DIFFERENTIAL ACCESS TO CAPITAL FROM FINANCIAL INSTITUTIONS
BY MINORITY ENTREPRENEURS

by

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Abstract

This paper examines if Minority small business borrowers have equal access to loans from financial institutions than similar White borrowers. Using matching methods, we find that African-American borrowers are rejected at a higher rate (17-22% higher) than similar risk White-owned firms. There is therefore a causal impact of discrimination for African-American borrowers. No such differential effect is found for Hispanic borrowers. Lumping both races together can give misleading results. We also find that unobservable variables are unlikely to change the discriminatory effect.

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1. Introduction

The importance of small business to economic growth and employment has long been understood by both policy makers and academics. For example, Federal Reserve Chairwoman Janet Yellen recently stated “After the onset of the crisis, the Federal Reserve took extraordinary steps to stabilize the financial system and halt the plunge in economic activity. Since then the Fed has continued to use its monetary-policy tools to promote the recovery… Crucial to this process… is job creation. … Small businesses, of course, are responsible for a large share of these new jobs.” (National Small Business Week event held the U.S, Chamber of Commerce, May 15, 2014). But banks are a critical part of financing for small firms. According to the 2003 Survey of Small Business Finance, 57% of debt funding for US small businesses is from banks.

But do entrepreneurs of different races (namely, African-American, Hispanic and White) have similar access to loans? The Equal Credit Opportunity Act of 1974 (ECOA), as amended, prohibits discrimination against any applicant with respect to any credit transaction. The Federal Institutions Examination Council (FFIEC) manual issued by the regulators explains that ECOA “applies to any extension of credit, including extensions of credit to small businesses.”

This paper makes the following contributions to the existing literature. First, we use three different causal inference methods to test if race-based discrimination exists in access to loans from financial institutions. We believe we are the first paper to use causal inference methods to test if there is a causal impact of race on access to entrepreneurial capital from financial institutions.

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1See Federal Institutions Examination Council, Intraagency Fair Lending Examination Procedures, August 2009, page i.
2See Section 3 of this paper for details on the literature on discrimination.
3See Imbens and Ruben (2014) and Section 2 of this paper for a detailed explanation of these methods.
These methods allow us to control for observable differences in credit risks between Minority- and White-owned startup firms. In other words, we are able to mimic in actual data, an experimental audit study wherein similar credit-risk firms are randomly assigned to lenders but differ only in one dimension, namely, the race of their principal owner. In the criticism of experimental audit studies, Heckman and Seligman (1992) and Heckman (1998) argue that testers are either consciously or unconsciously trained to look for effects that are consistent with their beliefs, and that it is extremely hard to erase all possible differences in the audit pair due to unobservable effects. Given that we are creating a pseudo-random experiment using actual market data and can measure the impact of unobservable variables on our results, we are not subject to these criticisms and have improved on the experimental audit study. Second, we use a database, Kaufman Firm Survey (from now on referred to as KFS), which provides the borrower’s wealth. Many studies of discrimination do not have the agent’s wealth. Third, we separately analyze African-American owned firms and Hispanic-owned firms rather than lumping them together as minorities. Finally, and importantly, we check and find that unobservable variables do not significantly bias our tests of discrimination. In doing so, we are the first paper to use the Rosenbaum bounds (2002) to capture the impact of unobservable variables on the probability of being denied credit.

We find the following results. First, we find that African-American owned firms have higher credit risks than White-owned firms. They also face a higher denial rate than White-owned firms (41.3% v. 14.8%). Second, controlling for observable credit risk differences, we find that African-American owned firms have lower access to capital than White-owned firms. They are generally rejected at a higher rate (17-22% higher) than similar risk White-owned firms. This suggests that there is a causal impact of race on access to capital for African-American owned

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4 See Section 2 of this paper for further details.
small business firms. Third, the above result is generally not dependent on unobservable variables being excluded in the matching methodology. Using the Rosenbaum (2002) bounds test, we find no bias in our results at the five-percent level of statistical significance. At the ten-percent level of significance we find that the impact of unobservable variables has to be 82.2% of the impact of the observable variables in order to change our results. This seems to be a high number given that we have already included the borrower’s actual credit score and net worth. Fourth, we find that Hispanic-owned firms do not generally have higher credit risks than White-owned firms. The only variable of statistical significance is that they have a lower wealth. They also do not face a higher denial rate than White-owned firms. This suggests that controlling for credit risk, there is no causal impact of access to capital between Hispanic-owned and White-owned firms. Lumping Hispanic-owned with African-American owned firms as minority-owned firms is therefore not optimal. Fifth, our results are robust to three different causal inference methods, namely, propensity score matching, inverse probability weighting matching, and nearest neighbor matching.

There are two limitations of this study. First, on the one hand, we have used Dun and Bradstreet’s business credit score which is independently verified by KFS, and is not self-reported by the borrower or the lender and is therefore not subject to manipulation. On the other hand, the lending officer might rely on a credit bureau such as Equifax, Experian or Trans Union. There might not be a high correlation between these credit scores. Second, the number of African-American and Hispanic principal owners who borrow from banks in our sample is small. Finding a statistical significant result in a small sample greatly increases the chances that the actual impact might be higher if we had a larger sample. But having a small sample suffers from the limitation that these observations may not be representative of the full population.
The paper proceeds as follows. Section 2 explains the causal inference methods and Section 3 describes the related literature. Section 4 describes our data and variables used in the analysis, and Section 5 presents our results. Section 6 concludes.

2. Causal Inference Methods

Explain econometrics later.

3. Related Literature

The study of discrimination in law and economics began with the seminal paper by Becker (1957). Under what is now often called the taste-based theory of discrimination, the motive that drives the discriminatory behavior is animus or prejudice towards a particular group, that is, the economic actors simply do not like that group and do not want to interact with members in that group. Alternatively, under the information-based or statistical discrimination theory of Phelps (1972) and Arrow (1973), the motive that drives the agent’s behavior is expected profit maximization. In an imperfect information world, economic agents discriminate against certain groups because they believe these groups have lower productivity (or in this context credit quality), which will reduce their profit. Bertrand, Chugh, and Mullainathan (1995) suggest that discrimination can take place through “implicit” attitudes which are unconscious mental associations towards agents of a certain group.\(^5\)

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\(^5\) We do not test which theory is correct for the source of any discrimination for two reasons. First, this is not an experimental study wherein we are able to design scenarios to capture differences in the three theories exactly, and second, we do not have time series data to estimate default rates using a hazard model.
Empirical studies have examined discrimination in different settings, from home mortgages, to the goods and services market, to labor market hiring. With respect to home mortgages, studies have found that the likelihood of denial by a lender is higher if the borrower is from a minority racial group (for example, Black et al. (1978), Holmes and Horvitz (1994), Berkovec et al. (1998), Munnell et al. (1996), Ross and Yinger (1999), Clarke, Roy and Courchane et al. (2009), and Hubbard, Palia and Yu (2012)). The above papers conduct regression analysis using actual market data. In contrast, Ayres and Siegelman (1995) present evidence from a paired audit experiment that shows new car dealerships in Chicago quote significantly lower prices to White males than to African-American or female buyers. List (2004) finds that minorities received lower offers in the baseball sports card market than majorities. Zusmann (2013) finds evidence that fictitious advertisements of used cars by Arab sellers got lower responses than similar fictitious advertisements by Jewish sellers. Ayres, Banaji and Jolls (2011) find that baseball cards photographed held by an African-American hand sold for less than cards photographed held by a White hand in eBay auctions. Goldin and Rouse (2000) find that hiding the identity of a musician via a screen increased the probability of female musicians being hired by a symphony orchestra. Fershtman and Gneezy (2001) find evidence of ethnic discrimination by Israeli Jewish males towards men of Eastern origin in a game of trust. In response to help-wanted ads, Bertrand and Mullainathan (2004) find that “black-sounding” names such as Lakisha and Jamal were less likely to be called back for job interviews than “white-sounding” names such as Emily and Greg. In different experiments, Gneezy, List and Price (2012) find discriminatory behavior against females, sexual orientation, disabled, nonwhites and the elderly in different settings. They find support for information-based discrimination when the source of discrimination is uncontrollable (such as race,
gender), and for taste-based discrimination when it is perceived to be controllable (such as sexual orientation).

More directly relevant to this study, a number of papers have examined whether African-American and Hispanic small business borrowers have the same loan acceptance rates as White small business borrowers. Bates (1997), Bostic and Lampani (1999), Cavalluzo and Cavalluzo (1998), Blanchflower, Levine and Zimmerman (2002) and Blanchard, Zhao, and Yinger (2008) find evidence in support of discrimination as African-American small business borrowers have a lower loan acceptance rate than White small business borrowers. But these studies either use the US Bureau of Census Characteristics of Business Owners database or the Federal Reserve’s Survey of Small Business Survey data. Both of these databases do not have the borrower’s wealth, a variable that both this paper and Cavullozo and Wolken (2005) show differs substantially between minorities and whites. This suggests that they suffer from an omitted variable problem. Importantly, the above papers are limited in that they cannot claim a causal effect of discrimination, as the race variable is correlated with the credit-risk covariates, (a result we will show later). As they are not an experimental audit study, they are unable to create a random sample of observationally equivalent small business borrowers that only differ in their race. By using our causal inference methodology, we are able to create a pseudo-random experiment using actual market data that successfully addresses the criticism of experimental audit studies by Heckman and Seligman (1992) and Heckman (1998).

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6Three studies use KFS data but ask different questions. Berger, Cerqueiro and Penas (forthcoming) find that small banks lend more and their borrowers have lower failure rates than large banks in normal times; but this differential disappeared in the recent financial crisis. Cheng (2014) finds that business closure rates for minority borrowers are not higher than white borrowers. Bates and Robb (2014) examine the impact of the 1977 Community Reinvestment Act, and find that firm location in a predominantly minority neighborhood is not a statistically significant predictor of loan application outcomes.
4. Data and Variables

As part of an effort to understand the contribution of small business entrepreneurship and innovation to the U.S. economy and job creation, the Ewing Marion Kauffman Foundation conducts a panel survey of new startup firms founded in 2004 and tracks them through 2011. The Kaufmann Firm Survey (KFS) first surveyed about 5,000 firms and followed them for eight years. But data on whether a bank borrower applied for a loan and was accepted or rejected is available only from 2008 onwards, restricting our sample to the four years 2008-2011. Our sample consist of 729 observations. Of this, 46 are African-American, 35 are Hispanic, and 648 are White borrowers. We create a dummy variable African-American, which is set to unity if the borrower is African-American, and set to zero if the borrower is White. A similar dummy variable is created for Hispanic borrowers (Hispanic). All variables are summarized in Table 1.

*** Table 1 ***

To create our covariates, we begin by including the borrower’s credit risk variable, cred risk, which we define as Dun & Bradstreet’s business credit score. KFS has the following six categories of the credit score: 1= 91-100 percentile; 2=71-90 percentile; 3=31-70 percentile; 4=11-30 percentile; 5=1-10 percentile; 6=open bankruptcy, out of business and highest risk. Note that a higher cred risk value suggests lower borrower risk. To control for rents from future income, we include education, defined as the borrower’s education level. KFS has the following categories for education: one equal to less than 9th grade; two equal to some high school but no diploma; three equal to high school graduate or GED; four equal to technical or vocational degree; five equal to some college but no degree; six equal to associate’s degree; seven equal to bachelor’s degree; eight equal to some graduate school but no degree; equal to master’s degree; and ten equal to professional school or doctorate. We also control for differences in the borrower’s experience in
the same industry by including the number of years she has worked in it (experience). We include a dummy variable, female, that is set to unity if the borrower is female, and zero if the borrower is a male.7

It is possible that managerial agency issues of corporate ownership impact the effort put forward by the borrower in making her firm successful. We therefore include as a control variable, ownership, defined as the percentage ownership of the borrower in the firm. To control for other differences in firm characteristics, we include variables to capture how a firm is organized as a company or not (company) and different categories of firm sizes. We define a variable size, defined by KFS to be equal to one if firm asset size is equal to $500 or less; equal to two if firm asset size is between $501 and $1,000; equal to three if firm asset size is between $1,001 and $3,000; equal to four if firm asset size is between $3,001 and $5,000; equal to five if firm asset size is between $5,001 and $10,000; equal to six if firm asset size is between $10,001 and $25,000; equal to seven if firm asset size is between $25,001 and $100K; equal to eight if firm asset size is between $100,001 and $1M; and equal to nine if firm asset size is greater than $1,000,001. To control for industry differences we create two dummy variables, high-tech and mid-tech. The dummy variable high-tech is set to unity if the business is in two-digit SIC codes consisting of chemical and allied products, industrial machinery and equipment, electrical and electronic equipment, and instruments and related products, and set to zero otherwise. The dummy variable mid-tech is set to unity if the business is in two-digit SIC codes consisting of petroleum and natural gas operations, cigarettes, miscellaneous textile goods, pulp, mills and miscellaneous converted paper products, petroleum refining and miscellaneous petroleum and coal products, nonferrous rolling and drawing, nonferrous rolling and drawing,

7There are no statistically significant differences in female representation between the races, and all our results hold whether we include this variable or not.
ordnance and accessories, motor vehicles and equipment, aircraft and parts, guided missiles, space
vehicles and parts, miscellaneous transportation equipment, computer and data processing services,
engineering and architectural services, research and testing services, management and public
relation, and services (not elsewhere classified) and set to zero otherwise.

We also include a variable that captures the borrower’s wealth (wealth). KFS has the
following categories for the wealth of the borrower: one equal to negative or zero net worth; two
equal to $41-$50K; three equal to $51-$100K; four equal to $100,001-$250K; and five greater
than $250K.

5. Tests and Results

5.1 Are there observable differences between Minority borrowers and White borrowers?

We begin by examining if there are differences between the observable credits risks and
firm characteristics between minority African-American borrowers and White borrowers. The
results of such an analysis are given in Table 2. In Panel A we present the results for differences
between African-American borrowers and White borrowers, and in Panel B the differences
between Hispanic borrowers and White borrowers. We use four types of tests. We explain them in
the context of African-American borrowers and White borrowers, but they are similar for testing
differences between Hispanic and White borrowers.

*** Table 2***

The first is a simple t-test in order to check if the means between African-American
borrowers and White borrowers are the same. It is given by \( \frac{x_a - x_b}{\sqrt{(\sigma_a^2/n_a + \sigma_b^2/n_b)/n_a + n_b}} \), where \( x_a \) is the mean value
for an African-American borrower, \( x_b \) is the mean value for a White borrower, \( \sigma_a \) is the standard
deviation for an African-American borrower, \( \sigma_b \) and is the is the standard deviation for a White
borrower, and \( n_a \) and \( n_b \) is the sample size of African-American and White borrowers, respectively. We find that African-American borrowers have a statistically significant higher rejection rate (41.3%) than White borrowers (14.8%). African-American borrowers also have higher credit risks, lower wealth levels, own firms that are smaller and with lower profits, and own a higher percentage of their firm than White borrowers. African-American borrowers are equally likely to be female when compared to White borrowers, and a similar equality exists with respect to their experience in the firm. The above t-test might potentially suffer from finding statistical significance because the sample sizes \( n_a \) and \( n_b \) might be large. Therefore Imbens and Wooldridge (2008) suggest using the normalized difference in means test, defined as 

\[
\frac{x_a - x_b}{\sqrt{\frac{\sigma_a^2 + \sigma_b^2}{2}}} 
\]

They suggest that if the absolute value of the normalized difference is greater than 0.25 then it shows that the means are statistically significant. We find similar results using the normalized difference test as the simple t-test, suggesting that sample size issues are not over stating our results for differences between African-American and White borrowers.

The third and fourth tests evaluate if the distributions are the same between African-American and White borrowers. The difference in dispersion test checks if there are differences in the standard deviations between African-American and White borrowers. It is defined as \( \ln(\sigma_a) - \ln(\sigma_b) \). The fourth test is the Kolmogorov-Smirnov test which is defined as \( \sup|F_{a,n}(x) - F_{b,n'}(x)| \), where \( F_{a,n} \) and \( F_{b,n'} \) are the empirical distribution functions of African-American and White borrowers, respectively. Both tests show that the distributions of the credit risk and firm variables are significantly different between African-American and White borrowers.

We now repeat the analysis for differences between Hispanic and White borrowers in Panel B. We find no significant differences between the rejection rate for Hispanic and White borrowers. The only statistically significant difference in the t-test is that Hispanic borrowers have
a lower wealth level than White borrowers, but the normalized mean difference statistic is lower than 0.25, suggesting that the difference is not statistically significant.

The above results show that there are significant univariate differences between the credit risks and firm characteristics of African-American borrowers and White borrowers, but there are no significant differences between the credit risks and firm characteristics of Hispanic and White borrowers. We now test if these differences hold up in a multivariate setting using a logistic regression. Table 3 presents the results of such analysis, wherein we present the marginal coefficients only.

*** Table 3 ***

In column (1) we still find that African-American borrowers also have higher credit risks, lower wealth levels, own firms with a smaller size and own a higher percentage of their firm than White borrowers. These results are generally consistent with those found in the univariate results. Examining for differences between Hispanic and White borrowers in column (2) we find the former to have lower wealth levels. No other variables including credit risk is statistically significant between Hispanic and White borrowers.

5.2 Causal inference tests to examine whether Minority borrowers are rejected more often than comparable White borrowers?

Before one can run the three causal inference methods, Imbens and Ruben (2014) suggest that we should check if the two distributions have common support. We use the min-max condition to find common support. We find that the minimum predicted value for African-American borrowers is 0.0099 and the maximum predicted value is 0.7307. Similarly, we find the minimum predicted value for White borrowers is 0.0022 and the maximum predicted value is 0.5530. The min-max criteria for common support is therefore 0.0099, 0.5530. We find that none of our
observations were excluded due to the lack of common support which is confirmed in the kernel density plot of propensity scores in Figure 1. A similar analysis is undertaken for Hispanic borrowers and the results are parallel and given in Figure 2.

***Figures 1 and 2***

We estimate three causal inference regressions to test whether Minority borrowers are rejected more often than comparable White borrowers. The results of such an analysis are given in Table 4. The first method, namely the propensity score method, matches the Minority borrower with the closest White borrower by propensity score. We find that an African-American borrower is rejected at a 22% higher rate than a similar White borrower. No significant difference for loan rejection rates are found between similar Hispanic and White borrowers. We also estimate the inverse probability weighting estimator.\(^8\) Consistent with our previous result, we find that an African-American borrower is rejected at a 21% higher rate than a similar White borrower, whereas there is an insignificant difference for loan rejection rates between similar Hispanic and White borrowers. The nearest-neighbor matching procedure uses a non-parametric weighting of the covariates rather than using the logistic functional form to estimate the propensity scores. It directly matches on the nearest-neighbor of the covariates.\(^9\) We find that an African-American borrower is rejected at a 17.4% higher rate than a similar White borrower, whereas there is an insignificant difference for loan rejection rates between Hispanic and White borrowers.

*** Table 4***

In summary, the above results suggest that an African-American borrower is rejected at a higher rate (between 17-22%) than a similar White borrower, suggesting differential access to

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\(^8\)See Busso, DiNardo and McCrary (forthcoming) for conditions wherein this method works well.

\(^9\)See Abadie and Imbens (2006, 2011) for a more detailed explanation.
capital to such borrower. In contrast, there are no significant differences in loan rejection rates between similar Hispanic and White borrowers. This also suggests that one should not lump the two sub-classes of minorities together.

5.3 Impact of unobservable effects on the differential impact on loan rejection rates of African-American and White borrowers

It is possible that the discriminatory effect that we find for African-American borrowers is because of excluding some other variables that the KFS database does not have. For example, Petersen and Rajan (1994) show that lending rates to small businesses are lower when the borrower and the bank have a longer relationship. Gan and Riddiough (2008) suggest that lenders possess proprietary credit quality information embedded in their screening technologies that is not observable to empirical researchers. Further, African-American borrowers might differ in their ability to negotiate with lenders when compared to White borrowers. Such excluded or unobservable variables could impact our finding for differential access to capital. For the logistic distribution, Rosenbaum (2002) shows that the odds ratio of two matched individuals \( (i, j) \) of receiving treatment is bounded as follows:

\[
\frac{1}{e^\gamma} \leq \frac{p_i(1-p_j)}{p_j(1-p_j)} \leq e^\gamma
\]

where \( p_j \) and \( p_i \) are the probability of being treated, and \( \gamma \) is the sensitivity of being treated to unobservable variables. If \( \gamma \) is equal to unity there is no bias, and increasing \( e^\gamma \) reflects the bias of overtreatment in our results. The overtreatment bias can be calculated using the Mantel and Haenszel test statistic. We provide the \( p \)-values of this statistic at different levels of \( \gamma \) in Table 5. We find no bias in our results at the five-percent level of statistical significance. At the ten-percent level of significance we find that the impact of unobservable variables has to be greater than 60% \( (\gamma = 0.6) \) to have an impact on our results. This translates to 1.822 \( (e^{0.6}) \), and suggests that the impact of overtreatment due to unobservable variables has to be 82.2% of the impact of the observable variables. This seems to
be a high number given that we have already included the borrower’s actual credit score and net worth.

*** Table 5 ***

6. Conclusions

This paper uses a unique database to examine if race-based discrimination exists in lending by financial institutions to small businesses. We are the first paper to use matching methods to test if there is a causal impact of race on access to entrepreneurial loan capital from financial institutions. These methods allow us to control for observable differences in credit risks between Minority- and White-owned startup firms. In other words, we are able to mimic in actual data, an experimental audit study wherein similar credit-risk firms are randomly assigned to lenders but differ only in one dimension, namely, the race of their principal owner. In the criticism of experimental audit studies, Heckman and Seligman (1992) and Heckman (1998) argue that testers are either consciously or unconsciously trained to look for effects that are consistent with their beliefs, and that it is extremely hard to erase all possible differences in the audit pair due to unobservable effects. Given that we are creating a pseudo-random experiment using actual market data and can measure the impact of unobservable variables on our results, we are not subject to these criticisms and have improved on the experimental audit study.

We find that African-American owned firms have higher credit risks than White-owned firms and have a higher loan rejection rate than White-owned firms. Controlling for observable credit risk differences, we find that African-American owned firms have lower access to capital than White-owned firms. They are generally rejected at a higher rate (17-22% higher) than similar risk White-owned firms. This suggests that there is a causal impact of race on access to capital for African-American owned small business firms. Third, the above result is generally not dependent on unobservable variables being excluded in the matching methodology. Using the Rosenbaum
(2002) bounds test, we find that the impact of unobservable variables has to be 82.2% of the impact of the observable variables in order to change our results. This seems to be a high number given that we have already included the borrower’s actual credit score and net worth. We also find no causal impact of access to loans from financial institutions between Hispanic-owned and White-owned firms. Lumping Hispanic-owned with African-American owned firms as minority-owned firms is therefore not optimal. Our results are robust to three different causal inference methods, namely, propensity score matching, inverse probability weighting matching, and nearest neighbor matching.

Finding a causal negative effect for access to loans from financial institutions for African-American borrowers might not be sufficient for plaintiffs to file a class-action suit under the disparate impact theory of discrimination. The Supreme Court’s decision in Wal-Mart Stores, Inc. v. Dukes\textsuperscript{10} has made such legal theory based on statistical evidence harder to successfully litigate. Last year, class certification in three fair lending class actions were denied by district courts on the basis of the Dukes case. The first appeal concerned the denial of class certification in In re Countrywide Financial Mortgage Lending Practices Litigation.\textsuperscript{11} The U.S. Court of Appeals for the Sixth Circuit held that the district court did not abuse its discretion by finding that Dukes foreclosed the plaintiffs’ proposed class because “the mere presence of a range within which acts of discretion take place will not suffice to establish commonality.”\textsuperscript{12} The Sixth Circuit acknowledged that Dukes does not prohibit the use of statistical evidence to prove a disparate

\textsuperscript{10}131 S. Ct. 2541 (2011). See also Ropiequet, Navaja, and Noonan (2013) for extensive discussion of this case on fair lending litigation.
\textsuperscript{12}Miller v. Countrywide Bank, N.A., id.
impact theory, but found, rather, that *Dukes* “reiterates that statistical correlation, no matter how robust, cannot substitute for a specific finding of class-action commonality.”\textsuperscript{13}

The second appeal was from the decision to decertify the class following the *Dukes* ruling in *Barrett v. H&R Block, Inc.*\textsuperscript{14} Like the *Countrywide* plaintiffs, the *Barrett* plaintiffs sought leave to appeal pursuant to Federal Rule of Civil Procedure 23(f), but instead of taking the appeal and ruling on its merits, the U.S. Court of Appeals for the First Circuit denied the petition.\textsuperscript{15}

The third appeal was from the decision to deny class certification in *Rodriguez v. National City Bank*,\textsuperscript{16} where the parties had agreed to a class settlement and the court had scheduled a fairness hearing before the *Dukes* decision came down.\textsuperscript{17} The *Rodriguez* plaintiffs thus had the additional argument, unlike the *Barrett* and *Countrywide* plaintiffs, that the parties had a binding and enforceable agreement to settle the case. However, the U.S. court of Appeals for the Third Circuit found no obstacle to affirming the denial of class certification.\textsuperscript{18} Although the court agreed that public policy generally prefers voluntary settlement of class actions, it held that courts are nevertheless bound by Rule 23(e) to ensure that class settlements are “fair, reasonable, and adequate.”\textsuperscript{19} This duty includes performing a “rigorous analysis” to determine whether the

\textsuperscript{13}Id. at 709.


\textsuperscript{16}277 F.R.D. 148 (E. D. Pa. 2011), aff’d. 726 F. 3d 372 (3rd Cir. 2013); see also Ropiequet, Navaja, and Noonan (2013) p. 646-47.

\textsuperscript{17}Rodriguez, 277 F.R.D at 151-53.


\textsuperscript{19}Id. at 379.
proposed settlement class meets the requirements of Rule 23(e), including the commonality element discussed in *Dukes*.\(^{20}\) Concerning the commonality issue, the Third Circuit noted that the case bore “a striking resemblance to *Dukes*”\(^{21}\) because it involved “the exercise of broad discretion by an untold number of unique decision-makers in the making of thousands upon thousands of individual decisions”\(^{22}\) and therefore affirmed the finding that the putative class lacked commonality.

\(^{20}\)Id at 380.
\(^{21}\)Id at 384.
\(^{22}\)Id at 386.
References


Figure 1. Differences between African-American and White borrowers

Figure 2. Differences between Hispanic and White borrowers
<table>
<thead>
<tr>
<th>Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>reject</strong></td>
<td>Dummy variable set to unity if loan application is always denied, and set to zero if always approved or sometimes approved/denied</td>
</tr>
<tr>
<td><strong>African-American</strong></td>
<td>Dummy variable set to unity if borrower is African-American, and set to zero if borrower is White</td>
</tr>
<tr>
<td><strong>Hispanic</strong></td>
<td>Dummy variable set to unity if borrower is Hispanic, and set to zero if borrower is White</td>
</tr>
<tr>
<td><strong>credit risk</strong></td>
<td>Dun &amp; Bradstreet’s business credit score. KFS has the following categories: 1=highest credit scores (91-100 percentile); 2=71-90 percentile; 3=31-70 percentile; 4= 11-30 percentile; 5=1-10 percentile; 6=open bankruptcy, out of business and highest risk</td>
</tr>
<tr>
<td><strong>education</strong></td>
<td>KFS has the following categories: 1=less than 9th grade; 2=some high school but no diploma; 3=high school graduate or GED; 4= technical or vocational degree; 5=some college but no degree; 6=associate’s degree; 7=bachelor’s degree; 8=some graduate school but no degree; 9=master’s degree; and 10=professional school or doctorate</td>
</tr>
<tr>
<td><strong>experience</strong></td>
<td>Number of years the borrower has worked in this industry</td>
</tr>
<tr>
<td><strong>gender</strong></td>
<td>Dummy variable set to unity if borrower is female, and set to zero if borrower is male</td>
</tr>
<tr>
<td><strong>ownership</strong></td>
<td>Percentage ownership of the borrower</td>
</tr>
<tr>
<td><strong>company</strong></td>
<td>Dummy variable set to unity if the business is set up as a corporation, and set to zero otherwise</td>
</tr>
<tr>
<td><strong>size</strong></td>
<td>KFS has the following categories: 1= $500 or less; 2= $501-$1,000; 3=$1,001-$3,000; 4=$3,001-$5,000; 5=$5,001-10,000; 6=$10,001-$25,000; 7=$25,001-$100K; 8=$100,001-$1M; 9=$1,000,001 and more</td>
</tr>
<tr>
<td><strong>high-tech</strong></td>
<td>Dummy variable set to unity if the business is in 2-digit SIC codes consisting of chemical and allied products, industrial machinery and equipment, electrical and electronic equipment, and instruments and related products, and set to zero otherwise</td>
</tr>
<tr>
<td><strong>mid-tech</strong></td>
<td>Dummy variable set to unity if the business is in 2-digit SIC codes consisting of petroleum and natural gas operations, cigarettes, miscellaneous textile goods, pulp mills and miscellaneous converted paper products, petroleum refining and miscellaneous petroleum and coal products, nonferrous rolling and drawing, ordnance and accessories, motor vehicles and equipment, aircraft and parts, guided missiles, space vehicles and parts, miscellaneous transportation equipment, computer and data processing services, engineering and architectural services, research and testing services, management and public relation, and services (not elsewhere classified), and set to zero otherwise</td>
</tr>
<tr>
<td><strong>wealth</strong></td>
<td>KFS has the following categories for the net worth of the borrower: 1= negative or zero net worth; 2=41-$50K; 3=$50,001-$100K; 4=100,001-250K; 5=greater than $250K</td>
</tr>
<tr>
<td><strong>profit</strong></td>
<td>KFS has the following categories for both gross profit and loss of the business: 0=$0; 1= $500 or less; 2= $501-$1,000; 3=$1,001-$3,000; 4=$3,001-$5,000; 5=$5,001-10,000; 6=$10,001-$25,000; 7=$25,001-$100K; 8=$100,001-$1M; 9=$1,000,001 and more. For each of them we use midpoint of each category and then take gross profits less losses (if any) to calculate net profits</td>
</tr>
</tbody>
</table>
Table 2: Univariate Differences between Minorities and White Borrowers

Panel A: African-American v. White Borrowers

<table>
<thead>
<tr>
<th>Variable</th>
<th>Means for African-American</th>
<th>Means for White</th>
<th>t-statistics for differences in means</th>
<th>Norm-Differences</th>
<th>Differences in dispersion</th>
<th>Kolmogorov-Smirnov p-values</th>
</tr>
</thead>
<tbody>
<tr>
<td>reject</td>
<td>0.413</td>
<td>0.148</td>
<td>3.552^a</td>
<td>0.397</td>
<td>0.337</td>
<td>0.003^a</td>
</tr>
<tr>
<td>credit risk</td>
<td>3.239</td>
<td>2.647</td>
<td>3.412^a</td>
<td>0.344</td>
<td>0.003</td>
<td>0.000^a</td>
</tr>
<tr>
<td>education</td>
<td>7.522</td>
<td>6.545</td>
<td>3.480^a</td>
<td>0.341</td>
<td>-0.069</td>
<td>0.000^a</td>
</tr>
<tr>
<td>experience</td>
<td>16.28</td>
<td>16.06</td>
<td>0.126</td>
<td>0.014</td>
<td>0.074</td>
<td>0.819</td>
</tr>
<tr>
<td>gender</td>
<td>0.174</td>
<td>0.193</td>
<td>0.331</td>
<td>-0.035</td>
<td>-0.031</td>
<td>1.000</td>
</tr>
<tr>
<td>ownership</td>
<td>83.72</td>
<td>75.94</td>
<td>2.711^a</td>
<td>0.260</td>
<td>-0.170</td>
<td>0.012^b</td>
</tr>
<tr>
<td>company</td>
<td>0.152</td>
<td>0.098</td>
<td>0.988</td>
<td>0.114</td>
<td>0.199</td>
<td>1.000</td>
</tr>
<tr>
<td>size</td>
<td>6.652</td>
<td>7.668</td>
<td>3.00^a</td>
<td>-0.366</td>
<td>0.632</td>
<td>0.004^a</td>
</tr>
<tr>
<td>high-tech</td>
<td>0.261</td>
<td>0.271</td>
<td>0.148</td>
<td>-0.016</td>
<td>-0.002</td>
<td>1.000</td>
</tr>
<tr>
<td>mid-tech</td>
<td>0.391</td>
<td>0.196</td>
<td>2.625^a</td>
<td>0.294</td>
<td>0.216</td>
<td>0.053^c</td>
</tr>
<tr>
<td>wealth</td>
<td>3.391</td>
<td>4.208</td>
<td>3.195^a</td>
<td>-0.365</td>
<td>0.365</td>
<td>0.003^a</td>
</tr>
<tr>
<td>profit ('000 $)</td>
<td>50.42</td>
<td>156.54</td>
<td>1.554^c</td>
<td>-0.162</td>
<td>-0.042</td>
<td>0.098^c</td>
</tr>
</tbody>
</table>

Panel B: Hispanic v. White Borrowers

<table>
<thead>
<tr>
<th>Variable</th>
<th>Means for African-American</th>
<th>Means for White</th>
<th>t-statistics for differences in means</th>
<th>Norm-Differences</th>
<th>Differences in dispersion</th>
<th>Kolmogorov-Smirnov p-values</th>
</tr>
</thead>
<tbody>
<tr>
<td>reject</td>
<td>0.229</td>
<td>0.148</td>
<td>1.101</td>
<td>0.144</td>
<td>0.182</td>
<td>0.971</td>
</tr>
<tr>
<td>credit risk</td>
<td>2.857</td>
<td>2.647</td>
<td>1.040</td>
<td>0.128</td>
<td>0.027</td>
<td>0.284</td>
</tr>
<tr>
<td>education</td>
<td>6.429</td>
<td>6.545</td>
<td>0.342</td>
<td>0.042</td>
<td>-0.003</td>
<td>0.935</td>
</tr>
<tr>
<td>experience</td>
<td>14.11</td>
<td>16.06</td>
<td>1.107</td>
<td>0.130</td>
<td>-0.070</td>
<td>0.576</td>
</tr>
<tr>
<td>gender</td>
<td>0.171</td>
<td>0.193</td>
<td>0.329</td>
<td>0.040</td>
<td>-0.033</td>
<td>1.000</td>
</tr>
<tr>
<td>ownership</td>
<td>80.06</td>
<td>75.94</td>
<td>0.924</td>
<td>0.108</td>
<td>-0.079</td>
<td>0.086^c</td>
</tr>
<tr>
<td>company</td>
<td>0.143</td>
<td>0.098</td>
<td>0.073</td>
<td>0.096</td>
<td>0.176</td>
<td>1.000</td>
</tr>
<tr>
<td>size</td>
<td>7.400</td>
<td>7.668</td>
<td>1.408^c</td>
<td>0.162</td>
<td>-0.103</td>
<td>0.197</td>
</tr>
<tr>
<td>high-tech</td>
<td>0.143</td>
<td>0.271</td>
<td>2.052^b</td>
<td>0.219</td>
<td>-0.225</td>
<td>0.569</td>
</tr>
<tr>
<td>mid-tech</td>
<td>0.200</td>
<td>0.196</td>
<td>0.054</td>
<td>0.007</td>
<td>0.021</td>
<td>1.000</td>
</tr>
<tr>
<td>wealth</td>
<td>3.514</td>
<td>4.208</td>
<td>2.836^c</td>
<td>0.350</td>
<td>0.183</td>
<td>0.006^a</td>
</tr>
<tr>
<td>profit ('000 $)</td>
<td>18.25</td>
<td>156.54</td>
<td>1.599^c</td>
<td>0.198</td>
<td>0.072</td>
<td>0.182</td>
</tr>
</tbody>
</table>

^a statistically significant at the 1% level; ^b statistically significant at the 5% level; ^c statistically significant at the 10% level.
Table 3: Logistic Regression of Differences between Minorities and White Borrowers

<table>
<thead>
<tr>
<th></th>
<th>African-American (1)</th>
<th>Hispanic (2)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>credit risk</strong></td>
<td>0.013&lt;sup&gt;a&lt;/sup&gt;</td>
<td>0.004</td>
</tr>
<tr>
<td></td>
<td>(3.29)</td>
<td>(0.73)</td>
</tr>
<tr>
<td><strong>education</strong></td>
<td>0.010&lt;sup&gt;a&lt;/sup&gt;</td>
<td>-0.000</td>
</tr>
<tr>
<td></td>
<td>(3.07)</td>
<td>(-0.11)</td>
</tr>
<tr>
<td><strong>experience</strong></td>
<td>0.000</td>
<td>-0.000</td>
</tr>
<tr>
<td></td>
<td>(0.37)</td>
<td>(-0.52)</td>
</tr>
<tr>
<td><strong>gender</strong></td>
<td>-0.002</td>
<td>-0.014</td>
</tr>
<tr>
<td></td>
<td>(-0.12)</td>
<td>(-0.76)</td>
</tr>
<tr>
<td><strong>ownership</strong></td>
<td>0.000&lt;sup&gt;c&lt;/sup&gt;</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>(1.82)</td>
<td>(0.68)</td>
</tr>
<tr>
<td><strong>company</strong></td>
<td>0.021</td>
<td>0.024</td>
</tr>
<tr>
<td></td>
<td>(1.03)</td>
<td>(1.00)</td>
</tr>
<tr>
<td><strong>size</strong></td>
<td>-0.007</td>
<td>0.001</td>
</tr>
<tr>
<td></td>
<td>(-1.64)</td>
<td>(0.18)</td>
</tr>
<tr>
<td><strong>high-tech</strong></td>
<td>0.031&lt;sup&gt;b&lt;/sup&gt;</td>
<td>-0.030</td>
</tr>
<tr>
<td></td>
<td>(2.03)</td>
<td>(-1.58)</td>
</tr>
<tr>
<td><strong>mid-tech</strong></td>
<td>0.038&lt;sup&gt;b&lt;/sup&gt;</td>
<td>-0.006</td>
</tr>
<tr>
<td></td>
<td>(2.47)</td>
<td>(-0.32)</td>
</tr>
<tr>
<td><strong>wealth</strong></td>
<td>-0.012&lt;sup&gt;a&lt;/sup&gt;</td>
<td>-0.013&lt;sup&gt;b&lt;/sup&gt;</td>
</tr>
<tr>
<td></td>
<td>(-2.70)</td>
<td>(-2.26)</td>
</tr>
<tr>
<td><strong>profit</strong></td>
<td>-0.000</td>
<td>-0.000</td>
</tr>
<tr>
<td></td>
<td>(-0.32)</td>
<td>(-0.92)</td>
</tr>
</tbody>
</table>

**Pseudo R<sup>2</sup>**

|              | 0.167 | 0.057 |

<sup>a</sup> statistically significant at the 1% level; <sup>b</sup> statistically significant at the 5% level; <sup>c</sup> statistically significant at the 10% level.
Table 4: Causal Inference Tests for Differences

<table>
<thead>
<tr>
<th></th>
<th>African-American (1)</th>
<th>Hispanic (2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Propensity score matching</td>
<td>0.217&lt;sup&gt;b&lt;/sup&gt;</td>
<td>0.057</td>
</tr>
<tr>
<td></td>
<td>(2.04)</td>
<td>(0.57)</td>
</tr>
<tr>
<td>Inverse probability weighting</td>
<td>0.211&lt;sup&gt;a&lt;/sup&gt;</td>
<td>0.028</td>
</tr>
<tr>
<td>matching</td>
<td>(2.80)</td>
<td>(0.38)</td>
</tr>
<tr>
<td>Nearest neighbor matching</td>
<td>0.174</td>
<td>0.014</td>
</tr>
<tr>
<td></td>
<td>(1.59)</td>
<td>(0.15)</td>
</tr>
</tbody>
</table>

<sup>a</sup> statistically significant at the 1% level; <sup>b</sup> statistically significant at the 5% level; <sup>c</sup> statistically significant at the 10% level.
Table 5: Sensitivity of results to unobservable variables (Rosenbaum bounds, 2002)

<table>
<thead>
<tr>
<th>Values of bias (γ)</th>
<th>African-American (1)</th>
<th>Hispanic (2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 (no bias)</td>
<td>2.283&lt;sup&gt;b&lt;/sup&gt;</td>
<td>0.554</td>
</tr>
<tr>
<td></td>
<td>(0.011)</td>
<td>(0.290)</td>
</tr>
<tr>
<td>1.10</td>
<td>2.096&lt;sup&gt;b&lt;/sup&gt;</td>
<td>0.404</td>
</tr>
<tr>
<td></td>
<td>(0.018)</td>
<td>(0.343)</td>
</tr>
<tr>
<td>1.20</td>
<td>1.914&lt;sup&gt;b&lt;/sup&gt;</td>
<td>0.263</td>
</tr>
<tr>
<td></td>
<td>(0.028)</td>
<td>(0.396)</td>
</tr>
<tr>
<td>1.30</td>
<td>1.748&lt;sup&gt;b&lt;/sup&gt;</td>
<td>0.134</td>
</tr>
<tr>
<td></td>
<td>(0.040)</td>
<td>(0.447)</td>
</tr>
<tr>
<td>1.40</td>
<td>1.595&lt;sup&gt;c&lt;/sup&gt;</td>
<td>0.015</td>
</tr>
<tr>
<td></td>
<td>(0.055)</td>
<td>(0.494)</td>
</tr>
<tr>
<td>1.50</td>
<td>1.454&lt;sup&gt;c&lt;/sup&gt;</td>
<td>-0.096</td>
</tr>
<tr>
<td></td>
<td>(0.072)</td>
<td>(0.538)</td>
</tr>
<tr>
<td>1.60</td>
<td>1.322&lt;sup&gt;c&lt;/sup&gt;</td>
<td>-0.200</td>
</tr>
<tr>
<td></td>
<td>(0.093)</td>
<td>(0.579)</td>
</tr>
<tr>
<td>1.70</td>
<td>1.199</td>
<td>-0.297</td>
</tr>
<tr>
<td></td>
<td>(0.115)</td>
<td>(0.617)</td>
</tr>
<tr>
<td>1.80</td>
<td>1.084</td>
<td>-0.242</td>
</tr>
<tr>
<td></td>
<td>(0.139)</td>
<td>(0.596)</td>
</tr>
<tr>
<td>1.90</td>
<td>0.975</td>
<td>-0.158</td>
</tr>
<tr>
<td></td>
<td>(0.164)</td>
<td>(0.563)</td>
</tr>
<tr>
<td>2.0 (largest bias)</td>
<td>0.871</td>
<td>-0.078</td>
</tr>
<tr>
<td></td>
<td>(0.192)</td>
<td>(0.531)</td>
</tr>
</tbody>
</table>

<sup>a</sup> statistically significant at the 1% level; <sup>b</sup> statistically significant at the 5% level; <sup>c</sup> statistically significant at the 10% level.