Math Skills and Labor-Market Outcomes: Evidence from a Resume-Based Field Experiment

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We examine the link between math skills and labor-market outcomes using a resume-based field experiment. Specifically, we send fictitious resumes in response to online job postings, randomly assigning some resumes to indicate stronger math skills, and measure employer responses. The resumes that are randomly assigned to indicate stronger math skills receive more interest from employers than the comparison resumes. Our findings add to the body of evidence showing that stronger math skills positively affect labor-market outcomes.

I. Introduction

We evaluate the effects of math skills on labor-market outcomes using a field experiment. Our methodology is similar to the one used by Bertrand and Mullainathan (2004) in their work on employer discrimination: we send fictitious resumes in response to online job postings, randomly assigning some resumes to indicate stronger math skills, and measure responses from employers. We send resumes to job postings in three occupational categories: clerical/administrative, customer service (including cashiering), and sales. These occupational categories include some of the largest occupations in the United States.[1]

Our study adds to a large literature in economics relating math skills to labor-market outcomes, and offers two unique contributions. First, by virtue of the occupational categories that we focus on in our experiment, we isolate the effects of stronger math skills for moderately-skilled workers. Moderately-skilled workers make up a substantial fraction of the workforce but have received little direct attention in prior work.[2] Second, we randomly assign math skills to resumes. This allows us to avoid the serious econometric challenges related to the endogenous formation of math skills in real data. It is also of interest that we performed our experiment during a period of high unemployment in the United States (the spring and summer of 2010).

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[1] See the Occupational Employment Statistics provided by the Bureau of Labor Statistics (BLS) for more information. For example, in May of 2009, the 15 largest occupations in the United States as reported by the BLS included retail salespersons, cashiers, office clerks, customer service representatives and secretaries. All of these occupations are represented in our study (see http://www.bls.gov/oes/current/largest_occs.htm). Also, among the major occupational groups as defined by the BLS, the two largest groups are "Office and Administrative Support Occupations" and "Sales and Related Occupations" (see http://www.bls.gov/oes/current/oes_nat.htm).

[2] Several studies estimate math-skill effects on wages for the general population (see, for example, Altonji, 1995; Murnane, Willet and Levy, 1995; Rose and Betts, 2002), but it is difficult to determine how the results from these studies apply to specific subgroups of workers. Joensen and Nielson (2009) and Tyler (2004) provide some insight by estimating math-skill effects for highly-skilled workers and high-school dropouts, respectively. The only study of which we are aware that separately estimates effects for workers who are likely to be moderately skilled is Levine and Zimmerman (1995). They evaluate wage outcomes and do not find a link, but their estimates are imprecise enough that they cannot rule out non-zero effects (their IV estimates are particularly noisy). Kukla-Acevedo (2009) finds some evidence that elementary-school teachers with stronger math skills perform better in the classroom.

For individuals seeking sales positions, we find that stronger math skills positively affect employer interest. We also find some evidence of a positive math-skill effect for prospective clerical workers, but we do not find any evidence that stronger math skills are important for individuals seeking employment in customer-service positions. Stronger math skills do not decrease employer interest in any of the occupational categories that we examine.

II. Motivation

Consider the following empirical model based on Mincer (1958), augmented for the purposes of this study to include a measure of observable math skills:

$$y = \gamma E + \lambda EXP + \delta MS + \varepsilon \tag{1}$$

In (1), y is a labor-market outcome (such as log-wages), E measures education, EXP measures work experience and MS measures math skills. The key empirical challenge in estimating equation (1) is that individuals' observable skills are likely to be endogenously determined. There is a large literature in economics that discusses the endogeneity problem in models similar to equation (1), mostly focusing on the endogeneity of education and experience. For the same reasons that education and experience are likely to be endogenous, other measures of observable skills are also likely to be endogenous.[3]

In our experiment, we distinguish math skills across individuals by assigning math-specific and non-math-specific qualifications to resumes (we provide details about these qualifications in Section III). The field-experiment design offers the important advantage that we can randomly assign qualifications to resumes, obviating the concern that the accumulation of math-specific and non-math-specific skills is endogenous. For example, with real data we might worry that unobserved factors encourage individuals to pursue math-specific skills and also push

[3] For brevity we avoid a lengthy discussion of this important but already well-understood problem. The interested reader can find detailed discussions in Altonji (1995), Behrman and Rosenzweig (1999), Cawley et al. (2001), Joensen and Nielson (2009), Levine and Zimmerman (1995), and Tyler (2004), among others.

them to search for employment more diligently. In the absence of an exogenous source of variation that affects the accumulation of math skills this would make causal inference difficult. But by virtue of the random assignment in our study, we can be confident that our findings will not be driven by any such confounding factors.

This benefit of our research design gives us a high degree of confidence in our results. However, while we are quite comfortable assigning a causal interpretation to our findings, we note that our experiment cannot be used to answer another important question: namely, where we find non-zero impacts of stronger math skills, we cannot separate out the relative importance of the effects of signaling and human capital (Spence, 1973). Instead, we rely on other studies in the literature to provide insight, noting that in analyses where signaling and human-capital effects can be distinguished, researchers consistently find that the human-capital-based returns to observable skills are larger than the signaling-based returns (e.g., see Ishikawa and Ryan, 2002; Kane and Rouse, 1995; or, for international evidence, see Boissiere, Knight and Sabot, 1985).[4]

III. Study Design

Resume Construction

We followed a procedure similar to the one used by Bertrand and Mullainathan (2004) to construct the resumes for our experiment. We began by finding real resumes that were posted online by job seekers in one of the occupational categories of interest in either Kansas City or St. Louis. At the onset of the project we identified four occupational categories: cashiering, clerical/administrative, customer service and sales.

Within each occupational category and labor market we found four resumes and grouped them into two matched pairs based on educational attainment –one pair of high-education (HE)

[4] The consistency of this finding in the literature makes it noteworthy; however, we are not aware of any studies that separate signaling and human-capital effects specifically for moderately-skilled workers. This leaves open the possibility that our findings are driven more by signaling than is the case in other studies.

resumes, and one pair of low-education (LE) resumes. We established the education levels that determined the HE and LE designations based on what we observed in the pools of real resumes within each occupational category. For the clerical resumes, the HE resumes had Associate's degrees and the LE resumes did not. For the other job categories, the HE resumes had at least some experience at a four-year college and the LE resumes had no more than an Associate's degree.[5] All of the resumes were adjusted to indicate that the individual had at least graduated from high school, even when this was not the case.

After identifying the matched pairs of resumes we switched their labor markets. That is, the resumes for job seekers in St. Louis were moved so that they would apply to jobs in Kansas City, and vice versa. The labor-market switches required that we "reconstruct" each resume to align it with its new labor market. First, we identified a new high school for each individual by finding a comparable high school in the new city along the dimensions of test scores and basic demographics. We were also careful to find similar schools in terms of being urban, suburban, or rural. In cases where a resume did not indicate a high school, we selected a high school comparable to the high school listed on the other resume in the matched pair.

We followed a similar procedure for colleges. All four-year and community colleges outside of the St. Louis and Kansas City metropolitan areas were left unchanged. Those within the metro areas were switched and assigned replacements that were as similar as possible. Four-year colleges were switched on the basis of size, whether they were public or private, and whether they were urban or suburban. Community colleges were switched on the basis of size, whether they were urban or suburban, and the local-area median household income (determined by zip code).

[5] Although a handful of the real resumes indicated attendance at a well-known four year university, this was uncommon. Examples of the universities listed on the final resumes include Webster University, American Intercontinental University, Rockhurst University and the directional state universities in Missouri.

We then switched prior employers with similar employers in the new labor market. As an example, a hypothetical resume from a job seeker who had previously worked at Wal-Mart, U.S. Bank, and Burger King in St. Louis might be adjusted so that in Kansas City, he would have worked at Target, Bank of America, and McDonalds.[6] The switching process involved scouring the yellow pages to find possible switches for the previous places of employment for all 32 resumes. After switching the employment histories we correspondingly adjusted job seekers' descriptions of their prior job responsibilities as needed. We were careful to avoid altering the qualitative content of the job descriptions from the original resumes.

Next, we randomly assigned one resume within each pair to be the high-math-skills (HMS) resume. We added additional math-related qualifications to this resume, and additional non-math-related qualifications to the comparison resume, which we refer to as the low-math-skills (LMS) resume. We began by adding or adjusting individuals' educational qualifications, such as college majors and minors.[7] For example, persons who attended community college were given Associate's degrees in either mathematics, or a non-math-related field, like English or history. Persons who attended four-year institutions were assigned majors in more-neutral areas of study such as business administration or psychology (to make them look more realistic), but were assigned minors in subject-specific disciplines. The websites of the colleges that were assigned to each resume were consulted to verify that the majors, minors and Associate's degrees that were listed on the resumes actually existed.

We also adjusted the "activities/skills" sections of the resumes. First, we added information about participation in a subject-specific high-school interest group like the math club

[6] This is a stylized example – a large fraction of the employment histories on the resumes involved work at lesser-known, local companies.
[7] Arkes (1999) finds that employers interpret educational credentials as signals of ability.

or the poetry club.[8] Then we added neutral activities to the resumes, like participation in sports or a community-service club, to make them look more balanced.[9] Finally, we added an additional skill or honor to the HE resumes, such as being a part of an academic honor society or on the Dean's List, or having volunteer experience or the ability to speak a foreign language.

In terms of last details, we randomly assigned fictional names to each resume based on the 50 most popular first and last names in 1990 according to the US Social Security Administration. Only male names were used to abstract from issues related to gender. We also randomly assigned each resume one of several resume templates, a phone number, and an email address. The email addresses were based on the fictitious names depending on what was available from online email providers.[10]

Applying to Jobs

The fictitious job seekers were registered on two popular job-search websites and we began sending out resumes on March 15, 2010. We continued sending resumes through July 15, 2010, and monitored the voicemail and email accounts through August 15.[11] The period over which we conducted our experiment was marked by relatively high unemployment in the United States. The Bureau of Labor Statistics reports that the unemployment rate in Missouri over the course of our study was between 9.1 and 9.5 percent.

[8] For individuals who did not pursue any schooling beyond high-school, the assignment of the subject-specific high-school activities provides the only source of information about math-specific skills on their resumes. We could not identify any other way to signal math skills on these resumes while maintaining their realism. The lack of more pronounced evidence of math skills for high school graduates in our study may partly explain why our findings are weaker for the low-education group, although from informal conversations with employers we learned that they do look at the activities/skills sections of the resumes.

[9] Where possible, we verified that the activities assigned to each resume were available at the assigned high school.

[10] We also assigned each job seeker a new home address. Using Google Earth, we ensured that the new addresses were not in particularly run down or wealthy areas. An appendix with sample resumes is available from the authors upon request.

[11] We considered extending this window, but we were receiving very few responses by August 15th.

We searched for and applied to jobs in each occupational category on a near-daily basis. We sent out four resumes in response to each job posting – one pair of HE resumes and one pair of LE resumes.[12] It quickly became clear that cashiering positions are not commonly advertised online, and when they are, they are often advertised under the heading of customer service. Therefore, we sent only a handful of resumes to explicit advertisements for cashiering positions, and in presenting our results we combine these resumes with the customer-service resumes.[13]

Data on employer responses were collected by monitoring email accounts and voicemail messages. We differentiated employer responses based on the level of interest in the job seeker, dividing them into three categories. Category-1 responses indicated direct interest in interviewing the job seeker. Category-2 responses did not explicitly mention an interview, but still indicated clear interest. Category-3 responses asked for further interaction, often requesting more information about the job seeker, and generally indicated less interest. Table 1 shows examples of responses in each category.[14]

At the midpoint of our study, on May 15, we reversed the HMS and LMS designations within each resume pair, leaving everything else on the resumes unchanged. An issue with the switch is that during the first wave of the study we were able to apply to some job openings that were posted prior to March 15, which means that we sent out more total resumes in the first wave than in the second wave. We weight the employer responses from the first and second waves to correct for the discrepancy when we present our findings.

[12] Our experiment imposed modest costs on employers in Kansas City and St. Louis. From informal conversations with several employers who regularly hire in these occupations, and with a customer-service agent from a major job-search website, we expect that employers received 40-100 resumes per job posting per month across the occupations that we consider during our study. Job postings for sales positions generate the fewest responses, which may explain the higher response rates to sales resumes (see Table 3).
[13] We sent out 3,236 resumes in all, and 36 resumes to positions advertised under cashiering.
[14] Our approach to categorizing employer responses is similar to that in Lahey (2008).

Table 2 shows weighted summary statistics for the final resumes that were sent to employers, overall and separately for the education and math-skill groups. The table reports information about individuals' education levels, years of work experience, the presence of an employment gap in the work history (more than six months without work), and job mobility (measured by the ratio of jobs to years of work experience).

There are not any meaningful or statistically distinguishable differences between the HMS and LMS resumes in Table 2, which is expected given our switch-and-weight procedure described above. In fact, the only reason that the resume characteristics for the HMS and LMS groups are not identical is that there were small differences in the shares of resumes sent to each occupational category and labor market before and after May 15th (the switch date). The descriptive statistics in Table 2 confirm the successful randomization of math skills to resumes in our experiment – any differences in employer responses to the HMS and LMS resumes will not be driven by other resume characteristics.

Table 2 also compares the resumes across education groups. Although differences between the HE and LE resumes will not affect our ability to identify math-skill effects, they are important for interpreting our findings. The table shows that in addition to the HE and LE resumes differing by educational attainment, which is expected, they also differ in their work histories. LE individuals have more experience, fewer gaps in their work histories, and fewer jobs per year of experience. The work-history differences are driven, at least in part, by the differences in educational attainment between the groups. More specifically, individuals with more education are likely to have had more overlap between work and schooling, which corresponds to shorter work spells, more employment gaps and less work experience overall. The effect of the work/schooling overlap on the work histories is amplified in our data because we purposefully selected resumes with short work histories for our experiment (we discuss the reason for imposing this selection criterion in the next section).[15]

Should the HE resumes be interpreted as being of higher quality than the LE resumes, despite the fact that the LE resumes have what appear to be stronger work histories? We suspect that the answer to this question is probably "yes" for several reasons. First, the HE individuals are primarily substituting between work and schooling, and they have higher combined values of education and experience. Second, the negative aspects of the work histories for HE individuals are not as negative as they may seem. For example, some of the employment gaps on the HE resumes occur during enrollment in college, whereas for the LE resumes the employment gaps are more likely to be unexplained.[16] Third, as indicated above, we added an additional skill or honor to each HE resume to further distinguish the HE and LE resumes, and the HE resumes also appear to be of higher quality in ways that are difficult to quantify but that may be important, like exposition.[17]

In summary, Table 2 shows that the randomization of math skills to resumes in our study was successful – the HMS and LMS resumes do not differ in any other way. Between the HE and LE groups there are important differences in educational attainment and work histories, which we expect to reflect real differences between more- and less-educated job seekers in the occupations that we consider (at least in the early phases of their careers). We hypothesize that

[15] That is, because our resumes all have short work histories, the overlap between work and experience for more-educated individuals occurs over a larger fraction of the total experience profile.

[16] This may help to explain why Bertrand and Mullainathan (2004), who define employment gaps as we do here, find a positive relationship between employment gaps and callback rates using a non-experimental correlation in their data. In results that we do not report for brevity, we also find a positive correlation between employment gaps and callback rates in our data, although it is generally small and not statistically significant.

[17] As was the case with all aspects of the resumes, we took considerable effort to make sure that the re-constructed resumes were of the same quality as the original resumes in terms of exposition. An appendix with sample resumes that illustrates the differences between the HE and LE resumes, and how the math skills were added to resumes, is available from the authors upon request.

these differences may correspond to differential math-skill effects across the HE and LE groups, and find some support for this hypothesis in our results.

IV. Limitations

There are several limitations of our research design that merit discussion. For one, as noted by Bertrand and Mullainathan (2004), employer responses to resumes are crude measures or labor-market outcomes. However, as long as there are at least moderate frictions in the search process; callback rates will translate into job offers, which will translate into employment and wage outcomes.[18] Therefore, we do not view the crudeness of our outcome measure as cause for concern.

An issue of greater importance is that our experiment could potentially create an artificial environment that is unrepresentative of reality for the fictitious job seekers. Goldberg (1996) raises this general issue in her critique of audit studies in the discrimination literature. An obvious concern for our analysis is that in the real world, individuals with stronger math skills may have different work histories than individuals with weaker math skills. By randomly assigning math-specific and non-math-specific qualifications to resumes, we risk creating resumes with experience profiles that are inconsistent with individuals' math skills as perceived by employers. To alleviate this concern to the extent possible we purposefully selected resumes for our study with short work histories. Job seekers with short work histories are less likely to have had jobs that depend crucially on specific skills, and in fact, a large fraction of the work histories from our resumes involve jobs that occurred concurrently with schooling. We expect

[18] Also see Lahey (2008), who provides back-of-the-envelope calculations that translates callback rates to job offers in her study of the labor market for older women.

our use of resumes with short work histories to reduce the likelihood that individuals' experience profiles will be noticeably mismatched with their randomly-assigned math skills.[19]

We also note three issues regarding the interpretation of our results. First, related to the previous discussion, stronger math skills will affect individuals' labor-market outcomes across and within occupations. That is, an individual with stronger math skills is likely to be qualified for different occupations than an individual with weaker math skills, and may be more or less successful conditional on occupation type. We can only identify within-occupation effects, although across-occupation effects are also likely to be important. Second, as discussed in Section II, we cannot distinguish signaling effects from human-capital effects. Because there is no obvious link between math skills and worker productivity in sales, where we find the strongest evidence of positive math-skill effects (see below), one could interpret our findings to suggest that signaling is important. However, we cannot rule out the possibility that math skills *do* affect productivity in sales, even if the effect is indirect. For example, general problem-solving skills could improve with math skills. Third, we cannot evaluate the influence of social networks, which we know to be important (Bayer, Ross and Topa, 2008; Schmutte, 2009), and their possible interactions with math skills.

Despite these limitations of our research design, it offers an important, and we feel overwhelming, benefit: math skills can be randomly assigned to resumes. This allows us to circumvent problems related to the endogenous formation of math skills in real data.

[19] A related issue that the resumes may be dismissed out of hand by some employers if they appear to be completely artificial. This concern is more likely to be a problem for the LE/HMS resumes because math skills are likely to be positively correlated with education levels in the population, making the combination of HMS and LE potentially problematic. We cannot directly evaluate the extent to which this issue may have affected employer responses in our study. But if some of the LE/HMS resumes were quickly dismissed by employers for this reason, then it would bias our estimate of the HMS effect for the LE resumes negatively.

V. Results

Table 3 shows average employer response rates to the resumes, overall and separately for the education and math-skill groups. We show both weighted and unweighted response rates, which are similar, where the weights are set so that the resumes from wave-1 and wave-2 contribute equally to the averages. In total, we sent out 3,236 resumes for 809 job openings, with twice as many resumes going out in wave-1 relative to wave-2.[20] Openings in sales were by far the most common, followed by openings in customer-service and clerical positions. Overall response rates are similarly ordered, with response rates for the clerical resumes being particularly low.[21]

We estimate math-skill effects for our entire sample, and separately by occupational category. Of the four resume types – HE/HMS, HE/LMS, LE/HMS and LE/LMS – we omit the HE/LMS resumes from our models, making them the comparison group. We estimate probits of following form, and report marginal effects in Table 4:

$$C_i = \beta_0 + O_i\beta_1 + KC_i\beta_2 + HH_i\delta_1 + LH_i\delta_2 + LL_i\delta_3 + \varepsilon_i \qquad (2)$$

In equation (2), C_i measures the employer response to resume i, O_i is a vector of occupational-category indicators, KC_i indicates that the resume was sent to a business in Kansas City, and HH_i, LH_i and LL_i are indicators for the resume being designated as HE/HMS, LE/HMS, and LE/LMS, respectively. The total "HMS effect" across education categories can be approximated

[20] As noted above, a big reason for the discrepancy is that in wave-1 we applied to jobs that had been posted prior to the start date of the project to increase our sample size. Additionally, we did not apply to multiple jobs from the same company. Companies that regularly advertised relevant jobs were applied to during the first wave.

[21] Bertrand and Mullainathan (2004) noted that males received fewer responses than females when applying to administrative-support positions, which is consistent with our low response rate in clerical jobs. It may also be that the economic climate during the time of our study had a particularly adverse effect on the demand for clerical workers, creating a larger surplus of workers than in the other job categories.

by subtracting the simple average of the LMS estimates (HE and LE) from the simple average of the HMS estimates, noting that the HE/LMS effect is normalized to zero.[22]

We estimate models for the three types of employer responses shown in Table 1. For the occupation-specific models we omit the vector O_i, of course; and in Appendix A, where we report results separately by labor market, we omit the labor-market indicator. The standard errors are clustered at the employment-ad level, and we present both weighted and unweighted results, which are similar.

We consider math-skill effects for the HE resumes first, which can be read from Table 4 by the marginal effects for the HE/HMS group (because the HE/LMS group is omitted). Our findings from the category-1 and caterogy-2 models indicate that HE individuals with stronger math skills receive more interest from employers. The estimates from the category-3 model are nominally positive but cannot be statistically distinguished from zero. The occupation-specific analysis reveals that our results from the overall models are driven by large and positive math-skill effects in the category-1 and category-2 sales models (the estimates in the category-3 sales model are positive but not statistically significant). For HE individuals seeking clerical or customer-service positions, we find no evidence that math skills affect employer interest.

Next we consider the LE resumes, for which the math-skill effects can be read from the table by comparing the marginal effects for the LE/HMS and LE/LMS groups. In sales, the estimates from the category-1 and category-2 models are consistent in direction with our findings for the HE resumes, but none of the differences between the HMS and LMS resumes are

[22] We do not emphasize these results because the math-skill qualifications differ across the resume groups, and additionally, distinguishing the effects across education levels is important for interpretation. But, for the interested reader, the total "HMS effect" (across education designations) is statistically significant in the following models in Table 4: Category-1, all resumes and sales resumes; Category-2, all resumes and sales resumes. The effect is suggestively positive (p-value between 0.10 and 0.25), in the following models: Category-3, all resumes, clerical resumes, sales resumes (weighted). The exact point estimates for the total HMS effect in each model are available from the authors upon request.

statistically significant.[23] For the LE clerical resumes, we find a positive math-skill effect in the category-3 model, but this finding is less compelling because there is not consistent evidence of a math-skill effect for clerical workers elsewhere in the data. For example, the LE/HMS resumes do not fair better in the interview-request model, even nominally; and among the HE resumes there is no indication that math skills affect employer interest in clerical workers. Again, for job seekers in customer service, math skills do not affect employer interest.

There are several potential explanations for why we find positive math skill effects for the HE sales resumes, but not for the LE sales resumes. One possibility is that some employers infer negative selection along a different dimension for the LE resumes that indicate strong math skills. That is, resumes that feature the combination of stronger math skills *and* low education levels may be poorly received if employers expect strong math skills to be positively associated with educational attainment in general. Resumes that do not display the expected combination of qualifications may convey a negative signal, which would offset any otherwise-positive HMS effects.[24] Another explanation is that our non-findings are the result of our being unable to sufficiently differentiate the LE resumes, which have fewer moveable education qualifications.[25]

[23] For the low-quality sales resumes, a rough calculation suggests that we would need a dataset approximately three times as large as our current dataset to be able to statistically detect the effect sizes in category-1 and category-2 responses that are suggested by Table 3.

[24] Related to this same issue and as discussed in Section IV (see footnote 19), some employers could even dismiss the LE/HMS resumes out of hand if the combination seems too extraordinary. In fact, there is some support for these explanations in the labor-market specific results for Kansas City, where the LE/HMS resumes received fewer responses than the LE/LMS resumes. However, the evidence is suggestive at best as it is not replicated in St. Louis. See the appendix for the labor-market-specific results.

[25] See discussion in Section III, and in particular, footnote 9.

VI. Interpretation

The Substantive Importance of Stronger Math Skills

How large are the math-skill effects that we document in the previous section? We benchmark our findings by comparing them to work-experience effects, which we estimate by augmenting equation (2):

$$C_i = \alpha_0 + O_i\alpha_1 + KC_i\alpha_2 + X_i\alpha_3 + HH_i\gamma_1 + LH_i\gamma_2 + LL_i\gamma_3 + u_i \tag{3}$$

The additional controls in equation (3), shown in the vector X_i, are for total experience, the presence of an employment gap in the work history (0 or 1), and the ratio of jobs to years of work experience.[26]

In shifting our focus from estimating math-skill effects to estimating experience effects, two issues merit attention. First, work experience is not randomized in our study, which means that we move from an experimental research design to a non-experimental design to estimate the experience effects. Second, because we purposefully selected resumes with short work histories, there is less variation in work experience in our data than in other similar datasets. For example, Bertrand and Mullainathan (2004) report that the standard deviation of work experience in their data is 5.04, while in our data it is just 2.47 (see Table 2).[27]

Noting these limitations, in Table 5 we report estimated marginal effects from equation (3) for a single year of work experience.[28] For brevity, we suppress the estimates corresponding to the other work-history controls. Like in our primary analysis, we find that experience is only

[26] Note that the addition of these controls does not meaningfully affect any of our findings in Table 4, which is consistent with the successful random assignment of math skills to resumes in our data.
[27] The standard deviation in experience by job category is 2.72, 2.23, 2.44 for clerical, customer service and sales resumes. While the limited variability in work experience in our data need not be an issue, it could result in estimates of experience effects that are different than what would be found in a dataset with more variability.
[28] The differences in the experience effects for HE and LE individuals are not statistically distinguishable so a single experience effect is estimated for each model.

meaningfully related to callback rates in sales.[29] By comparing the estimates in Tables 4 and 5 for the HE sales resumes, for which we find the consistently positive math-skill effects, we conclude that stronger math skills are substantively important for this group. The increased employer interest generated by the HMS resumes is roughly equivalent to what we would expect from an additional one to six years of work experience, depending on which employer response is considered. The math-skill effects are largest relative to the experience effects in the interview-request model, and smallest in the any-response model.

The effects of work experience get larger moving from left to right in Table 5. One interpretation of this finding, if we take the experience effects at face value, is that employers use work experience as a precondition for contacting job seekers in sales, but work experience alone is less likely to generate strong interest. Alternatively, our findings in Table 4, where the math-skill effects get *smaller* moving from left to right, are consistent with a different interpretation: it may be that only a fraction of employers are looking for individuals with strong math skills (lowering the category-3 effect), but they respond with clear interest when they encounter a resume that displays these skills (raising the category-1 and category-2 effects).

Why Sales?

We find consistent evidence of a positive math-skill effect only in sales. One explanation is that employers are more responsive in general to individuals' observable qualifications in sales. This hypothesis is supported by our experience findings in Table 5, and by informal

[29] We can only speculate as to why we do not find positive correlations in the data between experience and callback rates for the other occupational categories. Bertrand and Mullainathan (2004) do not report differential experience effects by occupational category, so it is difficult to determine whether this finding is unique. Notably, our estimate for the overall experience effect on callback rates, 0.9 percent (see Table 5), is larger but similar to the estimate from Bertrand and Mullainathan (2004), 0.4 percent. One source of the discrepancy may be that more of our resumes were sent to advertisements for sales positions (48 versus 32 percent).

conversations with several employers.[30] But this is probably not the whole story – for example, customer service resumes, not sales resumes, are the only resumes for which we identify a consistent differential response rate between the HE and LE groups.[31]

We are left to conclude that the differential effects of math skills across occupations in Table 4 partly reflect differences in how employers evaluate prospective employees across these specific occupations. It is not surprising that there are some differences – individuals working in these occupations may rely on different skills to succeed. Our finding that math skills sometimes positively affect employer interest is notable because *ex ante* none of the occupations that we evaluate would seem to require strong math skills as a prerequisite for success. Furthermore, our results for sales resumes are of independent interest given the large workforce representation of sales workers. Of the 22 major occupational categories in the United States as identified by the Bureau of Labor Statistics, the "Sales and Related Occupations" category is the second-largest (first: "Office and Administrative Support Occupations").[32]

VII. Conclusion

Our study adds to the literature relating math skills to labor-market outcomes, and makes two contributions. First, we evaluate the effects of stronger math skills for moderately skilled workers, who make up a large fraction of the labor force but have received little direct attention in prior work. Second, our field-experiment design offers a unique approach to evaluating the

[30] We interviewed several employers to gain insight into our findings at the conclusion of the experiment. They noted that sales workers are more likely to struggle than workers in other areas, and indicated that in particular, prior experience in sales is viewed positively. None of the handful of employers we spoke with volunteered that math skills are important, but with some prompting two employers indicated that they would view a sales resume that indicated stronger math skills favorably, and another unfavorably. The employers who view math skills favorably gave reasons including (1) that math skills are helpful for negotiating with customers, (2) that math skills suggest pragmatism, and (3) one employer indicated that stronger math skills would help salespeople understand the product better (albeit marginally). The employer who we spoke with who views math skills unfavorably takes them as a signal of weaker interpersonal skills.

[31] The differential response rates between the HE and LE resumes in all three customer-service models are statistically significant.

[32] See http://www.bls.gov/oes/current/oes_nat.htm.

effects of stronger math skills on labor-market outcomes. The key benefit is that we can randomly assign math skills to resumes, obviating concerns that they are endogenously determined.

In summary, we show that employers looking to fill sales positions are more likely to respond (with clear interest) to a resume that indicates stronger math skills, and the effect is large. This result is specific to high-education resumes. We also find some evidence that math skills positively affect employer interest in clerical resumes, but this finding is not consistent enough throughout our analysis to make strong inference. Math skills do not decrease employer interest in any of the occupational categories that we consider.

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Table 1. Examples of Employer Responses by Category, Either by Phone or E-mail (mildly edited).

	Category-1: Interview Request	Category-2: Clear Interest	Category-3: Other
1)	I received your resume. Thank you for your interest in XXX. I would like to schedule an interview with you sometime next week. Can you please contact me at the email address below.	My name is XXX and I am in the XXX department at XXX. I was going over your resume, and I would like to speak with you about a position we have available in your area. I can be reached at XXX from XXX to XXX. Otherwise, feel free to leave me a voice message and I will get back to you at my earliest convenience.	Dear XXX, Thank you for your interest in our company. Based on your resume we feel that you may be a potential match for the position and invite you to return to our recruiting site to complete an online application. Please be as accurate and detailed as possible when completing the form. Should you proceed in the interview process this form will be used as the basis for a background investigation so accurate information is very important. Thank you for your time.
2)	Hi, XXX, This is XXX from XXX. I was just giving you a call to follow up on the resume you sent to us and I wanted to touch base with you about it. Our number here is XXX. Just go ahead and give me a call back at the office to see if we can schedule an initial interview.	Hi XXX. This is XXX. You replied to a job posting for a sales position opening in your area. I just wanted to discuss this position. I was impressed by your background. So, give me a call back at XXX. Thank you.	Thank you for your interest in our XXX position for XXX. The first step in our process is to answer the questions on the attached questionnaire and return to me as soon as you're finished. Thank you for your time.
3)	Hi, this message is for XXX. This is XXX with XXX. I'm just calling because we received your resume for the administrative assistant position and I'm calling because I will be doing interviews tomorrow and just seeing if you'd be available for one. If so, please give me a call back, my number is XXX and you can ask for XXX. Thank you. Bye.	Yes, XXX, this is XXX. I'm the sales manager for XXX. You submitted a resume for an ad we ran for a sales position. You can call me back next week, Monday to Friday, at XXX. It's better to call me back in the morning if possible. So, give me a call back if you would, your resume looks good and I'd like to speak with you. Thank you.	Hello XXX. I just viewed your resume online and wanted the opportunity to talk to you about a XXX position in the greater area of St. Louis. If you are in need of work right now or if you know of someone that is seeking employment right now please reach out to me via email or phone call. Thank you!

Table 2. Descriptive Statistics for Sent Resumes, Weighted, Overall and by Math-Skills and Education Groups.

	Overall	High Math Skills	Low Math Skills	P-value	High Education	Low Education	P-value
Education							
BA	0.373	0.373	0.373	1.0	0.747	0	<0.01
	(0.484)	(0.484)	(0.484)		(0.435)		
Some college/ Associates	0.311	0.312	0.310	0.87	0.253	0.369	<0.01
	(0.463)	(0.464)	(0.462)		(0.435)	(0.483)	
High school	0.316	0.314	0.317	0.87	0	0.631	<0.01
	(0.464)	(0.464)	(0.465)			(0.483)	
Work Experience							
Total Experience	6.450	6.484	6.407	0.40	6.09	6.79	<0.01
	(2.466)	(2.482)	(2.448)		(2.47)	(2.41)	
Employment gap (0 or 1)	0.408	0.404	0.411	0.68	0.476	0.339	<0.01
	(0.491)	(0.491)	(0.492)		(0.500)	(0.474)	
Jobs per year of experience	0.686	0.692	0.679	0.20	0.732	0.640	<0.01
	(0.285)	(0.284)	(0.286)		(0.265)	(0.297)	
N	3236	1618	1618		1618	1618	

Table 3. Resumes Submitted and Average Response Rates by Occupational Category and Resume Designations.

	Response Rate by Type of Response								
	Category 1 Interview Request		Category 2 Interview or Clear Interest		Category 3 Any Response		Resumes Submitted		
	Unweighted	Weighted	Unweighted	Weighted	Unweighted	Weighted	Wave 1	Wave 2	Total
All Resumes	0.036	0.035	0.046	0.044	0.100	0.095	2156	1080	3236
High Math Skills	0.040	0.040	0.051	0.050	0.103	0.100	1078	540	1618
Low Math Skills	0.032	0.030	0.041	0.038	0.096	0.091	1078	540	1618
High Education	0.039	0.038	0.051	0.050	0.110	0.108	1078	540	1618
Low Education	0.033	0.032	0.040	0.038	0.089	0.083	1078	540	1618
Clerical (all)	0.013	0.012	0.015	0.016	0.027	0.027	484	300	784
High Math Skills	0.015	0.014	0.018	0.017	0.033	0.032	242	150	392
Low Math Skills	0.010	0.011	0.013	0.014	0.020	0.022	242	150	392
High Education	0.015	0.014	0.018	0.017	0.028	0.028	242	150	392
Low Education	0.010	0.011	0.013	0.014	0.026	0.026	242	150	392
Customer Service (all)	0.039	0.033	0.043	0.036	0.083	0.078	628	280	908
High Math Skills	0.040	0.033	0.044	0.036	0.084	0.078	314	140	454
Low Math Skills	0.040	0.033	0.042	0.036	0.081	0.077	314	140	454
High Education	0.046	0.041	0.053	0.048	0.101	0.097	314	140	454
Low Education	0.033	0.024	0.033	0.024	0.064	0.058	314	140	454
Sales (all)	0.045	0.048	0.063	0.063	0.147	0.141	1044	500	1544
High Math Skills	0.053	0.058	0.072	0.075	0.150	0.148	522	250	772
Low Math Skills	0.038	0.038	0.054	0.052	0.144	0.134	522	250	772
High Education	0.047	0.050	0.067	0.070	0.158	0.154	522	250	772
Low Education	0.044	0.046	0.058	0.057	0.136	0.128	522	250	772

Notes: Weights are occupation specific where relevant.

Table 4. Differential Response Rates by Resume Type. Reported Estimates are for Marginal Effects from Probit Specifications.

	Category 1 Interview Request		Category 2 Interview or Clear Interest		Category 3 Any Response	
	Unweighted	Weighted	Unweighted	Weighted	Unweighted	Weighted
All Resumes						
High Education/High Math	0.016	0.015	0.015	0.013	0.010	0.010
	(0.006)**	(0.006)**	(0.007)**	(0.007)*	(0.009)	(0.010)
Low Education/High Math	0.002	0.002	-0.001	-0.002	-0.013	-0.013
	(0.005)	(0.006)	(0.005)	(0.006)	(0.008)*	(0.008)*
Low Education/Low Math	0.001	-0.001	-0.005	-0.009	-0.017	-0.020
	(0.005)	(0.005)	(0.005)	(0.006)	(0.007)**	(0.008)**
Clerical						
High Education/High Math	0.011	0.006	0.005	-0.007	0.006	0.000
	(0.012)	(0.010)	(0.011)	(0.011)	(0.013)	(0.014)
Low Education/High Math	0.001	0.001	0.000	0.000	0.010	0.008
	(0.008)	(0.006)	(0.007)	(0.005)	(0.013)[a]	(0.012)[a]
Low Education/Low Math	0.001	0.001	-0.005	-0.006	-0.011	-0.013
	(0.008)	(0.006)	(0.008)	(0.008)	(0.010)[a]	(0.010)[a]
Customer Service						
High Education/High Math	0.004	0.003	0.008	0.002	0.008	0.005
	(0.009)	(0.006)	(0.011)	(0.009)	(0.018)	(0.017)
Low Education/High Math	-0.013	-0.016	-0.017	-0.022	-0.033	-0.034
	(0.009)	(0.009)*	(0.010)*	(0.010)**	(0.015)**	(0.014)**
Low Education/Low Math	-0.008	-0.012	-0.013	-0.018	-0.028	-0.031
	(0.008)	(0.009)	(0.009)	(0.010)*	(0.011)**	(0.012)**
Sales						
High Education/High Math	0.029	0.033	0.027	0.034	0.015	0.023
	(0.011)**	(0.014)**	(0.013)**	(0.016)**	(0.015)	(0.017)
Low Education/High Math	0.016	0.019	0.009	0.011	-0.015	-0.013
	(0.008)*	(0.011)*	(0.010)	(0.012)	(0.013)	(0.014)
Low Education/Low Math	0.009	0.007	-0.000	-0.002	-0.013	-0.016
	(0.008)	(0.009)	(0.010)	(0.010)	(0.014)	(0.015)

** Indicates statistical significance at the 5 percent-level.
* Indicates statistical significance at the 10 percent-level.
[a] Indicates a statistically significant difference between the point estimates for the HMS and LMS low-education resumes (at the 10-percent level).
Notes: The omitted resume in each model is the HE/LMS resume. The weights are occupation specific in the occupation-specific models. Standard errors are clustered at the employment-ad level and in parenthesis.

Table 5. Correlations between Callback Rates and Resume Experience. Reported Estimates are for Marginal Effects from Probit Specifications.

	Interview Request		Interview or Clear Interest		Any Response	
	Unweighted	Weighted	Unweighted	Weighted	Unweighted	Weighted
All Resumes						
Experience	0.002	0.002	0.003	0.003	0.010	0.009
	(0.001)	(0.001)*	(0.001)**	(0.001)**	(0.002)**	(0.002)**
Clerical						
Experience	-0.000	-0.000	-0.000	-0.000	0.001	0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Customer Service						
Experience	-0.004	-0.003	-0.006	-0.004	0.004	0.005
	(0.006)	(0.005)	(0.006)	(0.005)	(0.008)	(0.007)
Sales						
Experience	0.006	0.005	0.012	0.011	0.023	0.020
	(0.003)*	(0.003)*	(0.004)**	(0.004)**	(0.005)**	(0.006)**

** Indicates statistical significance at the 5 percent-level.

* Indicates statistical significance at the 10 percent-level.

[a] Indicates a statistically significant difference between the point estimates for the HMS and LMS low-education resumes (at the 10-percent level or better).

Notes: The weights are occupation specific in the occupation-specific models. Standard errors are clustered at the employment-ad level and in parenthesis.

Appendix A
Replication of Primary Analysis by Labor Market

In this appendix we replicate our primary results separately for the Kansas City and St. Louis labor markets. The labor-market-specific estimates are imprecisely estimated in some cases because our samples sizes within labor markets are smaller. Also, there were so few employer responses to the clerical resumes that the clerical models could not be meaningfully estimated in the separate labor markets.

There are two notable findings from this appendix. First, our key result – that math skills positively affect outcomes for HE sales resumes – is driven primarily by resumes from St. Louis (although the point estimates in Kansas City are consistent in sign). We examined the job postings across labor markets to determine whether differences in their compositions might explain the stronger results in St. Louis. Specifically, we looked to see if the job posting in St. Louis had a larger share of jobs that might require stronger math skills (e.g., technical sales). We did not find any consistent evidence to lead us to believe that the job markets in Kansas City and St. Louis are substantively different (for any job category, in fact). Additional details about this analysis are available from the authors upon request.

The second notable finding from this appendix is that among the LE sales resumes in Kansas City, the HMS resumes underperformed the LMS resumes. This is the only instance throughout our analysis, and the many cuts of the data, where the HMS callback rate is lower (and statistically distinguishable).

Table A.1. Differential Response Rates by Resume Type in Kansas City. Reported Estimates are for Marginal Effects from Probit Specifications.

	Interview Request		Interview or Clear Interest		Any Response	
	Unweighted	Weighted	Unweighted	Weighted	Unweighted	Weighted
All Resumes						
High Education/High Math	0.017	0.012	0.015	0.007	0.018	0.011
	(0.009)*	(0.008)	(0.010)	(0.009)	(0.014)	(0.014)
Low Education/High Math	-0.005	-0.005	-0.009	-0.011	-0.030	-0.028
	(0.005)	(0.004)	(0.006)	(0.006)*	(0.010)**	(0.009)**
Low Education/Low Math	0.003	0.002	-0.005	-0.008	-0.018	-0.020
	(0.006)	(0.006)	(0.007)	(0.008)	(0.010)*	(0.010)**
Clerical						
High Education/High Math	Models are not informative due to limited data					
Low Education/High Math						
Low Education/Low Math						
Customer Service						
High Education/High Math	0.007	0.005	0.013	0.003	0.006	0.010
	(0.012)	(0.009)	(0.016)	(0.014)	(0.025)	(0.024)
Low Education/High Math	-0.016	-0.011	-0.023	-0.022	-0.058	-0.050
	(0.010)	(0.007)	(0.012)*	(0.011)**	(0.020)**	(0.017)**
Low Education/Low Math	-0.007	-0.005	-0.015	-0.016	-0.042	-0.037
	(0.007)	(0.005)	(0.009)	(0.010)	(0.014)**	(0.014)**
Sales						
High Education/High Math	0.027	0.018	0.026	0.010	0.032	0.000
	(0.018)	(0.021)	(0.019)	(0.023)	(0.028)	(0.030)
Low Education/High Math	-0.008	-0.013	-0.014	-0.025	-0.055	-0.067
	(0.007)	(0.012)	(0.014)	(0.016)	(0.021)*,[a]	(0.023)**,[a]
Low Education/Low Math	0.007	0.005	-0.000	-0.007	-0.013	-0.023
	(0.013)	(0.019)	(0.017)	(0.021)	(0.024)[a]	(0.030)[a]

** Indicates statistical significance at the 5 percent-level. * Indicates statistical significance at the 10 percent-level.

[a] Indicates a statistically significant difference between the point estimates for the HMS and LMS low-education resumes (at the 10-percent level or better).

Notes: The omitted resume in each model is the HE, LMS resume. Standard errors are clustered at the employment-ad level and in parenthesis. The weights are labor-market specific, and occupation specific in the occupation-specific models. Callbacks for clerical positions were so rare that the results from the labor-market-specific models are uninformative (see Table 3 in the main text).

Table A.2. Differential Response Rates by Resume Type in St. Louis. Reported Estimates are for Marginal Effects from Probit Specifications.

	Interview Request		Interview or Clear Interest		Any Response	
	Unweighted	Weighted	Unweighted	Weighted	Unweighted	Weighted
All Resumes						
High Education/High Math	0.015	0.018	0.013	0.022	0.002	0.011
	(0.009)*	(0.010)*	(0.010)	(0.012)*	(0.012)	(0.014)
Low Education/High Math	0.010	0.011	0.006	0.009	0.004	0.003
	(0.008)	(0.010)	(0.008)	(0.010)	(0.011)[a]	(0.012)[a]
Low Education/Low Math	-0.000	-0.005	-0.005	-0.009	-0.015	-0.019
	(0.007)	(0.007)	(0.008)	(0.008)	(0.010)[a]	(0.012)*,[a]
Clerical						
High Education/High Math	Models are not informative due to limited data					
Low Education/High Math						
Low Education/Low Math						
Customer Service						
High Education/High Math	0.000	0.000	0.000	0.000	0.010	-0.002
	(0.009)	(0.008)	(0.009)	(0.009)	(0.026)	(0.021)
Low Education/High Math	-0.010	-0.023	-0.010	-0.023	-0.000	-0.018
	(0.016)	(0.019)	(0.016)	(0.019)	(0.025)	(0.024)
Low Education/Low Math	-0.010	-0.023	-0.010	-0.023	-0.010	-0.025
	(0.016)	(0.019)	(0.016)	(0.019)	(0.017)	(0.021)
Sales						
High Education/High Math	0.031	0.040	0.027	0.044	0.004	0.027
	(0.015)**	(0.019)**	(0.017)	(0.021)**	(0.017)	(0.020)
Low Education/High Math	0.031	0.037	0.023	0.031	0.008	0.015
	(0.013)**,[a]	(0.017)**,[a]	(0.013)*	(0.016)*,[a]	(0.016)	(0.017)
Low Education/Low Math	0.011	0.009	0.000	0.000	-0.013	-0.013
	(0.012)[a]	(0.008)[a]	(0.012)	(0.010)[a]	(0.016)	(0.017)

** Indicates statistical significance at the 5 percent-level. * Indicates statistical significance at the 10 percent-level.
[a] Indicates a statistically significant difference between the point estimates for the HMS and LMS low-education resumes (at the 10-percent level or better).
Notes: The omitted resume in each model is the HE, LMS resume. Standard errors are clustered at the employment-ad level and in parenthesis. The weights are labor-market specific, and occupation specific in the occupation-specific models. Callbacks for clerical positions were so rare that the results from the labor-market-specific models are uninformative (see Table 3 in the main text).