# Another Perspective on Discrimination: Incentives for Firms

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Name student: Patrick Barendse

Student number: 477735

Supervisor: prof.dr. HD Webbink

Second assessor: dr. J Delfgauw

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**Abstract**

By studying productivity differences, this paper aims to find out whether these differences could explain discrimination in the workplace. Productivity differences between subgroups of age, gender and nationality are estimated for different tasks that are performed in the firm that provided the data. The data includes 1578 labor migrants who work for a large firm in the agricultural sector. The results show some large significant differences between the subgroups. Especially if there is little information about new employees, these results and differences found in other studies could generate incentives to apply discrimination and therefore lead to discrimination in the workplace.

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# I. Introduction

Even though there is a general rejection towards discrimination (Collins, 2003) and discrimination is prohibited by law ("Algemene wet gelijke behandeling," 1994), there are still plenty events of discrimination which occur in the workplace (Lancee, 2019; Trentham & Larwood, 1998; Steinberg, Donald, Najman & Skerman, 1996)). This is exemplified by the American (EEOC, n.d.) and Dutch helpline for job application discrimination (Centraal Meldpunt Nederland, n.d.). Several studies have shown the need of this kind of helplines. Age discrimination (Shore & Goldberg, 2005; Steinberg et al, 1996), Racial discrimination (Lancee, 2019) and gender discrimination (Trentham & Larwood, 1998) are problems which still occur regularly.

Discrimination is generally prohibited by law ("Algemene wet gelijke behandeling," 1994), but there are a few exceptions for this rule such as objective justifications and positive discrimination ("Gelijkebehandelingswetgeving - Werving & Selectie Gids," n.d.). However, these exceptions are not relevant to this study. Therefore discrimination, described as "the unjust or prejudicial treatment of different categories of people, especially on the grounds of race, age, or sex." (Oxford University Press (OUP), n.d.), is in conflict with the law and therefore illegal discrimination.

One of the main problems that might occur related to discrimination, is that an expectation of productivity based on one of the grounds cannot be used in the selection process. If young men are expected to be relatively strong, an employer could have a preference for hiring relatively young male employees when the work requires physical strength. Even though the employer is allowed to select employees on physical strength, distinguishing between gender is not allowed. In this situation, it might not result into a problem, as the employer might have information about the physical strength of the employee. However, employers might not always have information about qualities of employees, causing a conflict between efficiency and law constraints. Even though this study will focus on workplace discrimination, the conflict described above also occurs in other parts of the society. An example of this is ethnic profiling by Dutch police agents (van der Leun & van der Woude, 2011). Even though certain groups of immigrants are overrepresented in crime statistics (Engbersen, Van der Leun & De Boom, 2007), it is not permitted to use ethnicity or nationality as criteria in police practices.

Several causes for discrimination will be addressed in this study, but the empirical part will solely focus on the predictive power of age, nationality and gender on productivity. By evaluating an incentive for discrimination in the workplace from an underexposed perspective, this study will contribute to this field of research. By understanding this cause of discrimination, policy can be improved to reduce discrimination in the workplace. An empirical study will be executed to find out whether these characteristics have a significant predictive power on productivity and could therefore be a cause of discrimination. This study does not review whether there is discrimination, but by evaluating the data, it will show whether there is an incentive to discriminate for firms.

The data is obtained from a large firm in the agricultural sector and it includes observations of 1578 employees. By performing a regression of productivity on the variables 'Age', 'Nationality' and 'Gender', the predictive power of these variables can be found. The productivity will be based on scores measured as kilogram per hour and plants per hour from 2019. These tasks are executed by full-time employees from different nationalities, genders and age groups. The tasks are relatively simple and therefore differences in these scores will be explained as differences in productivity. If a difference in productivity in this task can be explained by gender, age or nationality, then this shows that there might be an incentive to discriminate. Based on this empirical study and other literature, the incentive for discrimination for this firm and similar firms can be understood. This way, the main question of this study will be answered:

*Can differences in productivity generate incentives for discrimination?*

First, several views on causes of discrimination will be discussed. For the empirical part of this study, only the discrimination caused by the predictive power of age, nationality and gender will be evaluated. Then the data and the methodology of this study will be described. Following, the results of the empirical study will be evaluated. Based on this, the main question of this study will be answered. Lastly, the limitations, future research recommendations and recommend policy implementations will be discussed.

## II. Theoretical framework

In his book 'Capitalism and Freedom' Friedman (1962) states that competition in markets protects people from being discriminated. He argues that characteristics which are irrelevant to productivity as reason for not hiring employees reduces profits for firms. Therefore, the competition between firms will eventually force these discriminating firms out of the market, especially in free markets this is expected to occur (Friedman, 1962).

This would mean that if a protected characteristic is not relevant to productivity in a perfectly competitive market, that discrimination based on that characteristic does not occur. On the other hand, based on his reasoning discrimination will occur if and only if a protected characteristic such as gender, age or nationality is relevant to productivity. Protected characteristics are described in the British equality act and include age, disability, gender reassignment, race, religion or belief, sex, sexual orientation, marriage and civil partnership and pregnancy and maternity (Equality and Human Rights Commision, 2018). In most countries discrimination is usually regarded as unethical behavior (Collins 2003). When it is for economic reasons it is not always seen as unethical by majority groups (Valentine, 2010). Nevertheless, this sort of discrimination is also prohibited (Equality and Human Rights Commision, 2018). Despite this, it might still occur and this will be explained later in this section by the findings which Friedman (1962) provides.

The finding of Friedman (1962), that free markets protect people from being discriminated, conflict with multiple other studies that found other causes of discrimination. An example of this is the study of Trentham & Larwood (1998) who show statistical evidence of discrimination by gender, even when the productivity is equal. Shore & Goldberg (2005) who discuss age discrimination, also found conflicting outcomes. They found that age discrimination is partly caused by unfair stereotypes against older employees.

To understand the different findings about causes of discrimination, these causes should be divided in two categories. The first one is discrimination based on taste towards a group with protected characteristics. Becker (1957) described this phenomenon as taste-based discrimination. The second category is discrimination for economic reasons, that is discrimination based on different productivity expectations for protected characteristics. This type of discrimination can also be described as statistical discrimination, this is discrimination based on statistical differences in job-relevant factors between subgroups and therefore related to productivity (Arrow, 1973). Although both categories of discrimination are prohibited by law, acknowledging the difference between the two categories can be important for policy makers because of their different causes.

Taste-based discrimination causes firms to be inefficient and therefore we can expect markets to reduce this kind of discrimination (Friedman, 1962). But as mentioned before, competitive markets are not sufficient in eliminating this kind of discrimination (Shore & Goldberg, 2005; Trentham & Larwood, 1998). Even though there are ways to reduce this, there is little empirical evidence. An example of a way to reduce taste-based discrimination is given by Kontor (2018), who states that education reduces discrimination.

Applying statistical discrimination makes firms more productive. Therefore competitive markets do not reduce this type of discrimination (Friedman, 1962). Competition forces firms to produce efficiently, so if discriminating would increase productivity, free markets are even expected to stimulate discrimination. To test the relevance of statistical discrimination, it is essential to find out whether it is reasonable to expect different productivity based on protected characteristics. If this is not the case, then all discrimination would be taste-based discrimination.

Multiple studies have investigated subgroup differences, in which the groups are selected by protected characteristics. Ones & Viswesvaren (1998) have found significant differences by gender for outcomes of integrity tests, as well as by age. Although this does not necessarily correlate with productivity, it might be a reason for employers to select an employee. Hough, Oswald & Ployhart (2001) have investigated subgroup differences in cognitive ability, personality and physical ability. They find differences for the subgroups of age, gender and race. Especially cognitive ability might have a strong correlation with productivity. Ford, Kraiger & Schechtman (1986) provide evidence of differences of predictor tests and actual job performances between races. Based on these findings, significant differences in subgroups are expected.

The studies of Trentham & Larwood (1998) and Shore & Goldberg (2005), as well as multiple other studies that found discrimination in the workplace (Lancee, 2019; Shore & Goldberg, 2005; Steinberg, Donald, Najman & Skerman 1996), show the shortcomings of current anti-discrimination laws and regulations. Gollob (1984) states that it is difficult to have legal evidence that firms discriminate on race, sex, religion or nationality. He argues that firms can usually make up several justified reasons for not hiring or promoting an individual when the firm is actually discriminating.

Pager & Karafin (2009) have looked into the relationship between available information and discrimination. They argue that a lack of information about unobserved characteristics of job applicants increases statistical discrimination. Wood, Hales, Purdon, Sejersen & Hayllar (2009) have described these findings as followed:

> "Information is scarce when employers are making recruitment decisions. Knowing about the age and education of an applicant may be insufficient, given that the employer is also interested in other factors that influence productivity, such as motivation and social skills. In this situation, employers may rely on observable characteristics that they believe are correlated with the unobserved characteristics. The implication of this view is that employers are behaving in a manner that may appear rational (albeit what they are doing contravenes legislation on equal opportunities), rather than being motivated by 'preference-based' discrimination, when they make decisions that result in ethnic penalties."(Wood et al, 2009, p. 9)

The main conclusion that we can draw based on these findings is that when information about job applicants increases, statistical discrimination will reduce. If there are unobserved characteristics, then employers will base their expectations about these characteristics on observed characteristics. If these observed characteristics are protected characteristics, this will lead to statistical discrimination.

Even when statistical discrimination might increase productivity, managers might not always apply statistical discrimination. Besides the reason Gollob (1984) provided, there are also moral reasons why discrimination is undesirable (Collins, 2003). These reasons arise from a general aim for equal treatment.

Goodpaster (1991) and Trentham & Larwood (1998) argue that we cannot rely on managers morality if we want discrimination to disappear. Rational bias causes individuals to act differently as employee than as how they would act in their personal life. In the decision-making process as employee they might take preferences of clients and supervisors into account, which can result in treating certain groups unequally (Trentham & Larwood, 1998). The findings of Goodpaster (1991) are similar. He argues that managers do not make decisions based on their own preferences when these preferences conflict with the interests of their employee. Even though the findings of Goodpaster (1991) do not focus on discrimination particularly, the decision-making process which is described shows that morality of managers will usually not lead to moral behavior of their firm. In a hypothetical situation where discrimination would be to the interest of a firm, managers are expected to discriminate according to Goodpaster (1991) and Trentham & Larwood (1998). For this reason, we cannot rely on managers to stop discrimination, if discrimination would be beneficial to the firm.

The theory of statistical discrimination, as described by Arrow (1973), shows that discrimination can be beneficial to firms. The incentives to apply statistical discrimination show that current policies need improvement. Especially when information about job applicants is limited, profit-maximizing firms will be tempted to discriminate (Pager & Karafin, 2009). Even though managers might prefer not to discriminate, we cannot expect them not to apply discrimination when this is in the interest of the firm (Trentham & Larwood, 1998; Goodpaster, 1991). Last, the findings of Gollob (1984) show that in many situations, firms can apply discrimination without being punished, as a result of limitations of the anti-discrimination laws. Based on this, we can conclude that if discrimination is beneficial to firms, the disadvantages of discrimination are expected to be outweighed by the advantages in many situations. A difference in productivity between subgroups of protected characteristics is therefore expected to lead to discrimination.

Statistical discrimination is caused by other factors than taste-based discrimination and therefore reducing statistical discrimination might need another approach than reducing taste-based discrimination. In the empirical section, this study will focus on reasons for statistical discrimination. Possible solutions to this problem will therefore only apply to statistical discrimination. This does not necessarily mean that preventing taste-based discrimination is less important, but reducing this kind of discrimination requires other solutions.

# III. Data

For this study, a dataset from a large Dutch firm in the agricultural sector was obtained. This dataset includes productivity data of 2019. This contains productivity scores, measured as kilogram per hour or plants per hour for every week of the year. It also includes employee information, such as gender, nationality and age of the production workers. All of the workers in the sample are labor migrants. In the solicitation procedure, firms in this sector usually only refuse workers whenever they do not fit the requirements, which are ‘the ability to execute physical work’ and language skills in one of many languages. Because of the lenient criteria, which will not cause a problem for most jobseekers, there is little reason to expect discrimination in this process.

The comparison will be made for new workers only. This will be done to avoid multiple problems, such as the effect of experience on productivity and different wages. All workers start with the same hourly wage, so all workers in this dataset are assumed to have the same wage. The dataset contains 1578 foreign employees, aged between 18 and 57 and from 10 different nationalities.

For gender, we find that men represent approximately two third of the sample. The sample contains 544 female employees and 1034 male employees. Although this does not represent society, it represents the male/female ratio of labor migrants (Hitzert & van Wijk 2019).

For age, we find a distribution which is skewed to the right. This can be explained by the fact that all workers have to leave their home country, mostly without their family, which requires a certain maturity. Approximately half of the labor migrants are between 20 and 30-year-old (Hitzert & van Wijk, 2019), and this also seems to be the case in the sample (Table 1).

**Table 1**

*Age distribution of sample of migrant workers*

| | Frequency | Percentage | Cumulative |
|---|---|---|---|
| 18-21 | 258 | 16.35 | 16.35 |
| 22-25 | 373 | 23.64 | 39.99 |
| 26-29 | 273 | 17.30 | 57.29 |
| 30-34 | 230 | 14.58 | 71.86 |
| 35-39 | 160 | 10.14 | 82.00 |
| 40-49 | 252 | 15.97 | 97.97 |
| 50+ | 32 | 2.03 | 100.00 |

In most studies regarding workplace discrimination, race discrimination is tested. However, in our sample there is no information about races of employees and besides that, discrimination on nationality is more relevant in this sector. In the application process, in which firms usually do not know the race of the new employee, discrimination on race is usually not even possible. Discrimination on nationality however, could occur as firms and employment agencies choose where they want to hire new employees. As Table 2 shows, the majority of the employees are Polish or Romanian in this sample, so especially the productivity differences between these two nationalities will be relevant.

**Table 2**

*Nationality distribution of sample of migrant workers*

| Nationality | Frequency | Percentage |
|---|---|---|
| Bulgaria | 7 | 0.46 |
| CzechRepublic | 7 | 0.46 |
| Hungary | 8 | 0.52 |
| Latvia | 51 | 3.33 |
| Moldavia | 10 | 0.65 |
| Poland | 532 | 34.70 |
| Portugal | 1 | 0.07 |
| Romania | 890 | 58.06 |
| Slovakia | 23 | 1.50 |
| Ukraine | 4 | 0.26 |

Table 3 shows the multiple tasks (Appendix A) which are performed by the employees in the sample. All of the tasks are simple tasks and can be regarded as production work. Overall, nationality and age seem to be almost equally distrubeted for the most frequent tasks. However, in terms of gender, the tasks seem to be distributed unequally. The most frequent task, task E, seems to be the most representative for the firm, especially in terms of age. Task F is less representative, because it overrepresent male employees. Task A also does not represent the firm, as the share of female workers for this task is too large. Despite the unequal distribution of gender, productivity differences in tasks A, E and F will be investigated. The other tasks contain too little observations to include them in this study.

**Table 3**

*Gender, age and nationality distribution of the migrant workers per task*

| Task | Observations | Male | Average Age | Romania | Poland |
|---|---|---|---|---|---|
| A | 309 | 0.39 | 30.46 | 0.56 | 0.36 |
| B | 131 | 0.11 | 30.90 | 0.51 | 0.40 |
| C | 38 | 0.55 | 32.61 | 0.58 | 0.39 |
| D | 45 | 0.98 | 30.69 | 0.38 | 0.51 |
| E | 589 | 0.72 | 29.30 | 0.62 | 0.33 |
| F | 466 | 0.87 | 29.58 | 0.58 | 0.33 |
| **Total** | **1578** | **0.66** | **29.86** | **0.58** | **0.35** |

*Note.* The columns ‘Romanian’ and ‘Polish’ contain the share of workers from these countries; the column Male contains the share of male workers; see Appendix A for a specification of the Tasks.

In this dataset, the productivity in a certain week is represented by the productivity score, measured as harvested kilograms per hour or plants per hour on Wednesday in the specified week. The policy for this firm is that new employees start on Tuesdays. The productivity scores on this day might be subject to several problems not regarding employee productivity, such as unfamiliarity with firm policy and filling in paperwork. Therefore, Wednesday of week 1 represents the first day on which the productivity score can be regarded as the productivity.

The dataset also includes the variable ‘Weekrank’ which represents the number of weeks which the employees has worked since the observation took place. As the dataset only includes new employees, ‘Weekrank’ has the value 1 for the first observation of an employee, in other words the productivity score of his/her first week. For the regression, only the first five weeks will be studied. The reason for this is that there are many early quitters in this firm, approximately one third of the employees quits after 5 weeks. If a group is overrepresented in the group of early quitters, then this might affect the results. Especially because a part of the early quitters is caused by dismissals, which is likely to be correlated with low productivity. Also, as an employee works longer, uncertainty grows. Besides their main task, more experienced employees might perform other tasks, which can influence their productivity score. Moreover, when employees work at the firm for a longer time, their wages rise. For these reasons, only the first five weeks will be studied, even though this means that the effects on productivity only apply in the short term.

The firm is divided in different locations and different types of cultivations. The location is different for all kinds of cultivation. The cultivations represent the different products which are cultivated by the firm. Even though the tasks are similar for all cultivations, there might be differences caused by location and cultivations which affect the productivity score, such as the weight of the product and the state of the plants. Besides this, there are certain causes for differences in productivity scores which are related to a specific day or time period. These causes include all kind of differences, such as the weight of the product and the state of the plants. These differences are mostly time related differences, so they will be captured in the ‘Month’ variable.

## IV. Methodology

By studying differences in production scores between different subgroups, possible incentives for statistical discrimination will be illustrated. The empirical part of this study will show whether a firm can have incentives to discriminate on age, gender or nationality. Even though this firm does not represent all firms, or even all production firms, it mainly aims to illustrate a reason which firms might have for statistical discrimination. In this approach, the productivity score will be predicted based on the characteristic, this means that the estimate will not be the causal effect on the productivity score. However, the estimates should be interpreted as an effect of hiring a person with the certain characteristic. Equation I, Equation II and Equation III represent the function formulas of the regressions for Gender, Nationality and Age respectively. These regressions are performed to measure the estimates, so in these equations $\beta_1$ is the coefficient for the explanatory variable. In the three equations below, Y represents productivity.

**Equation I**

$$Y = \beta_0 + \beta_1 Gender + \beta_2 Cultivation + \beta_3 Weekrank + \beta_4 Month + \varepsilon$$

**Equation II**

$$Y = \beta_0 + \beta_1 Nationality + \beta_2 Cultivation + \beta_3 Weekrank + \beta_4 Month + \varepsilon$$

**Equation III**

$$Y = \beta_0 + \beta_1 Age + \beta_2 Cultivation + \beta_3 Weekrank + \beta_4 Month + \varepsilon$$

Besides the separate regressions, a fourth regression in which the variables ‘Age’, ‘Gender’ and ‘Nationality’ are all included is executed. This regression, described in Equation IV, will provide estimates of the association with productivity for the three variables. This regression will provide different estimates if the three variables appear to be correlated with each other. The coefficients $\beta_1$, $\beta_2$ and $\beta_3$, are for ‘Gender’, ‘Nationality’ and ‘Age’ respectively.

**Equation IV**

$$Y = \beta_0 + \beta_1 Gender + \beta_2 Nationality + \beta_3 Age + \beta_4 Cultivation + \beta_5 Weekrank + \beta_6 Month + \varepsilon$$

In Equation III, a linear relation between productivity and age is estimated. However, there is no reason to assume a linear relation. Therefore, a fifth regression will be executed. Age will be categorized in 7 dummy variables to find whether there is a significant differences between the age groups. The age groups are 18-21, 22-25, 26-29, 30-34, 35-39, 40-49 and 50+.

**Equation V**

$$Y = \beta_0 + \beta_1 Age + \beta_2 Cultivation + \beta_3 Weekrank + \beta_4 Month + \varepsilon$$

The regressions described by Equation I, II ,III, IV and V will be executed for the three tasks, task A, E and F, separately. This is because the productivity scores of these tasks are incomparable. The productivity of task A and E are measured in plants per hour and the productivity of task F is measured in kilograms per hour. As explained, 'Cultivation', 'Weekrank' and 'Month' are likely to affect the productivity score. Therefore, these three variables are included as control variables. The regression formula filters out the observations with a productivity score of zero. The reason for this is, that even if an employee is classified as a member of a certain task group, this employee could still perform another task that day. This does not mean that this person is actually unproductive, but according to the data the employee is. Therefore, these observations are filtered out. The variable 'Experience' represents how many days a worker has worked in 2018. Only productivity scores of new workers will be studied, so observations with a value higher than one for 'Experience' will be filtered out as well. As explained before, only the first weeks of the workers will be investigated, therefore only the productivity scores of the first five weeks of employees are used to estimate the productivity.

This empirical approach will show whether statistical discrimination could be beneficial for firms, only taking productivity into account. The productivity will be forecasted based on the three variables separately, and based on this can be concluded whether there is a significant difference between the groups. By doing this, we can find out whether it could be profitable for firms to recruit employees based on gender, nationality or age.

## V. Results

Although significant differences of productivity between the specified groups do not show discrimination, they show that firms are likely to get more productive by hiring specific groups of employees. Table 4 shows that only for task A a significant difference in productivity is estimated for gender. Male employees are expected to be more productive in task A. This finding is contradictive since there is an overrepresentation of female workers in task A (Table 3). Based on the higher productivity for male employees (Table 4), it would be logical for the firm to assign this task to more male workers, because generally they appear to be better at this task.

**Table 4**

*Regression estimates of the association between worker characteristics and productivity.*

| | Equation I | Equation II | Equation III | Equation IV |
|---|---|---|---|---|
| **Task A** | | | | |
| Male | 159.32***<br>(25.44) | | | 160.60***<br>(25.80) |
| Romanian | | -11.25<br>(24.25) | | -5.84<br>(23.98) |
| Age | | | 0.46<br>(1.28) | 0.27<br>(1.30) |
| Observations | 1194 | 1166 | 1194 | 1166 |
| $R^2$ | 0.33 | 0.32 | 0.31 | 0.35 |
| **Task E** | | | | |
| Male | -22.22<br>(19.89) | | | -23.31<br>(20.01) |
| Romanian | | 56.13***<br>(19.00) | | 57.47***<br>(19.49) |
| Age | | | 0.24<br>(0.80) | -0.19<br>(0.96) |
| Observations | 2210 | 2168 | 2210 | 2168 |
| $R^2$ | 0.26 | 0.27 | 0.26 | 0.27 |
| **Task F** | | | | |

| | | | | |
|---|---|---|---|---|
| Male | 4.84<br>(4.92) | | | 2.70<br>(5.08) |
| Romanian | | 18.00***<br>(3.48) | | 18.58***<br>(3.54) |
| Age | | | 0.04<br>(0.19) | -0.22<br>(0.21) |
| Observations | 1854 | 1769 | 1854 | 1769 |
| $R^2$ | 0.74 | 0.75 | 0.74 | 0.75 |

*Note.* See Appendix A for a specification of the Tasks; the reference group in Equation II and Equation IV is Polish employees; standard error in parentheses; *p<0.10, **p<0.05, ***p<0.01

Table 4 also shows that being from Romania has a significant effect on productivity for Tasks E and F. For both tasks, Romanian employees are expected to do significantly better than Polish employees. Based on this, Romanians are expected to do better overall. Age however, does not lead to any significant difference in productivity. All estimates for age are not significant, so based on this, no association between age and productivity can be made.

The insignificant results that were found for age could be caused by a non-linear relationship between age and productivity. To see whether that is the case, the regression described by Equation V is executed. Table 5 shows a few significant estimates, but only for task F. For this task, we find that employees between 22 and 39 years old seem to be the most productive. The younger and older ones are clearly less productive for this task, which also shows that there is no linear relation between age and productivity.

**Table 5**

*Regression estimates of the association between age categories of workers and productivity*

| | Equation V |
|---|---|
| **Task A** | |
| 22-25 | 33.29<br>(34.47) |
| 26-29 | 4.90<br>(38.19) |
| 30-34 | -51.92<br>(39.95) |
| 35-39 | 82.05*<br>(43.31) |

| | |
|---|---|
| 40-49 | 27.16 |
| | (40.54) |
| 50+ | -38.67 |
| | (65.57) |
| Observations | 1194 |
| $R^2$ | 0.31 |
| **Task E** | |
| 22-25 | -17.57 |
| | (24.61) |
| 26-29 | 27.26 |
| | (28.42) |
| 30-34 | -20.34 |
| | (29.29) |
| 35-39 | -1.33 |
| | (32.54) |
| 40-49 | 8.94 |
| | (28.03) |
| 50+ | -29.60 |
| | (59.61) |
| Observations | 2210 |
| $R^2$ | 0.26 |
| **Task F** | |
| 22-25 | 12.23** |
| | (5.06) |
| 26-29 | 9.41* |
| | (5.24) |
| 30-34 | 13.88** |
| | (5.85) |
| 35-39 | 13.00** |
| | (6.16) |
| 40-49 | 8.57 |
| | (5.84) |
| 50+ | -28.90* |
| | (15.11) |
| Observations | 1854 |
| $R^2$ | 0.74 |

*Note.* See Appendix A for a specification of the Tasks; the age category 18-21 is the reference group; standard error in parentheses; *p<0.10, **p<0.05, ***p<0.01

Even though not all estimates are significant, there are clear differences between tasks on how the characteristics affect productivity. An example of this is provided by Table 4, which shows that being a male leads to a much higher productivity estimation for task A, while this is not necessarily the case for the other tasks. This means that some groups are expected to more productive at certain tasks, relative to their productivity for another task. Only this result could already be a reason to apply statistical discrimination. Assigning tasks by distinguishing on age, gender and nationality could be considered as unequal treatment and therefore discrimination. In this case, this would be statistical discrimination within the firm and no group would be highly disadvantaged by doing this. In other situations however, if these different tasks would be performed by different firms, this could lead to statistical discrimination in hiring employees and therefore be disadvantageous for the least productive groups.

## VI. Conclusion & Discussion

The presence of many non-significant estimates prevents that we can forecast the productivity of all tasks based on age, nationality or gender. However, the significant estimates that were found show that hiring certain groups of nationality, age and gender at the expense of another group can improve productivity. So just like some other studies (Ford, Kraiger & Schechtman, 1986; Hough, Oswald & Ployhart, 2001; Ones & Viswervareen, 1998), this study also finds differences between these subgroups. When a firm decides who they should hire, it is important for them to estimate the productivity of the job applicants to hire the most productive ones. If non-protected information that can predict productivity about job applicants is available, then statistical discrimination would not be necessary. However, this information is often not available or incomplete (Wood et al, 2009), and in those situations discrimination on protected characteristics can increase the firm's productivity.

Age, nationality and gender appeared to have a predictive power on productivity, therefore distinguishing based on age and gender can lead to higher productivity. As discussed, anti-discrimination laws are difficult to control, so firms who apply discrimination are not likely to be punished for this by the law. This means that this choice will most likely depend on moral standards. Even though most people value equal treatment, economic reasons as argument to apply discrimination are regarded as ethical by others. Therefore, the predictive power of age and gender is expected to lead to an incentive for firms to discriminate.

During the selection process of new employees, the firm only has a small amount of information about these employees. Even though we expected no discrimination to occur at this firm, the described situation might lead to more incentives to apply discrimination. The more characteristics are unknown, the more predictive power the known characteristics are likely to contain. For this reason, to reduce discrimination, policy makers should force job applicants to provide a certain amount of non-protected information significant to productivity. By doing this, the incentive to distinguish based on a protected characteristic reduces. Another solution, blind hiring, is already used by some firms (Min, 2017). The disadvantage of this is that discrimination might still occur in a later stage of the selection process.

A rough result is that being Romanian, Male and between 22 and 39 years old is associated with a high productivity. Also, we found that most employees are Romanian, male and the average age is thirty years old. As mentioned, this study does not aim to find discrimination in this firm and only this information is insufficient to conclude that there is discrimination. Information about the current supply of labor migrants in the Netherlands is limited, but relevant to answer this question. By comparing the sample with the current supply of labor migrants, a difference might be found, which could be explained by discrimination. Due to the unavailability of this data about labor migrants, this conclusion cannot be drawn from these findings.

Future research can help to improve the understanding of the incentive to apply statistical discrimination. This can be done by investigating the predictive power of protected characteristics on productivity in other firms, but also by calculating the costs which can be saved by applying statistical discrimination. Also, the costs of discrimination, in terms of damage to the image of a firm and fines, require more future research. By doing this, the incentive can be measured in terms of money. Even though this paper shows that firms might have incentives to discriminate, we do not know yet whether these incentives actually lead to discrimination. By studying the demand for labor migrants, it is possible to find out whether the productivity differences between the subgroups leads to discrimination.

One of the main limitations of this study is that time-related effects are likely to be correlated to the different types of cultivations. Normally an interaction effect between these variables could control for this, but both variables contained a large amount of different values, therefore this was not possible. For that reason, we had to assume that workers' characteristics were not correlated with the weeks they worked. Another limitation is that experience is not measured task-specifically. So, if an employee has performed a task for a few weeks and then starts performing another task, then the experience in his first task is also measured as experience in his second task. In the firm, the task of a certain employee usually stays the same, especially in his first 5 weeks, so this is not expected to be a large problem.

The outcomes only apply to the first five weeks of employees. Although this is no limitation regarding reliability of this study, it might be a problem for the validity. For aforementioned reasons, only the first five weeks of new employees were used to estimate the outcomes. If the results for these weeks differ from the results over a longer period, then these outcomes cannot be used to predict overall productivity of the employees. Besides this, by only measuring the productivity, not all relevant aspects for employees are measured. An example of a relevant aspect is the quality of their work, which is not captured in the productivity. Besides this, even for production firms, diversity of the group can also be important. Furthermore, differences can be explained by unequal treatment, or treatment which unintentionally gives an advantage to a certain group. An example of this could be a team leader who is better at explaining the task in a certain language.

Something else that might question the relevance of this study, is that discrimination in the selection process is not likely to occur in the sector which is studied. The reason for this is that the demand for labor migrants as production workers is high (ABN AMRO, 2019). This also explains why the firm that provided the data only had a few requirements for new employees. However, these firms still have the possibility to assign tasks according to their preference. In our own sample for example, female workers were much more likely to perform task A than other tasks. A limitation of this study is that it cannot explain this by productivity differences.

Although this study might be interpreted as a reason to discriminate, this is not the intention and in no way this study aims to doubt equal treatment. This study has aimed to show that firms can have reasons to discriminate, and by understanding these reasons, discrimination in the workplace can be reduced. Despite the focus on statistical discrimination in this study, this category of discrimination does not explain all discrimination that occurs. As well as statistical discrimination, taste-based discrimination also deserves attention to deal with the contemporary problem of discrimination.

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# Appendix A

**Specification of the tasks**

The dataset consists of six different tasks. All six tasks are performed daily and individually. The productivity score of task F is measured in harvested kilogram per hour, all other productivity scores are measured in treated plants per hour. Even though the productivity scores of all other tasks are measured in the same measurement unit, these scores cannot be compared for the reason that all tasks are different.

Task A, described as ‘draaien’, is necessary for the growth of plants. As these plants need to grow upwards, while having small stems, the plants need ropes to assist growing upwards. By performing task A, employees turn the rope around the stems to secure them to grow upwards. Task B is the task of pruning plants. By doing this, the plants are formed in the preferred way and the plants can focus on the remaining parts of the plant. Task C consists out of multiple task, which all aim to support the truss. The trusses can be weak, so by attaching a bracket to the truss, these weak trusses will not break. The plant grows fast, while the greenhouse in which the product grows has a limited height. Therefore task D is performed to lower the rope which is attached to the plant. By doing this, the plant can grow taller without reaching the ceiling. The plants tends to grow too many leaves, so task E consists of cutting these redundant leaves. Last, task F is harvesting the product. As mentioned before this is the only task which is not measured in plants per hour. The main reason for this is that the amount of products differs per plant, so this would not be a fair measure.