$$

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 linguistic 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

Table A1
Descriptive statistics. $N = 39{,}885$.

	Mean	Standard deviation	Name	Mean	Standard deviation
Log value added	9.418	1.297	Linguistic diversity	0.115	0.145
Log total capital	7.963	2.177	Linguistic diversity –low	0.081	0.142
Log intermediates	9.824	1.614	Linguistic 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	Diversity Genetic	0.038	0.126
Share high-skill immigr.	0.024	0.052	Diversity Religion	0.120	0.230
Share high-skill natives	0.151	0.167	Linguistic div.-Herfindahl	0.145	0.173
Workforce age	43.449	4.761	Linguistic div.-Parrotta	0.126	0.165
Hiring rate	0.130	0.145	Linguistic div.-Parrotta-low	0.091	0.163
Diff Age-Years since arrival	2.448	3.859	Linguistic div.-Parrotta-high	0.125	0.179
Good Norwegian proficien. $\frac{1}{4}$	0.400	0.446	Good Norwegian proficien. $\frac{1}{2}$	0.588	0.441
Good Norw. prof. centred $\frac{1}{4}$	0.000	0.446	Good Norw. prof. centred $\frac{1}{2}$	0.000	0.441
Good Norwegian proficien. $\frac{3}{4}$	0.215	0.348	Good Norwegian proficien. 1	0.181	0.325
Good Norw. prof. centred $\frac{3}{4}$	0.000	0.348	Good Norw. prof. centred 1	0.000	0.325
			Good English proficiency	0.968	0.071
			Good English prof.centred	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. Good Norwegian proficiency is estimated for 4 time alternatives (alt. $\frac{1}{4}$, $\frac{1}{2}$, $\frac{3}{4}$ and 1, see text). Measured for the immigrant population only, good Norwegian proficiency and good English proficiency are 0.18 and 0.54 respectively. The centred variables are measured as deviation from global mean. Cultural and religious diversity are measured either by Inglehart and Welzel's (2005) two measures as reported in the World Value Surveys (secular and self-expression) or by the genetic and religious diversity measures of Spolaore and Wacziarg (2016, 2018).

Table A2
The impact of lagged linguistic diversity of the local labour supply on linguistic diversity.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Lagged labour supply LD-index	0.428***	0.242***	0.238***	0.032*	0.080***	0.118***	0.157**	0.278***
	(0.037)	(0.044)	(0.042)	(0.017)	(0.028)	(0.020)	(0.063)	(0.051)
Additional controls								
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Workforce comp. -basic			Yes	Yes				
Workforce comp. -extended				Yes				
Within (FE) workplace		Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry time-trends				Yes				
Method	OLS	FE	FE	FE	FE	FE	FE	FE
Population:	All	All	All	All	All	All	Low hiring	High hiring
Workplaces(F)	3995	3995	3995	3995	3995	3995	3995	3995
Observations(FXT)	29,991	29,991	29,991	29,991	29,991	29,991	29,991	29,991

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. dependant variable: Models 1–4, 7–8: the workplace language diversity index. Model 5: the workplace linguistic diversity index for low educated workers; Model 6: the workplace linguistic diversity for high-educated workers. Controls: Note that lagged labour supply linguistic diversity indexes in models 5 and 6 are measured for low-educated and high-educated workers, respectively. Workforce composition-Basic controls for log workforce size and share of high-educated workers. Workforce composition-extended controls for log capital, share high-educated immigrants, share low-educated immigrants, share high-educated domestic workers, log total hours, linear time trend share low-educated immigrants, linear time-trend share high-educated immigrants, linear time-trend share high-educated domestic workers, and the genetic diversity and the religious diversity indice of Spolaore and Wacziarg (2016, 2018). OLS denotes ordinary least square regressions, FE denote fixed effects regressions based on the within transformation. Robust standard errors adjusted for workplace-level clustering are reported in parentheses. In models 7 and 8, the regressions are estimated on selected sub-populations: Low hiring denotes workplaces with no more than 8% yearly hiring rate, while High hiring denotes workplaces with more than 8% yearly hiring rate. ***, ** and * denote significant at the 1, 5 and 10% level of significance, respectively.

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 linguistic diversity on productivity.

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

$$L^N_{lsit} + \beta^{Nhs} L^N_{hsit} + \beta^{Ils} L^I_{lsit} + \beta^{Ihs} L^I_{hsit}$$

$$= L_{it}\left[1 + \left(\beta^{Nhs} - 1\right) l^N_{hsit} + (\beta^{Ils} - 1) l^I_{lsit} + \left(\beta^{Ihs} - 1\right) l^I_{hsit}\right],$$

where $l^m_{nit} = \frac{L^m_{nit}}{L^m_{nit}}$ and m ∈ (N, I) and n ∈ (ls, hs), i.e., the low-case l denote the labour share. Furthermore, note that

$$\ln\left[1 + \left(\beta^{Nhs} - 1\right) l^N_{hsit} + (\beta^{Ils} - 1) l^I_{lsit} + \left(\beta^{Ihs} - 1\right) l^I_{hsit} \approx\right]$$

$$\left(\beta^{Nhs} - 1\right) l^N_{hsit} + (\beta^{Ils} - 1) l^I_{lsit} + \left(\beta^{Ihs} - 1\right) l^I_{hsit}.$$

Thus we transform Eq. (2) into its log-equivalent:

$$lnY_{it} = lnA + \beta^{\delta}\delta_{it} + \beta^{L} lnL_{it} + \beta^{k} lnK_{it} + \left(\beta^{Nhs} - 1\right) l^N_{hsit}$$

Table A3
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 linguistic 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.
Workplace linguistic diversity (Parrotta et al., 2014): average linguistic distance between two randomly chosen employees at the workplace, constructed based on language groups and the Herfindahl-index.
Workplace linguistic diversity-Herfindahl: the reverse of the Herfindahl-Hischman index based on workers' country of origin and the majority language in these countries (ignoring the linguistic proximity between languages).
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.
Diversity genetic: The average genetic distance in the workplace is based on of Spolaore and Wacziarg (2016, 2018)'s weighted Fst genetic distance measure expressing the expected genetic distance between two randomly selected individuals, one from each country, and constructed as a generalized fractionalization index.
Diversity religious: The average religious distance at the workplace is based on the weighted religious distance measure from Mecham et al. (2006) as recommended by Spolaore and Wacziarg (2015), which expresses the expected religious distance between two randomly selected individuals, one from each country, and constructed as a generalized fractionalization 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 so communication between natives and immigrants is costless at alternative values of time to perfect proficiency of Norwegian: $\frac{1}{4}$, $\frac{1}{2}$, $\frac{3}{4}$, and 1. 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).

$$+\ (\beta^{Ils}-1)\ l^{I}_{lsit}+\left(\beta^{Ihs}-1\right)l^{I}_{hsit}+\omega_{it}+u_{it}+\gamma_t \tag{3}$$

In Eq. (3) β^{δ} expresses how linguistic 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 (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 et al. (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: $\omega_{it}=E(\omega_{it}\ |\Omega_{\text{it}-1})+\xi_{\text{it}}=E(\omega_{it},|\omega_{it-1})+\xi_{\text{it}}=g(\omega_{it-1})+\xi_{\text{it}}$. However, we also estimate the relationship using the Ackerberg et al. (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 linguistic 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 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.[14]

[14] This approach takes into account the possibility that some workplaces were on different productivity trends a priori, and when labour migration increases

Finally, another difficult estimation problem we address is the *potential endogeneity of linguistic 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 linguistic 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 Eq. (2)) by OLS. We address these issues using 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 linguistic diversity measure as an endogenous variable and let this be instrumented or determined by lagged regional language diversity.[15] This approach is similar to Parrotta et al. (2014), which uses lagged linguistic diversity within commuting zones as instrument for workplace linguistic diversity. By shifting the labour supply curve one identifies labour demand characteristics.[16] 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.[17]

Third, as described in Section 4, we use two kinds of data on cultural distance. First, we use data from Spolaore and Wacziarg (2016, 2018), to measure the weighted (expected) genetic distance between two randomly selected individuals, one from each country, and a similar measure on the weighted religious distance. Second, we apply 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). Our regressions then comprise these cultural diversity measures in addition to our workplace linguistic diversity measure.

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

6. The relationship between workplace linguistic diversity and the linguistic diversity of the local labour supply

In this section, we examine the relationship between the linguistic diversity of the lagged local labour supply and the language diversity of the workplace. We assume a priori that this relationship should be positive, quite simply since when an employer recruits workers to jobs at the workplace, they pick workers from the local labour supply. To shed light on this issue descriptively, we start by averaging 20 equal-sized binned observations of the workplace linguistic diversity and lagged language diversity of the local labour supply. A priori, we have residualized the data by applying a regression controlling for year dummies, thus measuring the relationships while taking into account variation across years. Fig. 3 presents this relationship. As evident from the figure, when the lagged linguistic diversity increases, so does workplace linguistic diversity.

To substantiate further that the relationship between the linguistic diversity of the lagged local labour supply and the linguistic diversity of the workplace is positive, in Table A2 in the appendix we present the results from several linear regressions. The linguistic diversity of the workplace is the dependant variable in all the regressions. The linguistic diversity of the lagged local labour supply is the key explanatory variable. We see that adding fixed workplace effects as well as industry time trends and workforce controls does not change the underlying positive relationship. We even estimate separate regressions for workplaces with high vs. low hiring rates, and observe positive relationships for both, but that the positive relationship is stronger for those with high hiring rates compared to those with low hiring rates.

7. Main empirical results

Our key question is how workplace productivity is affected by workplace linguistic diversity. To illustrate the relationship and the variation we use, we start by averaging 20 equal-sized binned observations of the linguistic diversity and log value added. Prior to binning, 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. Fig. 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 linguistic diversity.

Tables 2 and 6 presents our main results, while Tables 3–5 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 linguistic diversity 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 linguistic diversity index by 10% reduces value added by 1.2–1.3%.

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. In Model 7 we do not take into account that immigrant and natives might have different levels of educational qualifications.

The results are remarkably robust across these models. Increased linguistic diversity implies reduced value added, in the range of 1–1.6% for a ten percent increase in language diversity. In Model 6 we let linguistic diversity acts as an additional state variable, and let this be determined by lagged linguistic diversity within the workplace's region of labour supply. This model might be interpreted as a specification where we shift the labour supply curve to identify labour demand characteristics. We still see a negative impact on value added from increased linguistic diversity, but the negative impact becomes thrice as strong as the previous results.[18] In Model 8 we repeat the analysis of Model 3, but

from 2005 and onwards, immigrant groups simply sorted into workplaces on lower productivity trends, thus yielding a negative relationship between diversity and productivity.

[15] This implies that the first-order Markov process can be written: $\omega_{it} = g(\omega_{it-1},\ \delta_{it-1}) + \xi_{it}$, and thus takes into account firms updating their expectation of the productivity level and adjust their investments based on the optimal level of the linguistic diversity.

[16] Admittedly, this approach entails a weakness in that the exploited variation does not rest on a random experiment or on an exogenous reform. Some of criticism that has been raised against the shift-share-instrument (Jaeger et al., 2019; Goldsmith-Pinkham et al., 2019) might thus be relevant in our case as well. The central identification worry is that the lagged labour supply linguistic diversity predict value added through channels other than we posit. This could be the case e.g., if local technology or business opportunities entail long-term changes to the local labour supply's linguistic diversity, through a lengthy process. We have also applied instruments based on futher lags of the local labour supply's linguistic diversity. This yields comparable estimates to those that we presents. Of course, if the process very lengthy, this would still constitute a problem. To a certain degree, however, this will be taken care of when we control for skill-related productivity trends in some of the specifications.

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

[18] This might seem as an overly strong negative impact. However, remember that if the treatment effects are heterogeneous, the negative effects obtained

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

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
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)		
LD-index (Parrotta)								−0.166***	−0.025
								(0.037)	(0.055)
Share low-educated imm.	0.022	0.246***	0.116**	0.046***	0.162***	0.171***		0.140**	−0.015
	(0.056)	(0.061)	(0.057)	(0.003)	(0.060)	(0.062)		(0.050)	(0.076)
Share high-educated imm.	0.535***	0.506***	0.424***	0.565***	0.338***	0.476***		0.468***	0.298***
	(0.080)	(0.092)	(0.073)	(0.008)	(0.084)	(0.076)		(0.070)	(0.088)
Share high-educated natives	0.752***	−0.094***	0.521***	0.769***	−0.029	0.510***		0.521***	0.522***
	(0.023)	(0.035)	(0.021)	(0.003)	(0.033)	(0.021)		(0.021)	(0.021)
Log employment	0.952***	0.797***	0.684***	0.974***	0.601***	0.676***	0.684***	0.685***	0.682***
	(0.006)	(0.011)	(0.005)	(0.018)	(0.011)	(0.005)	(0.005)	(0.005)	(0.005)
Log capital	0.088***	0.032***	0.060***	0.109***	0.025***	0.060***	0.060***	0.060***	0.060***
	(0.005)	(0.003)	(0.004)	(0.042)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
Share high-educated							0.500***		
							(0.020)		
Method	OLS	OLS	WRDG	ACF	WRDG	WRDG	WRDG	WRDG	WRDG
Within (FE) workplace		Yes			Yes				
State			LnCapital	LnCapital	LnCapital	LnCapital+LDI	LnCapital	LnCapital	LnCapital
Proxy			Ln materials	Ln materials	Ln materials	Ln materials	Ln materials	Ln materials	Ln materials
Polynomial			3	3	3	3	3	3	3
Excluded instrument						Lagged regional LDI			
Workplaces(F)	3995	3995	3995	3995	3995	3995	3995	3995	3995
Observations(FXT)	29,991	29,991	25,837	29,943	25,837	25,837	25,837	25,837	25,837

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. dependant 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 et al. (2005). In Model 6, lagged regional linguistic diversity is excluded in the second step and thus act as an instrument. See text for details. In Model 8, we measure linguistic diversity index by the Herfindahl-index based on language groups (see Parrotta et al., 2014). In Model 9, we measure linguistic diversity index by the Herfindahl-index based on the majority-language in a country. Robust standard errors adjusted for workplace-level clustering are reported in parentheses. ***, ** and * denote significant at the 1, 5 and 10% level of significance, respectively.

Table 3
The relationship between linguistic diversity and productivity: the importance of workplace and local labour market size.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
LD-index(LDI)	−0.103	−0.329***	−0.236**	−0.290**	−0.154***	−0.185***
	(0.086)	(0.118)	(0.095)	(0.146)	(0.077)	(0.061)
Population	Small workplaces and small labour market	Large workplaces and small labour markets	Small workplaces and large labour markets	Large workplaces and large labour markets	Low hiring	High hiring
In all models: All regressions are based on the WRDG method, using log capital as the state variable and applying log materials as additional proxy variable in a 3rd degree polynomial. All regressions include the additional variables: the share of native and domestic workers with high and low education, log capital and log employment.						
Workplaces(F)	1794	1448	1882	1628	1699	2296
Observations(FXT)	7150	6871	4045	3812	13,226	12,611

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. dependant variable: the residuals from the auxiliary regression. Small/large workplaces are defined as below/above the median in the workplace size distribution. Small/large labour markets are defined as labour markets below/above the median in the local labour market size distribution. Low/high hiring workplaces are workplaces below/above the median of the workplace hiring distribution. WRDG denotes Wooldridge GMM-approach (Wooldridge, 2009). Robust standard errors adjusted for workplace-level clustering are reported in parentheses. ***, ** and * denote significant at the 1, 5 and 10% level of significance, respectively.

replace our linguistic diversity measure by the language-group based Herfindahl- linguistic diversity measure of Parrotta et al. (2014). We

using IV recover the local average treatment effects (LATE), rather than the average treatment effect on the treated (ATT), and thus picks up the effect where it is strongest and only related to changes in linguistic diversity. As we will see in later tables, the negative impact of linguistic diversity on value added becomes more negative when controlling for measures of cultural diversity. 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 instrument these 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.

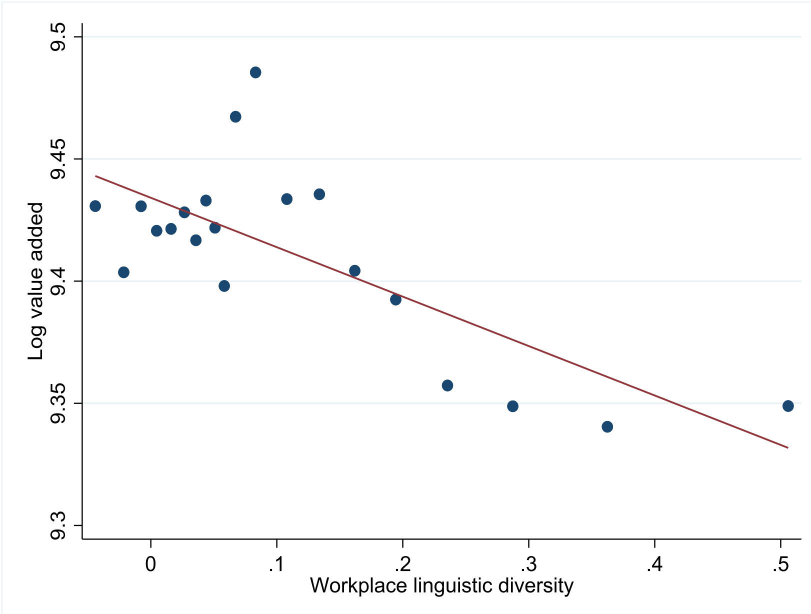


Fig. 4. The correlation between productivity and linguistic diversity
Note: The figures are based on averages of 20 equal-sized binned observations of the linguistic diversity and log value added, where one a priori has residualized data applying a regression controlling for year dummies and log workforce size, thus measuring the relationships while taking into account variation across years and workforce size.

Table 4
The relationship between linguistic diversity and productivity: the importance of cultural, genetic and religious diversity as confounding factors.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
LD-index(LDI)	−0.180***	−0.195***	−0.238***	−0.207***	−0.266***	−0.231***
	(0.048)	(0.072)	(0.075)	(0.075)	(0.076)	(0.076)
Genetic diversity	0.097***	0.086***			0.090***	0.077***
	(0.025)	(0.024)			(0.025)	(0.025)
Religious diversity	−0.027*	−0.024*			−0.022	−0.017
	(0.015)	(0.014)			(0.015)	(0.015)
WVS-self-expression			−0.142	−0.227*	−0.085	−0.181
			(0.130)	(0.129)	(0.133)	(0.133)
WVS-secular/religious			0.286***	0.249**	0.255**	0.225*
			(0.103)	(0.102)	(0.105)	(0.103)
Other controls						
Compositional prod. trend		Yes		Yes		Yes
In all models:						
All regressions are based on the WRDG method, using log capital as the state variable and applying log materials as additional proxy variable in a 3rd degree polynomial. All regressions include the additional variables: the share of native and domestic workers with high and low education, log capital and log employment.						
Workplaces(F)	3995	3995	3995	3995	3995	3995
Observations(FXT)	25,837	25,837	25,837	25,837	25,837	25,837

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. dependant 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 either by Inglehart and Welzel's (2005) two measures as reported in the World Value Surveys or by the genetic and religious diversity measures of Spolaore and Wacziarg (2016, 2018). 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% level of significance, respectively.

see that also this measure yields a negative impact of linguistic diversity on value added, which is comparable to Model 3's estimate. Finally, in Model 9 we repeat the analysis of Model 3, but replace our linguistic diversity measure with a simple Herfindahl-lingustic diversity measure based on the majority-language in countries (this measure ignores the linguistic differences between languages). When we ignore the linguistic differences between languages, the detrimental impact of linguistic diversity disappear, i.e., it is the linguistic proximity of languages that matters for productivity.

Thus, all our results indicate that increased linguistic diversity implies reduced productivity and value added.

Next, it might be reasonable to suspect that the costs and benefits to linguistic diversity might differ according to the workplace size and to the size of the local labour market. For example, our identification might exploit variation that occurs disproportionally in small workplaces, simply capturing the disruption of having new staff in a small team. Similarly, in small labour markets for large workplaces, one could assume that the marginal non-native speaker is more productive than the marginal native speaker. To address such issues, first we split our observations into four groups depending on whether the observation is below or above median workplace size and below or above the median size of the local labour market. Then we estimate model 3 of Table 2 sep-

Table 5
The impact of linguistic diversity on productivity: the importance of time in Norway, learning Norwegian, and universal language.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
LD-index(LDI)	−0.172***	−0.200***	−0.225***	−0.159***	−0.146***	−0.159***	−0.315**
	(0.049)	(0.049)	(0.057)	(0.073)	(0.059)	(0.059)	(0.055)
LDI X Diff. age-time of residence	−0.025***	−0.027***					
	(0.004)	(0.004)					
LDI X Share good Norw. language proficiency			0.323***	0.280***	0.280***	0.280***	
			(0.064)	(0.073)	(0.071)	(0.073)	
LDI X Share good English language proficiency							0.896***
							(0.168)
Difference age-time of residence	−0.009***	−0.007***	−0.006***	−0.009***	−0.008***	−0.009***	−0.011***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Share good Norw. language proficiency			0.056***	0.044***	0.053***	0.044***	
			(0.010)	(0.010)	(0.010)	(0.010)	
Share good English language proficiency							−0.326***
							(0.047)
Time to good Norwegian proficiency			1/4	1/2	3/4	1	
Other controls							
Genetic/religious diversity	Yes	Yes	Yes	Yes	Yes	Yes	
In all models:							
All regressions are based on the WRDG method, using log capital as the state variable and applying log materials as additional proxy variable in a 3rd degree polynomial. All regressions include the additional variables: the share of native and domestic workers with high and low education, log capital, log employment, compositional trend.							
Workplaces(F)	3995	3995	3995	3995	3995	3995	3995
Observations(FXT)	25,837	25,837	25,837	25,837	25,837	25,837	25,837

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. dependant variable: the residuals from the auxiliary regression. 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 (genetic) and religious diversity are measured by the measures of Spolaore and Wacziarg (2016, 2018). 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. Time to good Norwegian profiency then estimated for four time alternatives: $\frac{1}{4}$, $\frac{1}{2}$, $\frac{3}{4}$ and 1 of the time given by the 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% level of significance, respectively.

arately for these four groups.[19] Models 1–4 of Table 3 presents the results from these regressions.

We see that our estimates based on these restricted populations are always negative. For small workplaces operating in a small labour market, the estimate is not significant, but the point estimate is quite similar to what we found in Model 3 of Table 2. Due to the larger standard errors, this estimate is not significantly different from what we find for the other three groups, but we see that these point estimates are more negative. From Table 3, however, we can safely conclude that neither is our results driven by the small workplaces, nor does the results support the idea that a marginal non-native speaker is more productive than the marginal native speaker for large workplaces in small labour markets. In the final two models of Table 3, we estimate the model separately for high and low hiring workplaces (defined as above/below the median in the workplace hiring distribution). We see that this yields quite similar negative estimates. Thus, it appears that the negative impact of linguistic diversity on productivity is not related to workplace size, disruptions caused by new staff or the size of the local labour supply.

However, as discussed previously, we might worry that our results regarding linguistic diversity in reality is just a reflection of cultural diversity. Thus, in Table 4 we explore the importance of cultural diversity. We add as controls in our analysis, four measures of cultural diversity. Furthermore, to take into account that our linguistic 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. Table 4 reports the results from our regressions.

We see that the measures for cultural diversity to a varying degree correlates with value added, and some have positive correlations. The key finding, however, is that by adding these controls, we still find a negative impact of linguistic diversity on value added. Compared to most estimates in Table 2, the estimates in Table 4 imply that linguistic diversity is more detrimental to productivity when controlling for cultural diversity. Thus, we conclude that our results in Table 2 are not conflated with effects of genetic, religious or cultural diversity. We argue that this

[19] When splitting the observations depending on workplace size we admittedly conduct selections on an endogenous variable. Thus, these estimates are primarily to shed light on the correlations between diversity and size.

Table 6
The impact of linguistic diversity on productivity: skill-dependant effects.

	AJSP+gen.index			Herfindahl (Parrotta et al., 2014)	
	Model 1	Model 2	Model 3	Model 4	Model 5
LD-index low educated (LDI-L)	−0.067***	−0.080***	−0.060	−0.108***	−0.141***
	(0.024)	(0.033)	(0.033)	(0.027)	(0.030)
LD-index high educated (LDI-H)	−0.149***	−0.203***	−0.166***	−0.164***	−0.168***
	(0.028)	(0.034)	(0.035)	(0.029)	(0.031)
Genetic diversity low edu.			0.027		0.016
			(0.031)		(0.031)
Religious diversity low edu.			0.011		0.043***
			(0.015)		(0.016)
Genetic diversity high edu.			0.095***		0.080**
			(0.031)		(0.031)
Religious diversity high edu.			−0.021		−0.017
			(0.016)		(0.017)
Method	WRDG	WRDG	WRDG	WRDG	WRDG
State	LnCapital	LnCapital, LDI-L, LDI-H	LnCapital	LnCapital, LDI-L, LDI-H	LnCapital
Proxy	Lnmaterials	Lnmaterials	Lnmaterials	Lnmaterials	Lnmaterials
Polynomial	3	3	3	3	3
Excluded instruments		Lagged regional LDI-L/LDI-H	Lagged regional LDI-L/LDI-H		Lagged regional LDI-L/LDI-H
Other controls					
Log employ, log capital	Yes	Yes	Yes	Yes	Yes
Shares native/domestic workers, high/low educ.	Yes	Yes	Yes	Yes	Yes
Compositional prod. trend			Yes		Yes
Workplaces(F)	3995	3995	3995	3995	3995
Observations(FXT)	25,837	25,837	25,837	25,837	25,837

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. dependant variable: the residuals from the auxiliary regression. WRDG denotes Wooldridge GMM-approach (Wooldridge, 2009). In Models 1–3 language indices are calculated separately for low and high educated workers, based on AJSP and based on generalized indices of fractionalization. In Models 4–5 we estimate the linguistic indices based on language threes and apply the Herfindahl index (as Parrotta et al., 2014). In Models 2–3 and 5, 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 (genetic) and religious diversity are measured by the measures of Spolaore and Wacziarg (2016). 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% level of significance, respectively.

makes it less likely that our results are driven by discrimination of employers, wo-workers or customers.[20]

So far, we have implicitly assumed that immigrants do not learn Norwegian after arrival. This assumption is obviously false, and it might introduce measurement errors that biases our estimates. If people quickly learn Norwegian, our estimates will reflect confounding unobserved factors such as skills and ability. Moreover, 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 Sections 1 and 2) treat English as a Lingua Franca. English is particularly important in business and science.

To tackle these issues 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 expresses how much shorter time immigrants have been exposed to Norwegian than natives. Second, as described in Section 4, we estimate the share of the workplace's workforce expected to having learnt good Norwegian language proficiency (for 4 different time alternatives). 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 immigrants might learn each other languages as time goes by. 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. To ease interpretation, we measure good Norwegian and English proficiency and the linguistic diversity index as deviation from global mean, and interact these. Then we estimate regressions equivalent to Model 3 of Table 2 but with interaction terms added. Table 5 presents these results.

[20] Immigrants experience lower call-back rates than natives in field experiments in Norway (Midtbøen, 2016; Larsen and Di Stasio, 2019). This is the case also for second generation immigrants, who master the language.

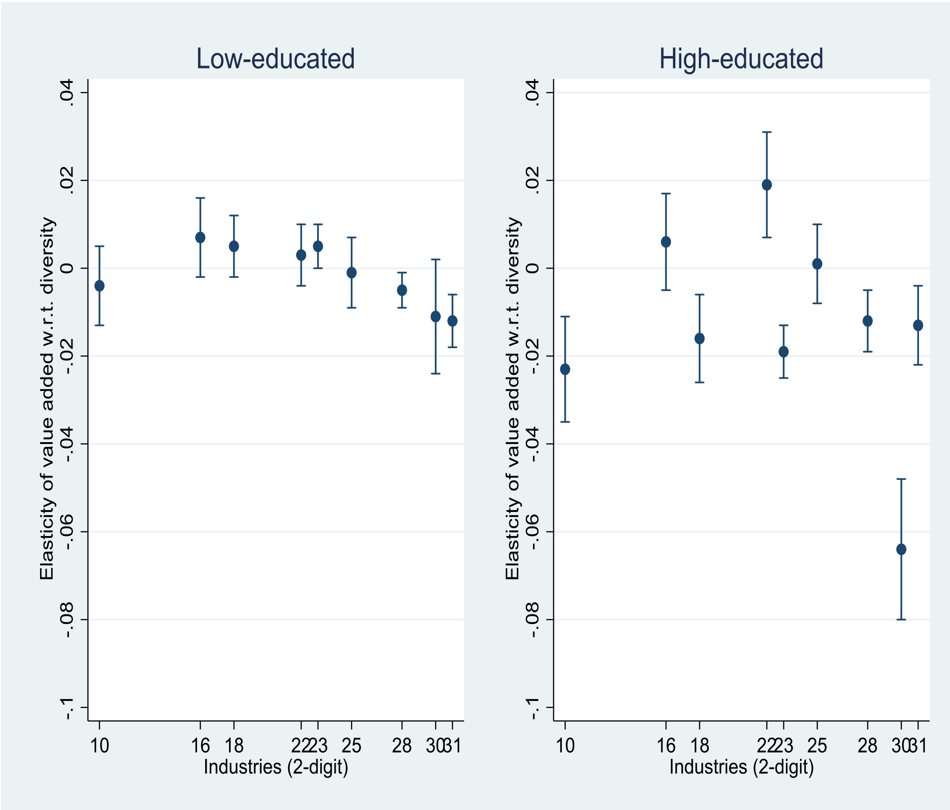


Fig. 5. The impact of linguistic diversity on productivity for selected industries
Note: The reported estimates and standard errors are from industry-specific regressions similar to Model 3 of Table 2, but where we measure linguistic diversity indices separately for low- and high-educated workers. The 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).

In Model 1 we interact the difference between age and time of residence with linguistic diversity, while controlling for workplace age, the difference between age and time of residence, the linear productivity time trends. Model 1 shows that the shorter time the workforce has been exposed to Norwegian, the more detrimental impact linguistic diversity is for productivity.

In Model 2, we repeat the analysis, but add in the diversity measures for genetic and religious diversity as controls. If our previous results follow from discrimination against non-native which is diminishing over time, then adding these controls should qualitatively change the estimated parameters of Model 1. We see, however, that they are qualitatively unchanged.[21] We argue that our findings strongly indicates that we observe diminishing (mis)communication costs.

Models 3, 4, 5 and 6 interact linguistic diversity with expected good Norwegian proficiency for the four alternative assumptions regarding the time it takes to master Norwegian sufficiently good. The biggest negative impact of linguistic diversity is when we assume that it is quick to learn Norwegian sufficiently good. However, in all cases, we find that as the share of the workforce expected to have good language proficiency increases, the detrimental impact of linguistic diversity reduces. When all workers are expected to be proficient in Norwegian, linguistic diversity no longer matter negatively for productivity.

In Model 7 we shift to study good English proficiency. We see that as workers are expected to be more proficient in English, the detrimental impact of linguistic diversity is reduced. However, even when all workers are expected to be proficient in English, still we find a negative impact.

Table 5 has shown that residence time matter, in that respect that as time goes by, most immigrants learn the native language, and linguistic 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 linguistic diversity. However, even the analyses of Table 5 clearly shows that linguistic diversity has a negative impact on productivity, at least for a time.

In the analyses so far, we have assumed that linguistic diversity has the same importance for low and high-skilled workers. This might not be the case. Thus, we estimate the linguistic diversity separately for low- and high-skilled workers. Next, we repeat several of the analyses of Table 2. The results are presented in Table 6. In Model 1, we add the linguistic diversity measures for low- and high-skilled workers. In Model 2, we treat these linguistic diversity measures as endogenous, and instrument these by the lagged regional linguistic diversity measures (similar to Model 6 in Table 2). In Model 3, we add linear productivity time trends and diversity measures for cultural diversity (religious and genetic diversity measured separately for low- and high-skilled workers). Then in Models 4–5 we repeat these regressions, but replace the linguistic diversity measures with the Herfindahl-based linguistic diversity measures of Parrotta et al. (2014).

The models mostly reveal the same pattern: when it comes to productivity, linguistic diversity is more detrimental for high skilled workers than for low-skilled workers. Increasing the language diversity for high-skilled workers by 10% reduces the workplace productivity by 1.5–2.0%. Similarly, increasing the linguistic diversity for low-skilled workers by 10% reduces the workplace productivity by 0.6–0.8%. Thus, even for this latter group linguistic diversity should not be ignored. Finally, we see that the Herfindahl-based linguistic diversity measures for the low-skilled yield considerably (significantly) higher detrimental impact on productivity, and smaller differences between high- and low-skilled workers when it comes to how linguistic diversity affects productivity.

Finally, since high- and low-skilled workers are employed to a different degree in different industries, we ask whether the language diversity has different impacts depending on type of industry. Therefore,

[21] We have even estimated Model 2 with cross-terms between genetic and religious diversity and the difference in age-time of residence (not shown), yielding identical estimates as those of Model 2.

we repeat the analysis in Model 3 of Table 2 separately for the 2-digit Manufacturing industries. Fig. 5 presents the results in the form of elasticities.[22] 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 linguistic diversity on productivity are, with one exception, all negative and mostly significant.

8. 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 due to migration. In this paper, we study the importance of related costs of diversity, namely those associated with linguistic diversity, and studied how such diversity influence productivity. In a workplace, linguistic 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 linguistic diversity at the workplace. We find that higher workforce linguistic diversity decreases productivity.

Our estimates are slightly smaller than what other researcher have found, when measuring the impact of linguistic diversity on productivity, but our linguistic diversity index measures truly language dissimilarity and not cultural or country differences. If we construct a linguistic diversity measure ignoring the linguistic proximity of languages the detrimental effect even disappears. Furthermore, our results survive even when we take into account cultural diversity along several dimension (genetic, religious and cultural). We argue that this makes our results less likely the consequences of discrimination by employers, co-workers and customers.

We find strong evidence supporting the notion that the improvement of proficiency in Norwegian of foreign workers since their time of arrival in Norway is important. Linguistic diversity does no longer matter when the expected proficiency in Norwegian is good. This clearly indicates that when we find linguistic diversity as detrimental to productivity, this is because of communication costs. Similarly, we find less detrimental impact of linguistic diversity as the share of workers expected to speak English well, increases.[23] The policy implication is that it is important to improve the language skills of immigrants.

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

[23] 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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