Is Credit Status a Good Signal of Productivity?

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Abstract. Many employers screen new hires by examining the credit reports of job applicants. The practice has sparked debate, with opponents asserting that it amounts to discrimination and proponents maintaining that it is an important tool for employers to assure the quality of new employees. To date, little evidence exists on the validity of credit status as a screening device. The issue is complicated both by the lack of available data and the difficulty in establishing causality. This paper uses a unique identification strategy along with credit proxy variables in a national dataset to test whether credit status reveals information about an employee's character that is predictive of employee productivity. The paper finds that the character-related portion of credit status is not a significant predictor of worker productivity.

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With the recent economic downturn and deterioration in household finances, the issue of the use of personal credit status as a criterion in the hiring process has drawn increased scrutiny (Hughes 2012, Murray 2010, Martin 2010). Evidence from employer surveys indicates that about half of employers use credit reports as screens for at least some of their hires (SHRM 2012, SHRM 2010a, b). In 2010, the Department of Labor won a court case against Bank of America over the improper use of credit checks as an employee-screening device (Traub 2013). Ten states have passed laws limiting the practice, and over the past few years legislation has been introduced to ban credit screening at the federal level in both the House of Representatives and the Senate (Dwoskin 2013, NCSL 2012, Deschenaux 2011). Employers and their advocates maintain that credit checks are a useful tool in judging the quality of some potential hires. They cite the importance of credit checks in assessing employee character and minimizing fraud (SHRM 2010a, b). Opponents of the practice, by contrast, see the use of credit reports as a backdoor form of discrimination. They maintain that personal credit status is not related to job performance and that the practice is likely to disproportionately harm minority workers due to the lower incomes and greater incidence of poor credit in minority populations (EEOC 2010, Fremstad 2010, Fellowes 2006).

This topic is also of interest due to the growing use of Big Data in hiring and employment practices. In many ways, the management and use of databases containing personal credit files over the past few decades foreshadows the rapidly expanding use of a broader range of personal data that is occurring today. The same issues about the validity of making hiring decisions based on observed correlations arise with Big Data as with the case of credit checks.

Despite the prevalence of the practice, little is known about the relationship between credit status and productivity. If credit status is a strong predictor of employee productivity, then the use of this information by employers may result in better job matches and increased economic efficiency. However, if poor credit is merely a sign that an individual has lost an income stream in the past, but is not a good predictor of the individual's work performance, then credit checks may violate federal civil rights law due to their disparate impact on minorities.[1] The literature on the relationship between credit status and labor market outcomes is thin. The industrial psychology literature focuses on the correlation between credit status, worker characteristics and employment outcomes such as performance evaluations (Bernerth et al. 2012a, 2012b; Palmer and Koppes 2003, 2004). However, these studies are typically focused on single organizations and do not include causal research designs. The statistical discrimination literature in economics has tested whether increased information from employer screening mechanisms leads to an improvement in the labor market outcomes of stigmatized groups (Autor and Scarborough 2008). For example, does the increased availability of criminal records improve labor market outcomes for minority job applicants who do not have criminal records (Holzer et al. 2006, Finlay 2008, Stoll and Bushway 2008)? However, this literature has generally not tested whether the underlying characteristic—credit status in the case of this paper—is in fact predictive of labor market productivity.

The principal challenges in tackling the topic of the impact of credit status on labor market productivity are data availability and causation. Datasets that combine detailed individual credit reports with economic and demographic variables are hard to come by. Credit reports are proprietary, and even were they available, they lack the longitudinal labor market data that

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[1] See Title VII of the Civil Rights Act of 1964.

researchers often rely on to disentangle difficult economic questions. Leaving aside the challenges of measuring credit status, it might seem that we could simply compare over time the labor market outcomes of individuals with good and bad credit to determine whether bad credit harms productivity. However, simple correlations in national datasets cannot tell us whether factors relating to an employee's credit status are causing bad labor market outcomes, or economic shocks relating to bad labor market outcomes are causing the observed credit status. Furthermore, as will be discussed below, there are multiple potential motivations for employer use of credit checks; the validity of these different motivations cannot be simultaneously tested with a single identification strategy. In this paper I focus on testing a key belief that employers frequently cite in support of credit checks: the idea that credit status reveals productivity-relevant information about an employee's character.

To address the data challenge, I rely on proxy variables for credit quality contained in the National Longitudinal Survey of Youth from 1979 (NLSY79). The NLSY79 contains a rich set of credit-relevant variables, including data on net worth, rejections of credit applications, and credit card debts, among other indicators. Because employers examine the contents of credit reports rather than credit scores (see below for discussion), and because these proxy items reflect the components of credit reports, this dataset allows us to make valid assessments of credit quality.

To rigorously test whether employer beliefs about credit status and character are justified, I employ a unique two-part identification strategy. First, to isolate the character effect and resolve endogeneity problems, I use the future value of an individual's credit status as a measure of any time-invariant, person-specific ("character-related") aspects of bad credit status. I then employ a firm-learning model to test whether character-related credit status has any predictive

value for an individual's productivity in the labor market. The results of this analysis indicate that the portion of credit status that is related to an employee's time-invariant character does not have a significant relationship with the employee's productivity as the employer learns about the employee's unobserved characteristics.

Credit History Background

Any individual who accesses credit—including credit cards, car loans, and mortgages—will generally have a record of credit-related activity at a firm called a credit reporting agency (or credit bureau). There are three major credit reporting agencies in America: Equifax, Experian, and TransUnion. The records these firms keep are generally referred to as credit reports or credit histories. To indicate the general quality of an individual's credit report, I will use the term "credit status." It is important to make a distinction between credit reports/histories and credit scores. A credit score is a single number that is designed to represent the level of credit risk a particular individual represents to a lender. Although the credit score is based on the contents of an individual's credit report, it is the result of an algorithm that is specific to consumer lending. Employers access credit reports, but they do not typically look at credit scores (EEOC 2010).

Although the format of credit reports varies by credit bureau, all of the various reports contain the following components (Avery et al. 2010):

- Personal information (address, social security number, etc.)

- Summary of credit accounts and payment history (including late payments, etc.)

- Information on non-credit related bills in collection (utility bills, medical bills, etc.)

- Inquiries (requests from companies to see the credit report)

- Monetary-related public records (judgments, liens, bankruptcies, etc.)

The Fair Credit Reporting Act (FCRA), which was passed by Congress in 1980, gives employers the right to request a job applicant's credit report after obtaining the individual's written permission.[2] Although this theoretically gives the applicant a measure of control, the employee has very little bargaining power as the employer is free to make signed permission a condition of application. I will refer to the act of an employer accessing a job applicant's credit report as a "credit check."

Theory and Evidence: Employer Beliefs about Credit Status

To explore the connection between credit status and worker productivity, it is necessary to be more specific about the various scenarios that lead to bad credit and the employer beliefs associated with these scenarios. Bad credit can result either from choices that an individual makes or from events that are beyond the individual's control. An employer, in turn, could care about an employee's credit status for several reasons. On the one hand, the employer could review a credit report in order to try to learn about an enduring characteristic of the employee, such as a personality trait or a fixed non-cognitive skill. The idea in this case is that the personal attributes that lead to bad credit will also lead to low productivity on the job. This unproductive behavior could simply be subpar performance, or it could include fraud or negligence. I will heuristically refer to this employer belief as the "character" screen.[3]

Employers could also care about credit status because they believe that a difficult personal financial situation will prevent the employee from doing a good job, regardless of character traits. An employee who must spend time dealing with creditors may be distracted on the job, even if the ultimate cause of the credit problems was beyond the employee's control. I

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[2]See 15 U.S.C. § 1681b.
[3] The character screen can be seen as an aggregate form of the personality-based hiring measures that are the focus of the industrial psychology selection literature (Bernerth 2012, Oppler 2008).

will heuristically refer to this employer belief as the "distraction" screen. Note that these two

beliefs have very different relationships with causality and the source of credit problems. The

character screen assumes a causal relationship that runs from an individual's personal

characteristics to both credit status and employment outcomes. Only credit problems that stem

from an individual's choices are informative in this regard. By contrast, the distraction screen

does not involve causality: it is the existence of credit problems rather than their source that is

relevant.

Having established a typology of employer beliefs about credit status, we can now evaluate

what employers actually say about their reasons for using credit status as a hiring screen.

Interestingly, in surveys and in legislative testimony, employers and their advocates tend to point

to character-based reasons for performing credit checks. For example, in testimony before the

Equal Employment Opportunity Commission (EEOC), a representative of the U.S. Chamber of

Commerce stated: "Employers are much less likely to be concerned with a debt that arose as a

result of a medical issue, a period of unemployment or a divorce. On the other hand, some types

of debt might raise red flags more quickly such as gambling debt." The Chamber spokesman

later asserts: "And I think the employers I've spoken with realize that most people out there

don't have perfect credit . . . . And in my experience they're looking to find out something

more than that. Is this just a rough patch someone went through, a medical issue, a divorce, or; is

there something more that calls into question this potential employee's ability to represent our

company with integrity?" (EEOC 2010, testimony of Michael Eastman). From a distraction point

of view, the source of the debt is not important. By contrast, the Chamber's defense of

employers' ability to conduct credit checks seems to rely on the argument that certain types of

debt—such as gambling debt—imply something about a job applicant's judgment or character that other types of debt do not.

The Society of Human Resource Management (SHRM) is the principal employer association that both collects data on this issue and testifies on behalf of employer interests at hearings regarding employee credit checks. In a survey released in July 2012, SHRM asked employers about their primary reason for using credit reports as a screening device (SHRM 2012). Two of the top three reasons employers gave—specifically, preventing theft and assessing trustworthiness—involve the relation of credit checks to some aspect of employee character.

The SHRM survey also provides information on how employers use credit checks. Among employers responding to the survey, 64 percent stated that in certain circumstances they allow job candidates to explain the negative factors on their credit reports. Because the origin of the credit problems is not relevant to the distraction screen, this behavior primarily makes sense if employers are interested in determining whether issues of judgment or character were involved in the generation of bad credit results.

Taken as a whole, the evidence indicates that the character screen provides an important rationale for employer use of credit checks. The distraction screen may or may not be important in practice, but the public statements of employers and their advocates point to the centrality of character-based arguments for the reliance on credit status as a screening device. In this paper I will focus on testing these character-related claims.

Identification Strategy Part 1: Isolating Character-Related Credit Status

Now that we have established the importance of the character-related portion of credit status as a potential explanatory variable for labor market outcomes, the question is how to isolate this character-based component and to establish causality. To the extent that we observe a

correlation between an individual's bad credit and a bad labor market outcome, we cannot be

sure what this correlation implies. The correlation could stem from a distraction effect, from the

causal impact of bad character/judgment on labor market performance, or from bad luck. Indeed,

the bad labor market outcome could cause the bad credit, as when an employer cuts wages due to

macroeconomic conditions and the worker's credit deteriorates. We do not escape these

problems even if we estimate the impact of credit status from a prior period on current period

labor market outcomes because employer wage reductions or other exogenous sources of bad

credit could have occurred in periods prior to the measurement of credit status. Only a strategy

that both isolates the portion of credit status related to character and establishes causality can

assist with an evaluation of the validity of the character screen.

To gain traction on this problem, we can develop a model that decomposes the elements

of an individual's credit status. Let r_{it} be a measure of individual i's credit status at time t, and

let b_{it} be the portion of an individual's credit status that reflects transient economic

circumstances. Let p_i be the portion of an individual's credit status that reflects permanent

character or judgment. Think of b and p as indices. Thus we have:

(1) $$r_{it} = b_{it} + p_i$$

Note that p_i does not have a time subscript. The idea is that character is a permanent

attribute that persists beyond the fluctuations of the transient economic factors that otherwise

affect credit status.[4] Also note that as long as both b and p are present, we can't disentangle the

effect of the character-related portion of credit status by observing r. Furthermore, if the

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[4] For credit status to have predictive value, as opposed to being an endogenous reflection of current economic circumstances, there must be a time-invariant component of credit status that "stays with the person." In other words, if poor credit status reveals that a person has bad judgment in a way that will affect future work performance, then this bad judgment must continue over time: it must be a persistent characteristic of this individual. If it is not, then knowing about an individual's credit status today could not possibly reveal anything about that individual's judgment or reliability tomorrow.

individual has poor credit ($r > z$, where z is a critical value defining bad credit) and experiences

certain transient economic shocks ($b > 0$), we cannot establish the direction of causality within a

given time period.[5] Suppose, though, that we identify a sample S of individuals who have credit

problems at a future point in time. Let the time period during which we will measure labor

market outcomes (the "base" period) stretch from time t-s to time t. Let the future time period

when we will measure credit status (the "future reference" period) be noted as time t+y. For the

individuals who will one day have credit problems, $r_{i,t+y} > z \; for \; i \in S$. If character-related

factors are important causes of credit problems, then on average we would expect $p > 0$ across

the sample of individuals with credit problems. However, while p is persistent, the transient

economic factors vary over time. Although at time t+y it is the case that $b_{i,t+y} > 0$, during the

base period these future contemporaneous economic conditions do not yet exist. Thus we can

eliminate the effect of the future contemporaneous economic factors by evaluating future credit

status in the base period: $b_{i,t+y} = 0 \big|_{time \leq t}$. As a result, when evaluated in the base period, the

variable indicating poor credit status at time t+y will be an indicator for the permanent character-

related component of credit status $\left(r_{i,t+y} = p_i \big|_{time \leq t} \right)$. Because the value of p is fixed over time, it

will have a causal interpretation in a regression model. The use of future credit status thus

isolates the character-related portion of credit status and identifies a causal effect.[6]

The principal challenge to this strategy is the possibility that $b_{i,t+y}$ is a function of b_{it}. In

other words, if current economic conditions determine future conditions via serial correlation,

then the coefficient on future credit status will be biased. I discuss the steps that I take to address

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[5] Even if the credit problems are observed in a time period prior to the labor market outcomes, we cannot know that these problems are not the outcome of earlier labor market processes.
[6] See Altonji (2010) for an example—in a different context—of the use of future values of variables as an identification strategy.

this challenge below in the "Threats to Validity" section of the paper. Most importantly, I show that the bias from this correlation is negative, thus making my finding of no significantly negative effect a conservative one.

In terms of mechanics, I refer to the period in which we measure labor market outcomes as the "base period," and the period in which we measure future credit status as the "future reference period." As described below, the base period in my empirical specifications stretches from 1979 to 1992. This period is followed by a gap to address issues related to serial correlation/reverse causality stemming from the use of future credit status (see discussion below). Finally, there is a future reference period that contains indicators of credit status during the years 1999-2010. I measure credit status using a variety of proxy variables. Some of these variables cover a single year, while others cover a range of years (see data section for more details).

The above-described strategy isolates the character-related component of credit status. However, we still need to take some additional steps to complete the identification strategy. We cannot simply compare the difference in static labor market outcomes—say wage levels as an indicator of marginal productivity—between individuals with and without future bad credit for two reasons. First, there are a number of variables that employers can observe at the point of hiring but that are invisible to researchers. These include the outcome of a personal interview, elements of a candidate's resume, and factors such as school quality. As a result, we cannot perfectly control for the impact of these items on initial wage levels. Second, we are exploring the effect of a hidden character trait that is generally unobservable to employers. We expect employers to learn about this characteristic over time to the extent that it has an impact on work-related productivity. Thus we need a strategy to identify the effect of firms learning about

unobservable characteristics over time.[7] The firm-learning models of Farber and Gibbons (1996;

hereafter FG) and Altonji and Pierret (2001; hereafter AP) provide a means to accomplish this

goal.

Identification Strategy Part 2: Developing a Firm-Learning Model for Credit Status

Based on the discussion above, we can now develop a firm-learning model involving

credit status. Let a worker's log productivity, y, be a linear function of the transient and

permanent components of credit status (b and p), a vector of variables that the employer observes

(G), and a vector of variables that the employer does not observe (M), along with a concave

polynomial function of experience, $H(x)$:

(2) $$y_{it} = \alpha_1 b_{it} + \alpha_2 p_i + G_{it}\alpha_3 + M_{it}\alpha_4 + H(x_{it})$$

Schooling would be an example of a "G" variable that the employer observes, while an

applicant's score on a standardized test would be an example of an "M" variable that the

employer does not observe. From this point on I will drop the time and individual subscripts

unless they are required to clarify the model.

Employers cannot observe b, p, or M. As a result, they form expectations of these

variables conditional on the variables that they do in fact observe:

(3) $$b = E[b|G] + u$$

(4) $$p = E[p|G] + v$$

(5) $$M = E[M|G] + e$$

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[7] In principle, one could pursue a propensity score or matching identification strategy in order to compare the levels of outcome variables rather than the growth of these variables over time. However, in practice not only are we are unable to match on key variables witnessed up front by employers, but, even for the variables we possess, the reduction in sample size for longitudinal datasets such as the NLSY79 through such a matching process is prohibitive. Both of these limitations point to the use of employer learning over time as an effective identification strategy.

The final terms in equations 3-5 (*u, v,* and *e*) are the errors in employer beliefs regarding the

variables that the employer cannot see. Assume that (*G,M,b,p*) are jointly normally distributed,

and that all three error terms are normally distributed. We can now rewrite an employee's log

productivity as a function of the variables that the employer sees:

(6) $y = \alpha_1 E[b \mid G] + \alpha_2 E[p \mid G] + G\alpha_3 + E[M \mid G]\alpha_4 + \alpha_1 u + \alpha_2 v + e\alpha_4 + H(x)$

In equation (6), $\alpha_1 u + \alpha_2 v + e\alpha_4$ represents the difference between employer expectations and true

productivity, net of the effect of the experience profile. This overall employer error can be

decomposed into three components: one resulting from incorrect beliefs about the transient

component of credit status $(\alpha_1 u)$, one resulting from erroneous beliefs about the character

component $(\alpha_2 v)$, and one stemming from all other employer errors regarding the factors

affecting employee productivity $(e\alpha_4)$.

Every period, the employer sees a noisy signal of the employee's true productivity. As

the employer observes the employee's output, the employer witnesses its own errors as well as

the random noise from the signal. Over time the employer is able to distinguish the errors in its

beliefs about worker productivity $(\alpha_1 u + \alpha_2 v + e\alpha_4)$ from the random noise associated with the

signal. The employer thus places greater weight on observed productivity in the wages it pays,

and reduces the error it makes every period by updating its beliefs about worker productivity. We

can see that if employees with bad credit status have lower productivity due to bad

character/poor judgment, and if employers do not expect this negative effect due to lack of

knowledge, then the portion of the error term associated with the character effect $(\alpha_2 v)$ will be

negative. Thus as the employer incorporates more of this observed effect on productivity into

wages over time, the wages of individuals with bad credit due to character issues should fall

relative to individuals with good credit. In absolute terms, the wages of all workers are rising due

to increased experience (H(x)). As a result, the differential effect of the character portion of

credit will show up empirically as relatively slower growth in the wages of "irresponsible"

individuals compared to individuals with good credit.[8] The gist of this strategy is thus to compare

the wage-experience profiles of individuals with and without the key unobservable characteristic

(future bad credit).

It is worth emphasizing that this identification strategy is based on differential wage

growth over time, not on initial differences in wage levels. Because we cannot perfectly control

for initial wage levels due to variables that are witnessed by employers but not by researchers,

and because credit problems are more prevalent among lower wage populations, we generally

expect individuals with future credit trouble to have lower starting wages. Also, whatever factors

cause the initial difference in wage levels, this difference is unlikely to be attributable to credit-

related character as proxied by future credit status because employers only learn about this

unobservable characteristic over time. From a policy point of view we are interested in whether

analyzing credit status reveals hidden worker characteristics that are relevant to productivity.

Initial wage differentials are attributable to factors that are observable to the employer up front.

To ensure that observation of credit status is not one of these initial factors, I limit the estimation

sample to individuals who do not have signs of bad credit during the base period (see discussion

below).

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[8] Measured productivity can change for more than one reason. In addition to firm learning about true productivity, it can also be the case that different individuals learn or acquire skills at different rates, thus generating heterogeneous productivity growth (Kahn and Lange 2013). Although I have motivated the above discussion by focusing on firm learning, the identification strategy and the paper's conclusions apply to the case of heterogeneous productivity growth as well. The key question is whether a measure of credit-related character can predict individuals who either have lower levels of unobserved productivity or who will experience lower productivity growth over time (due to lower learning or skill acquisition).

The impact of employer learning on wages in this style of firm-learning model extends beyond individual worker-employer matches. The market learns about an employee's productivity at the same time as the employer. Thus we can apply this model to a worker's labor market experience at a succession of employers.[9]

To implement this strategy empirically, we can estimate:

(7) $$w_{it} = \beta_1 C_i + \beta_2 A_i + \beta_3 E_{it} + \beta_4 (C_i * E_{it}) + \beta_5 (A_i * E_{it}) + X_{it}\beta_6 + \varepsilon_{it},$$

Where w is log wages, C is an indicator for negative future credit status, A is a measure of the individual's cognitive ability (specifically, the individual's score on the Armed Forces Qualification Test [AFQT]), E is experience, and X is a vector containing other relevant variables, including education, the interaction of education and experience, gender, marital status, race/ethnicity, and initial occupation on entry into the labor force. The key variable of interest is the interaction between future credit status and experience.

As a benchmark, we can compare the behavior of the interaction between future credit and experience with the interaction between AFQT scores and experience. FG and AP show that AFQT scores, as an unobserved measure of ability, gain in predictive power over time as employers learn about worker productivity and adjust the wages of high-scoring individuals upward to reflect their relatively higher productivity. If it is the case that poor credit indicates something about a potential worker's time-invariant character that is harmful to productivity, then the coefficient on the interaction between future credit and experience should be negative, significant, and economically meaningful in magnitude.

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[9] See FG and AP for more discussion of "public learning" regarding worker productivity. Although the exact degree of public learning can be debated, the FG and AP models appear to fit empirical labor market data well. In addition, the fact that a worker's wages do not typically fall back to their level at initial transition into the labor market provides additional evidence of some degree of public learning.

Threats to Validity

There are several potential threats to the validity of this empirical approach. First, it might be the case that credit-related character manifests itself through unemployment or time out of the labor force rather than lower productivity. Ultimately, investigating these alternative labor market responses requires a different identification strategy, as they are not revealed via firm learning. To the extent that individuals who spend time unemployed or out of the labor force eventually earn wages again, the strategy in this paper will pick up the differential wage profiles of these individuals. This paper will focus on productivity and wages, while acknowledging that more work remains to be done on other labor market responses.

Another threat is that the current and future contemporaneous economic determinants of credit status ($b_{it}, b_{i,t+y}$) might be correlated. In this case, even though future economic conditions don't yet exist, future credit status would not provide a clean measure of the character-related component of credit status because future credit status would be a function of current economic determinants of credit status. I minimize this concern by only selecting individuals in the base period who do not have indications of credit problems. By doing so, I am effectively comparing the wage growth of two sets of individuals who do not have obvious signs of credit trouble in the base period. The treatment group will be the set of individuals who will one day develop credit problems despite the fact that they do not show signs of these problems in the current period.[10]

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[10] Individuals who have signs of bad credit in the base period as well as future bad credit exhibit lower wage growth than individuals without such signs. However, as noted in the identification strategy discussion, this negative correlation between bad credit and wage growth is not interpretable. We do not know if exogenous economic shocks or character was responsible for the initial credit problems. As a result, due to the persistence of shocks and serial correlation, we cannot assign a character interpretation to this outcome. In order to isolate the character effect, it is necessary to drop individuals who show signs of base-period credit distress.

Even after we have eliminated individuals who have signs of poor credit in the base period, we might still worry that the labor market outcomes in the base period (say, wages) are causing the future credit problems. This would result in correlation due to reverse causality. I take several steps to minimize this problem. First, I leave a gap of 7-18 years between the end of the base period (during which we measure labor market outcomes) and the future reference period (during which we measure future credit status). For example, wages are measured from 1979 to 1992, while future credit is measured from 1999 to 2010, depending on the particular credit proxy. This gap reduces issues of serial correlation and reverse causality. In addition, I eliminate individuals who report serious medical conditions at the end of the base period because such conditions are known to be a cause of credit problems and are likely to persist over time. I also control for marital status/divorce to minimize the effect of another potentially persistent factor.

Taken together, these adjustments should lessen the threat to validity. However, even after taking these steps, it is still the case that some level of serial correlation and potential for reverse causality remains. To deal with this remaining threat, it is helpful to sign the bias and incorporate this directional bias into our interpretation of the results. We can start by noting that the regressor of interest is the interaction between future credit status and experience. Due to the potential endogeneity of actual experience, I follow AP and Lange (2007) in using potential experience in the empirical specifications. Because potential experience is simply a mechanical calculation (age-education-6), the serial-correlation bias in the interaction term results from whatever bias is present in the measure of future credit. We can represent single-period bias from serial correlation in the transient component of credit status in the following manner:

(8) $$b_{i,t+1} = f(b_{it}) = \alpha b_{it} + \varepsilon_{t+1},$$

where ε is distributed ~i.i.d.$(0, \sigma)$. To the extent that economic conditions from recent time

periods are more highly correlated with each other than with conditions from the more distant

past, we expect that $\alpha < 1$.

Given equation (8), the measure of future credit status evaluated in a prior time period,

takes the following form:

$$(9) \qquad\qquad\qquad\qquad r_{i,t+y} = p_i + f(b_t)\big|_{time=t}.$$

For a given gap y between the future reference period (T) and the base year (t), we can use the
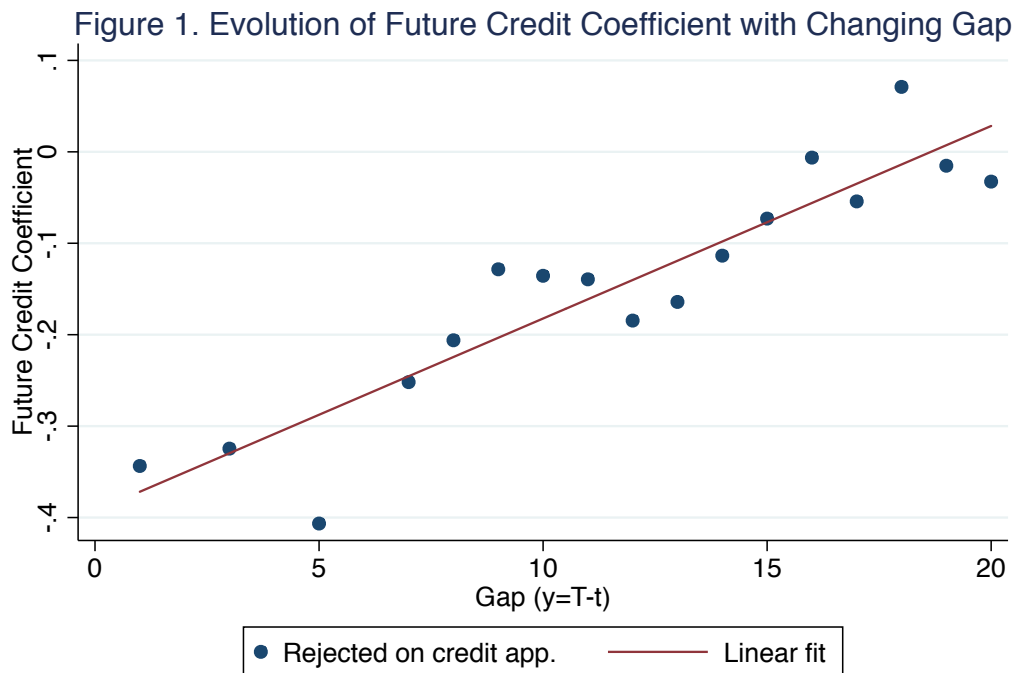
right-hand side of (8) to expand the expression to:

$$(10) \qquad\qquad\qquad\qquad r_{i,t+y} = p_i + \alpha^y b_t + \sum_{s=1}^{y} \alpha^{y-s}\varepsilon_{t+s}\bigg|_{time=t},$$

where $y=T\text{-}t$. Although future credit is evaluated in a prior period that predates

contemporaneous economic conditions, serial correlation results in persistent bias. The key fact

to note about equation (10), however, is that as the gap y gets arbitrarily large, for $\alpha < 1$ we

asymptotically recover the unbiased measure of the character-related component of credit status

(p). Although in practice the gap does not necessarily become large enough to eliminate bias, we

can use the tight relationship with y to sign the bias. As y increases, the bias diminishes. If the net

bias is positive, then we would expect coefficients estimated with increasingly larger gaps

(bigger y) to become smaller (more negative). If, on the other hand, the net bias is negative, then

we would expect coefficients estimated with larger gaps to become larger (less negative).

To test the directionality of the bias, we can take advantage of the fact that the effect of

future credit status is identified by differences between individuals (each individual has only one

future credit value). Thus we can estimate the future credit status coefficient through repeated

cross-sections based on a single base year of data. Each base year will imply a fixed gap between

the base period and the future reference period. We can then observe how the coefficient behaves

as the gap increases. It is important to note that although this method eliminates the longitudinal

panel structure of the data that we will use in the main empirical specifications, it retains the type

of serial correlation we are concerned about. Because each individual-year observation contains

economic variables from that year as well as a future credit variable, serial correlation between

b_t and b_{t+1} remains in the cross-section.

Figure 1 contains the results of this exercise. The coefficient on the future credit status

variable from the primary empirical specification (an indicator for rejection on a future credit

Figure 1. Evolution of Future Credit Coefficient with Changing Gap

Source: NLSY 1979-1992, main and supplemental samples.

application; see empirical discussion below) becomes larger (less negative) as the size of the gap

between the base period and the future reference period increases. The regression line reveals a

tight linear relationship (R-squared=.84) and a correlation between future credit status and the

size of the gap that is significant at the 99 percent level. Other measures of future credit status

have similar results (not shown).

These outcomes indicate that the net bias stemming from serial correlation due to the use

of a future credit variable is negative. Given that we are using potential experience as our

experience measure, it follows that the serial correlation bias in the interaction between future

credit status and potential experience—the main variable of interest—will reflect the bias in the

main future credit variable and will thus be negative. If we find that the actual coefficient on the

credit-experience interaction variable is significantly negative, we cannot be certain whether

character or serial correlation generated the result. However, if we find an insignificant negative

or a positive coefficient, then the effect of the character-related component of credit status on

workplace productivity is likely to be negligible since it is counteracting rather than amplifying

any existing negative bias.

Data

Following FG and AP, I employ the National Longitudinal Survey of Youth 1979

(NLSY79) to estimate the empirical model. The NLSY79 is a panel survey that follows a

nationally representative sample of men and women who were aged 14-22 in 1979. The sample

members were surveyed annually from 1979 through 1994. In 1994 the NLSY79 switched to a

biennial survey format. There are several advantages to using the NLSY79 for this research.

First, it allows us to track individuals over long periods of time, so we can implement the future-

credit-status identification strategy described above. Second, because the survey focuses on a

sample of young individuals who are moving into the labor force, it is ideal for studying the

impact of unobserved characteristics that firms (and the market) learn about over time. Third, the

NLSY79 contains data on assets and liabilities that allow us to construct proxies for credit

quality. Finally, the fact that the NLSY79 extends back into the pre-Internet era allows us to

analyze data from a time period when credit checks were arguably less widespread. Along with

other measures, this helps to isolate the firm-learning effect (as distinct from firms' explicit

credit evaluations).

        The NLSY79 contains three samples. The first is a random sample of 6,111 non-

institutionalized men and women; the second is an oversample of 5,295 Hispanics, blacks, and

disadvantaged whites; and the third is a military sample. I restrict the analysis to the main sample

and the minority/disadvantaged oversample. I eliminate individuals with less than eight years of

education, as well as individuals who have reported hourly wages of less than two dollars or

more than 100 dollars in constant 1992 dollars (deflated by the Bureau of Economic Analysis

PCE deflator). To address reverse causality, I drop survey respondents who have negative net

worth any time from 1979 to 1998, as well as individuals with medical conditions as of 1992. I

also drop individuals with missing values for wages, education, and relevant measures of credit

status. I additionally drop observations before an individual has made his or her first transition

into the labor market. After making all of the other adjustments, I use all observations that are

not missing the key independent variable for a given specification. Sample size ranges from 966

to 4,364 individuals, depending on the specification. Total observations range from 7,834 to

40,453. The Data Appendix contains more details about the adjustments to the sample as well as

summary statistics.

For my dependent variable, I use the log of hourly wages from the respondent's main job (the "CPS" job in NLSY79 parlance). For the main explanatory variable, I employ several measures of credit status. The first is a variable indicating whether the respondent has been rejected on a credit application in the last five years. The second is an indicator variable that takes a value of one if the individual has negative net worth (that is, the individual's debts and other liabilities exceed the individual's assets). For the net worth measure, I do not include the effect of assets and liabilities related to housing because housing asset values are more volatile than other asset values and have more potential to create a situation where the individual has negative net worth that is not reflected in the individual's credit status. In addition to these measures, I also use the following proxies: credit card debt as a percentage of income, net worth as a percentage of assets, negative net worth status exclusive of student debt, and an indicator for whether the individual was ever more than two months late on his or her mortgage payment from 2007 to 2010.

For each of these proxies, the question exists whether the variable is measuring credit quality in a manner similar to employers' use of credit reports. The first thing to note is that, as described above, employers do not evaluate credit *scores*. Rather, employers idiosyncratically examine a multi-page credit report looking at indicators of credit behavior. The credit variables that I employ are designed to proxy for either the outcome or the components of this process. The credit rejection variable is a sign that the individual's overall credit status is not strong enough to meet credit-underwriting standards for additional indebtedness (thus reflecting a negative credit evaluation outcome). The negative net worth indicator variable reflects a situation in which an individual would be unable to meet current debt obligations by liquidating assets. Such a situation is almost certain to be reflected in the items contained in a credit report. Credit-

card debt as a percentage of income relies on a popular conception of financial prudence that

may be influential with employers. Net worth as a percentage of assets provides a measure of

how close to the financial "red line" individuals live, taking into account their levels of wealth.

Negative net worth status exclusive of student debt provides a measure that eliminates one

scenario in which an individual may have poor credit status that employers nevertheless view

favorably. The late mortgage payment variable reflects an inability to meet obligations that

would unquestionably be reflected in a credit report.[11] Although none of these measures is

complete by itself, taken together they represent a robust approximation of credit quality.

Furthermore, because employers engage in idiosyncratic assessment of multi-page credit reports,

there is no single measure that could proxy for the entire employer evaluation process. In many

ways the varied and disaggregated picture painted by these variables is closer to the reality of the

screening process than a single summary variable such as a credit score.

Following AP and Lange (2007), I treat actual experience as endogenous and use a

measure of potential experience as an independent variable (age – education – 6). I also divide

experience by ten in order to make the resulting coefficients easier to read. I utilize unweighted

observations. I use observations from 1979-1992 as the base period, and observations from 1999-

2010 as the future reference period. For comparison's sake, I have included the interaction

between AFQT and experience, as it is a significant and economically meaningful indicator of

firm learning about unobservable productivity. I employ the 1989 standardized AFQT scores,

which are adjusted for age group (NLS User Services 1992). I have also included the interaction

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[11] The reason for including a measure of late mortgage payments while excluding housing assets and mortgage liabilities from the net worth calculation is that these mortgage-related items have very different relationships with credit reports. In the case of net worth, the value of housing is volatile and could lead to a situation in which an individual has negative net worth but is able to pay bills and otherwise maintain good credit. By contrast, late mortgage payments represent a concrete violation of financial covenants that will appear in credit reports and will be interpreted by reviewers of these reports as a decline in credit quality.

between education and experience, along with the main effects of the interaction terms. All

specifications include a cubic in experience; indicator variables for black, Hispanic, and female

status; interactions between experience and black, Hispanic, and female status; year effects; an

indicator for urban location; and an indicator for divorce. In addition, following AP, I include

fixed effects for the first occupation that individuals have when they transition to the labor

market (using two-digit 1970 Census occupation codes). The idea with this latter control is that

different occupations may have different wage trajectories, and otherwise similar individuals

may get "tracked" into different trajectories based on this initial choice of occupation. I cluster

standard errors at the individual level.

Results

In all of the empirical specifications, I estimate versions of equation (7) via linear

regression. In the first specification, the future credit status variable is an indicator that takes on a

value of one if the individual reported that he or she had been rejected on a credit application in

the last five years. I pool the responses to this question from the 2004, 2008, and 2010 surveys

(the question was not asked in 2006). The key explanatory variable in the first specification is the

interaction between the future credit variable (indicator for rejection on a credit application) and

experience. Twelve percent of the individuals in this specification have an indication of future

bad credit.

Before discussing the detailed results, it's worth presenting a simple visual representation

of the relationship between credit status and the wage-experience profile. Figure 2 contains

wage-experience profiles for both credit groups based on the NLSY79 data. The credit status

variable is the credit rejection measure used in the first empirical specification.

Figure 2. Wage-Experience Profiles, 1979-1992

Source: NLSY 1979-1992, main and supplemental samples.
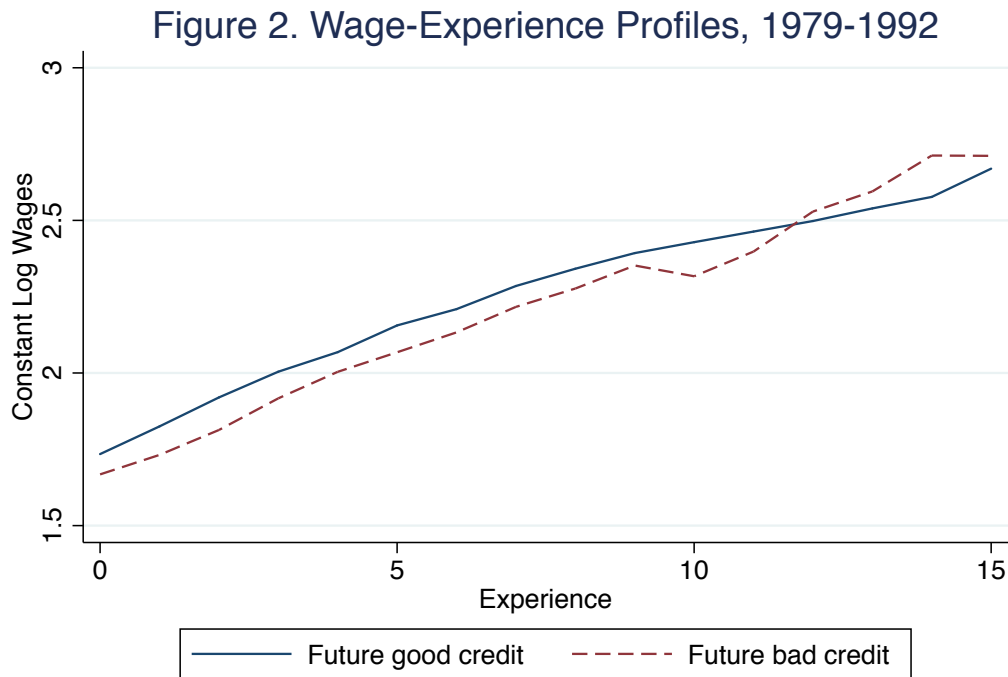
We can see from Figure 2 that the wages of individuals with future bad credit do not show slower growth than the good credit group as employers learn about any unobservable characteristics of the future bad credit group. This pattern is not what we would expect if character-related credit factors were significant determinants of productivity. However, we cannot draw firm conclusions from this graphical exercise. The profiles in Figure 2 do not control for other determinants of wages. In addition, Figure 2 uses actual experience, which may itself be endogenous. We can now turn to more detailed multivariate estimation, including exogenous potential experience and multiple different measures of credit status, to get a more accurate sense of relative wage-experience profiles.

Main Results

The baseline regression results are contained in Table 1. As the first column of Table 1 shows, both future credit rejections and AFQT scores have significant main effects on the level of initial wages. Future credit rejection is associated with an initial wage level that is 6.8 log points lower (7 percent lower) than those who will not experience this condition, while a one standard deviation increase in AFQT is associated with a 6.5 log-point increase (6.7 percent increase) in initial wage levels. Note that these wage differentials occur before employers learn about unobservable characteristics (such as future credit status and AFQT), so these effects reflect the impact of other correlated variables that employers can witness up front but that are not observable by researchers. As noted above our main interest is with the variables that describe what happens as employers begin to learn about the elements of employee productivity that are related to unobservable characteristics.

Our prior expectation is that the interaction between future bad credit and experience will be negative and significant. This expectation is reinforced by the fact that any bias stemming from serial correlation/reverse causality should be negative. However, in contrast to this expectation, the coefficient on the interaction of future credit rejections and experience is positive, implying that individuals with future credit rejections experience a 6.4 log point increase (7.5 percent increase) in wages over 10 years of experience relative to other individuals. Furthermore, the 95 percent confidence interval rules out values smaller than -0.008 (-0.8 percent), indicating a "precise" zero or positive effect. Thus as employers learn about the unobservable character-related components of credit status—and the associated productivity characteristics that accompany them—they do not find this group of employees relatively less productive than other individuals after adjusting for initial wages. It is helpful to compare this

finding with the behavior of a known unobservable predictor of employee productivity, namely the interaction of standardized AFQT scores and experience. In the first specification, this interaction is associated with a significant increase of 4.0 log points in wages when experience is equal to 10 years. In other words, in this sample, and with this specification, unobservable AFQT scores behave as predicted in a firm-learning model, showing a significant association with higher wages. In contrast, unobservable future credit rejections fail to show an equivalent negative and significant impact on wages over time.

One question that might arise about the inclusion of two unobservable characteristics in the regression specifications is whether some type of collinearity might affect the estimates of the future credit variables. The second specification in Table 1 explores this possibility by excluding the AFQT variables. We can see that the magnitudes of the future credit variables remain basically the same. Because the AFQT variable measures a conceptually distinct concept (cognitive ability) that employers learn about separately from credit-related character, and because it provides an instructive contrast with credit status, I include the direct and interacted AFQT variables in all the remaining specifications.

[Table 1 about here.]

The next specification involves the use of a different measure of future credit status (column three of Table 1). Because the NLSY collects detailed information on assets and liabilities, we can determine whether individuals had positive or negative net worth. Net worth is defined as total assets minus total liabilities, not including housing assets or liabilities (due to volatility). In this specification I use an indicator that takes on a value of one if an individual had negative net worth in 2000, 2004, or 2008 (the relevant variable is not available for 2010).[12]

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[12] Net worth and other asset/liability data are measured at the family level for each individual in the NLSY sample.

The results for this specification are somewhat similar to the prior ones, with one key difference. AFQT and future negative net worth have significant main effects that are consistent with the prior results. The AFQT-experience variable remains significant, positive and large in magnitude (5.4 log points). The one difference is that the future credit-experience interaction is now negative, although it is small in magnitude and not significantly different than zero. Nevertheless, this change in sign is worth exploring. It turns out that this negative shift in the earnings-experience profile comes entirely from 2008 data. In the next specification, I include separate variables for negative net worth in 2008, and experience interacted with 2008 negative net worth. The overall negative net worth-experience variable reverts to the previous pattern of positive and insignificant, while the 2008 negative net worth variables display very different behavior. The 2008 negative net worth variable has a positive value that is significant at the ten-percent level, while the 2008 negative net worth-experience interaction is strongly negative and significant at the ten-percent level.

Is this result evidence that the character-related component of credit status is associated with lower productivity and wage growth? In making sense of this result, it's important to note that 2008 was a very unusual year in terms of economic shocks. The data based on 2000 and 2004 conform to the earlier pattern from the prior specification. In 2008, it's possible that a strong economic shock amplified the level of correlation between negative economic outcomes in the base period and the future reference period, thus exerting a stronger downward bias than is seen in other years. In other words, similar groups of people might have gotten hit by exogenous economic shocks in both 2008 and the base period for estimation (1979-1992). In the discussion of the economic model above, this would take the form of correlation between contemporaneous economic determinants of credit status ($b_{it}, b_{i,t+y}$). To explore this possibility, we can begin by

noting that the economic shocks of 2008 hit the housing market particularly hard. Despite the

fact that our measure of net worth does not include housing assets or liabilities, these shocks

were clearly large enough that their impact spread beyond narrow measures of home values and

mortgage debts. If these unique shocks, rather than the character-related component of future

credit status, are responsible for the 2008 results, then individuals who were less exposed to

housing equity shocks should show a different pattern than those who were more exposed.

We can operationalize this approach by estimating the future negative net worth

specification for a population of renters (again pooling future data from 2000, 2004, 2008).

Specifically, I drop individuals who owned a home in 2004 or 2008. Although the sample size

suffers from these exclusions, we can see in column 5 of Table 1 that the results for renters

conform to the earlier pattern. The AFQT-experience variable is positive, large, and significant,

while the future negative net worth-experience variable is positive and insignificant. We can

additionally test this explanation by limiting the future negative net worth variable to data from

the 2000 and 2004 surveys, thus excluding the macroeconomic effects of the 2008 meltdown.

The results from this specification demonstrate the same pattern in which AFQT-experience is

positive and significant, and negative net worth-experience is neither negative nor significant. On

this basis, it appears that, in the absence of the effect of severe economic shocks, unobserved

future negative net worth is not conveying significant negative character-related productivity

information to employers as they learn about employee characteristics over time.

Additional Specifications and Robustness Analysis

To further explore the relationship between the character-related components of credit

status and productivity, we can look at the behavior of several other measures of future credit

status. One issue that might be raised is whether it is better to have a discrete measure of future

bad credit (like rejection on a credit application or negative net worth), or whether a continuous

measure would better capture the dynamic of credit quality. In the first specification in Table 2, I

have used credit card debt as a percentage of an individual's annual income to construct one

continuous measure. The idea is that individuals who carry higher levels of credit card debt

relative to their income may be less responsible than otherwise similar individuals who carry less

debt. To account for any nonlinearities involving the individuals who have zero credit card debt,

I have controlled for zero debt via an indicator variable (Angrist and Pischke 2010). I have

estimated results for this credit card specification for both 2004 and 2008. From the first two

columns of Table 2, we can see that the interactions of future credit with experience are small

and not significantly different from zero in the 2004 and 2008 specifications. Because the credit-

card debt variable is stored as a decimal, these results imply that a 100 percentage point increase

in credit card debt as a percentage of income is associated with an insignificant 0-1.5% increase

in wages over 10 years of experience. The 95 percent confidence interval rules out negative

effects larger than -0.002 and -0.007, thus implying a precise zero. By contrast, the interaction of

AFQT and experience is positive, significant, and substantially larger in magnitude.

[Table 2 about here.]

We can see the same pattern in another continuous measure of future credit status. The

third column of Table 2 contains a specification that employs an individual's net worth as a

percentage of total assets in 2004 (stored as a decimal). The idea is that individuals who live

more prudently may accumulate relatively more assets relative to liabilities than otherwise

similar individuals. This net worth figure is then normalized by the individual's total asset

wealth. Although there are obviously many different interpretations of why this percentage might

vary that do not rely on character, the goal of this exercise is to present many different potential measures of credit quality to see if any of them yield results consistent with the prior expectation that bad credit signals a character trait that negatively affects productivity. As we can see from Table 2, the results of the percentage net worth specification are consistent with the results of the other specifications. For this specification, our expectation is that higher levels of percentage net worth will be associated with a large and significant positive effect on wages (implying that lower levels of percentage net worth have a large and significant negative impact). However, the percentage net worth-experience coefficient is very small (0.001) and precisely estimated. The 95 percent confidence interval includes no effects larger than 0.0008. By contrast, the AFQT-experience coefficient is positive, significant at the 99 percent level, and sizable in magnitude (.053). Overall, the continuous future credit variables do not provide any evidence that the character-related component of future credit status is a meaningful predictor of employee productivity.

An additional issue that might be raised about these results concerns the way in which the sample is trimmed. As discussed above, it is important for this estimation strategy to remove individuals with prior signs of bad credit (negative net worth) in order to minimize serial correlation. However, it might be asked whether all forms of negative net worth should be treated equally. In particular, negative net worth from student loan debt may not imply the same type of serial correlation in credit outcomes as other sources of bad credit status. Twenty-nine percent of those with negative net worth report having had some type of student loan. In general, excluding student loan-holders along with other negative net worth individuals in the main estimation samples is a conservative approach because individuals with student loan debt have

significantly faster income growth than other individuals in the NLSY79. However, the

dynamics can be complicated, and I explore the effect of alternative approaches.

In the fourth column of Table 2, I present a specification for the credit rejection

dependent variable from Table 1 in which I retain all individuals who have negative net worth

but who report having had a student loan from 1979 to 1998. As with other specifications, the

future credit-experience coefficient is positive and insignificant, while the AFQT-experience

interaction is positive, large in magnitude, and highly significant. The drawback of this blanket

approach is that many of the individuals retained may have negative net worth from other causes

than their student loans. For the next specification, I calculate which individuals had a volume of

student debt that was large enough to have reversed their negative net worth status.[13] I retain

these individuals in the sample. In this specification (column five of Table 2), the future credit-

experience interaction is positive, large in magnitude (0.079), and significant at the 95 percent

level. The 95 percent confidence interval rules out any coefficient value smaller than 0.007,

again pointing to a precise zero or positive effect.

Another student-debt related concern involves not the composition of the sample but the

construction of the future credit variable. Incurring student loan debt may be associated with

higher productivity, while irresponsibly running up other debts may indicate the type of poor

judgment that could negatively affect worker productivity. Thus including student debt in the

calculation of negative net worth could "dilute" a negative character effect. To explore this

possibility, I employed a specification that nets out the effect of student loan debt on future

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[13] There are a number of challenges in working with the data on student loan amounts in the NLSY79. The student loan variables measured debt ever incurred until 1989, at which point they began to measure the annual flow of debt. Furthermore, these variables do not measure the outstanding debt but rather the unamortized original loan amount (the 2004 survey reports on outstanding quantities). Nevertheless, it is possible to construct a noisy measure of the unamortized loan total. It turns out that most individuals with negative net worth maintain this status even after netting out the effect of student debt.

negative net worth in 2004.[14] The results in the sixth column of Table 2 demonstrate the familiar

pattern. The AFQT-experience coefficient is positive, large, and highly significant (.072), while

the negative net worth-experience coefficient is neither negative nor significant (.030).

Finally, one might also ask how a future credit indicator that is directly tied to the recent

housing crisis behaves. In the seventh column of Table 2, I employ a credit quality indicator

variable that takes on a value of one if an individual reported having been late on or missed a

mortgage payment in the last three years. The question was asked in the 2010 survey, so the

years covered are 2007-2010. The late mortgage-experience interaction has a coefficient that is

negative, small, and not significantly different than zero (-.002). However, unlike all the other

specifications, in this specification the AFQT-experience coefficient is not significant. The

coefficient is positive and of reasonable magnitude (.029), and it is more precisely measured than

the late mortgage-experience coefficient, but the contrast in predictive value between the AFQT

and the future credit interaction variables is less pronounced in this specification. One potential

explanation may be that the dynamics associated with housing market shocks are different than

those that relate to other time periods and populations that are less exposed to these particular

economic shocks. Another explanation may be that the sample that contained non-missing values

for this independent variable is not large enough for precise estimation. I explored this possibility

by altering the method by which the sample was trimmed. Specifically, I added back in

individuals who reported negative net worth anytime from 1979 to 1998. The downside of

adding these individuals back is that it increases the potential for reverse causality and negative

bias in the future credit-experience variable due to serial correlation of economic outcomes. The

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[14] The 2004 NLSY79 permits more accurate measurement of this student loan contribution to negative net worth than prior years as it asks about the amount of currently outstanding student debt (rather than unamortized debt incurred).

benefit is that it will increase the size and variation of the sample. In the original sample six

percent of individuals reported being late or missing mortgage payments. In the expanded

sample, nine percent report this condition. The additional sample variation should also improve

the precision of the AFQT estimates. We can see the results in the final column of Table 2. The

AFQT-experience coefficient is positive, large, and highly significant (.055). By contrast, the

late mortgage-experience coefficient is very small and not significantly different from zero

(.003). The results thus appear to be broadly consistent with the results of the other

specifications.

Discussion

In multiple different specifications, measures of future credit status do not convey

negative information about the character-related component of employee productivity as firms

learn about unobservable employee characteristics over time. Indicators of future bad credit are

associated with significantly lower *initial* wages, but this wage differential is the result of factors

that are visible to employers at the beginning of the employment relationship. Because we have

dropped individuals with signs of prior bad credit, and because most individuals are not

subjected to credit checks for a particular job, these initial wage differentials are likely due to

heterogeneity that is correlated with future credit status.[15] The comparison with AFQT scores is

instructive. AFQT scores are unseen by employers, but they nevertheless are associated with a

large and significant effect on initial wage levels due to other correlated factors that are visible to

employers up front. The key point, however, is that as employers learn about workers' true

productivity (or as workers differentially acquire skills to enhance productivity), AFQT scores

become highly predictive of the resulting wage growth. The character-related component of

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[15] Only 13 percent of employers in a 2010 SHRM survey used credit checks for all of their hires (SHRMb 2010). Although data are not available, in the pre-Internet 1980s, this figure was almost certainly much lower.

credit status, as measured by future credit indicators, is also correlated with initial level effects,

but unlike AFQT scores it does not contain a significant prediction of hidden productivity or

productivity growth in the expected direction.[16]

There is an alternative interpretation of these results. A critic might say that the above-

described methodology does in fact isolate the character effect, but note that a distribution of

credit-related character (p) exists. The fact that the empirical specifications show no significant

negative effect on the wage-experience profile could be due to either the fact that on average

credit-related character is not predictive of worker productivity, or to the fact that the threshold

values above which p harms productivity are high, and most individuals who experience (future)

bad credit have values of p below this threshold. The first thing to note is that these competing

explanations dramatically narrow the scope of the debate on this topic: the character-related

portion of credit status is either uninformative about employee productivity or it is only

meaningful at extreme values that infrequently occur. Even if the latter were true, from a policy

perspective we should be concerned that the likelihood of employer errors in identifying this

threshold through the review of credit reports rises as the condition becomes more improbable.

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[16] One question that might be raised about the results is what factors might generate a positive relationship between the future bad credit-experience variable and wage growth, as some specifications show magnitudes that are similar to the AFQT-experience variable. The first thing to note is that most of the specifications show point estimates for the credit-experience interaction that are much smaller than the AFQT-experience effects. Although not all of these measures are strictly comparable, as some of the credit measures are binary and some are continuous, the percentage credit card debt, percentage net worth, and late mortgage payment specifications have credit-experience interactions that are very nearly zero. In addition, only the AFQT-experience confidence intervals consistently rule out values of zero. All of the AFQT-experience coefficients but one are positive and significantly different that zero at the 95 percent confidence level or greater. By contrast, only one of the credit-experience confidence intervals excludes zero at the 95 percent level. The specifications that utilize the credit rejection dependent variable are the principal ones that show reasonably large positive magnitudes and significance or borderline significance for the future credit interactions. It is possible that future credit rejections identify some aspect of credit-related character that differs slightly from the aspects identified by other measures such as future negative net worth or future high amounts of credit card debt. This character trait might have a more positive association with wage growth than other credit-related character measures. Regardless, the point remains that all of the specifications point to effects that contradict our prior expectations of significant and large negative effects.

However, the empirical results cast doubt on the idea that a significant negative character effect is being masked by more benign sources of future credit problems. The specifications where I eliminate more "blameless" sources of credit trouble—such as student debt—and thus raise the potential proportion of character-related causes show the same patterns as the other more general specifications. Likewise, the specifications that show a higher proportion of credit problems due to exogenous macroeconomic factors (i.e., the 2008 results) do not show more positive effects of character on the wage-experience profile. In fact, they show more negative results. Continuous measures such as credit card debt as a percentage of income—commonly thought to indicate "personal responsibility"—also show the same patterns as the baseline specifications.

There are some limitations to the approach adopted in this paper. In order to isolate the character effect via future bad credit, it is necessary to drop individuals with signs of bad credit in the base period. Developing identification strategies to test for character effects in this group is an appropriate task for future research. In addition, the methodology employed in this study does not allow us to evaluate the validity of non-character-related rationales for credit checks such as the distraction screen. Finally, this paper focuses on wages as a sign of worker productivity. Testing for impacts on other labor market outcomes is another promising direction for future studies. Despite these caveats, the identification strategy in this paper allows us to evaluate the causal claims behind an important argument for credit checks.

Conclusion

The practice of screening workers by conducting credit checks is a controversial one, with advocates insisting that it improves the quality of job matches and opponents maintaining that it results in discrimination against disadvantaged groups with poor credit. The rise of similar

screening practices that rely on correlations present in Big Data further increases the salience of the issue. The contribution of this paper to the literature is to utilize an economic identification strategy along with credit proxies in a national dataset (the NLSY79) to determine whether credit status contains information about a worker's character that is predictive of worker productivity. The identification strategy consists of the use of a novel mechanism—future credit status—to identify time-invariant character traits, along with a firm-learning model to identify the impact of unobserved variables on productivity growth. While there are other rationales, such as distraction effects, for the use of credit checks, character-related factors are a major rationale offered in support of the practice. The results of this analysis indicate that credit status does not contain a meaningful signal about the unobserved character-related components of employee productivity.

Data Appendix

The data used in this study come from the 1979-2010 waves of the NLSY79, a nationally representative survey of individuals aged 14-21 in 1979. As described above, the base period data, in which labor market outcomes and contemporary economic variables are measured, are from the 1979-1992 period. The future credit variables come from the 2004-2010 waves (although some of the retrospective questions in the 2004 survey cover the period going back to 1999). The NLSY79 consists of a main sample with 6,111 individuals, a supplemental sample focused on disadvantaged populations with 5,295 individuals, and a military sample. I exclude the military sample, yielding a starting point of 11,406 individuals. After excluding time periods after 1992, there are 159,684 observations. I take a number of further steps to prepare the sample used in the empirical specifications. I exclude those who have made the transition to the labor market before the first observation in 1979 (94 individuals). Following Altonji and Pierret

(2001), I drop observations that are missing wage data (for the "CPS" job) or that have values for

real wages in 1992 dollars that are less than $2/hour or more than $100/hour (eliminates 322

individuals). I also drop individuals with missing education or who report less than eight years of

education (183 individuals). Likewise I drop individuals who did not take the tests comprising

the AFQT or who have missing AFQT scores (553 individuals). Finally, to reduce serial

correlation I take two further steps. I eliminate individuals who, in the final base period year

(1992), report work-limiting health conditions that have persisted since the prior year (456

individuals). I also drop respondents who have reported negative net worth in 1998 or earlier

(5,045 individuals). I then use the maximum sample available for the respective dependent

variables (i.e., I drop individuals with missing values for the dependent variables). These

adjustments leave a sample of 2,061 individuals with 19,371 observations for the credit rejection

specification and 3,307 individuals with 30,023 for the negative net worth specification.

Below are summary statistics for individuals in 1992 with and without future bad credit

status. The significant differences between these populations are one of the prime motivations for

using a longitudinal firm-learning identification strategy rather than a comparison of level

effects.

Table A1. Summary Statistics for Main Specifications, 1992 Values

	Credit Reject ('04, '08, '10)		Neg. Net Worth ('00, '04, '08) + '08 Control	
	No	Yes	No	Yes
Hourly wage	12.72	11.17	11.94	9.47
	(7.12)	(9.35)	(7.40)	(6.85)
Education	13.74	12.84	13.38	12.54
	(2.25)	(2.15)	(2.26)	(2.08)
Experience (years)	14.18	12.92	13.73	12.00
	(5.08)	(5.68)	(5.16)	(5.84)
AFQT (standardized)	0.42	-0.14	0.16	-0.34
	(0.84)	(0.85)	(0.97)	(0.99)
Female	0.47	0.47	0.43	0.49
	(0.50)	(0.50)	(0.50)	(0.50)
Black	0.15	0.36	0.24	0.35
	(0.36)	(0.48)	(0.43)	(0.48)
Hispanic	0.15	0.27	0.16	0.27
	(0.36)	(0.45)	(0.37)	(0.44)
Number of individuals	1,814	247	2,630	289
Number of observations	17,140	2,231	24,299	2,378

Source: NLSY79 main and supplemental samples. Standard errors in parentheses.

Table 1. Effect of Character-Related Credit Status on Productivity (Wage Growth), 1979-1992

	Measure of Future Credit Status					
	Credit Reject ('04, '08, '10)	Credit Reject w/o AFQT	Neg. Net Worth ('00, '04, '08)	Neg. Net Worth ('08 control)	Neg. Net Worth Renters	Neg. Net Worth ('00 and '04)
Future credit status variable	-0.068**	-0.082***	-0.086***	-0.120***	-0.117***	-0.125***
	(0.029)	(0.029)	(0.030)	(0.041)	(0.044)	(0.034)
Future credit*experience/10	0.064*	0.067*	-0.026	0.042	0.033	0.025
	(0.037)	(0.038)	(0.039)	(0.054)	(0.062)	(0.045)
Future credit 2008				0.101*		
				(0.056)		
Future credit '08*experience/10				-0.163**		
				(0.074)		
AFQT	0.065***		0.071***	0.081***	0.052**	0.069***
	(0.017)		(0.013)	(0.013)	(0.021)	(0.013)
AFQT*experience/10	0.040**		0.055***	0.050***	0.074***	0.060***
	(0.020)		(0.015)	(0.016)	(0.024)	(0.015)
Education	0.072***	0.085***	0.076***	0.075***	0.081***	0.077***
	(0.008)	(0.007)	(0.006)	(0.006)	(0.011)	(0.006)
Education*experience/10	-0.010	0.006	-0.021***	-0.017**	-0.045***	-0.023***
	(0.009)	(0.008)	(0.007)	(0.008)	(0.013)	(0.007)
Number of individuals	2,061	2,061	3,307	2,919	966	3,204
Number of observations	19,371	19,371	30,023	26,677	7,834	29,205
Adjusted R-sq.	0.342	0.328	0.345	0.351	0.288	0.347

Data: NLSY79. Notes: Standard errors are clustered at the individual level. All models control for year effects, a cubic in experience, urban residence, divorce, and female, black, and Hispanic interactions with experience. Non-fixed effects models control for female, black, and first occupation. Experience is potential experience. Standard errors are in parentheses; *=p<.10, **=p<.05, ***=p<.01.

Table 2. Effect of Character-Related Credit Status on Productivity (Wage Growth), 1979-1992: Additional Specifications

	Measure of Future Credit Status							
	Credit Card Debt % of Inc. ('04)	Credit Card Debt % of Inc. ('08)	Net Worth as % of Assets ('04)	Credit Reject Incl. All Student Loan Holders	Credit Reject (Netting Out Student Loans)	Neg. Net Worth ('04 no student debt)	Late Mort. Pmt. (2007-2010)	Late Mort. Pmt. Expanded Sample
Future credit status variable	-0.001	-0.020*	-0.001***	-0.076***	-0.089***	-0.088	0.022	0.002
	(0.001)	(0.012)	(0.000)	(0.022)	(0.029)	(0.054)	(0.043)	(0.024)
Future credit*experience/10	-0.000	0.015	0.001***	0.020	0.079**	0.030	-0.002	0.003
	(0.001)	(0.012)	(0.000)	(0.031)	(0.037)	(0.070)	(0.045)	(0.029)
AFQT	0.078***	0.080***	0.070***	0.051***	0.065***	0.072***	0.078***	0.055***
	(0.014)	(0.015)	(0.014)	(0.014)	(0.017)	(0.013)	(0.015)	(0.011)
AFQT*experience/10	0.037**	0.039**	0.053***	0.050***	0.039**	0.059***	0.029	0.048***
	(0.018)	(0.018)	(0.018)	(0.017)	(0.0196)	(0.017)	(0.020)	(0.013)
Education	0.079***	0.077***	0.077***	0.077***	0.072***	0.078***	0.070***	0.075***
	(0.007)	(0.007)	(0.007)	(0.006)	(0.007)	(0.007)	(0.007)	(0.005)
Education*experience/10	-0.016*	-0.012	-0.022***	-0.023***	-0.009	-0.024***	-0.006	0.020***
	(0.009)	(0.009)	(0.008)	(0.008)	(0.009)	(0.008)	(0.009)	(0.006)
Number of individuals	2,375	2,393	2,681	3,056	2,159	2,898	2,108	4,364
Number of observations	22,521	22,600	25,046	27,483	20,107	26,563	19,931	40,453
adj. R-sq	0.353	0.350	0.346	0.316	0.337	0.347	0.354	0.320

Data: NLSY79. Notes: Standard errors are clustered at the individual level. All models control for year effects, a cubic in experience, urban residence, divorce, race, gender, and female, black, and Hispanic interactions with experience. Models also include controls for first occupation, except for models with controls for first wage. Credit card models also include zero-debt controls (see text for discussion). Experience is potential experience. Standard errors are in parentheses; *=p<.10, **=p<.05, ***=p<.01.

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