General Mental Ability and pay: Nonlinear effects [☆]

Yoav Ganzach [a,*], Chemi Gotlibobski [b], Doron Greenberg [c], Asya Pazy [d]

[a] Tel Aviv University, Israel
[b] The Academic College Tel-Aviv Yafo, Israel
[c] Ariel University, Israel
[d] Center of Academic Studies, Or Yehuda, Israel

ABSTRACT

While many studies have examined the linear relationship between intelligence and economic success, only few, if any, examined their nonlinear relationships. The current study examines such relationships in a large, nationally representative sample, using pay as an indicator of economic success. The results show that the effect of General Mental Ability (GMA) on pay depends on occupational complexity; the greater the complexity, the stronger the effect. They also show that, by and large, there is a marginally decreasing (concave) effect of GMA on pay. Methodological and practical questions concerning the relationship between cognitive ability and pay are discussed.

© 2013 Published by Elsevier Inc.

1. Introduction

Most, if not all studies that examined the effect of intelligence on wealth estimated linear models, both on the individual level (e.g., Ganzach, 2011; Herrnstein & Murray, 1994; Ng, Eby, Sorensen, & Feldman, 2005) and on the national level (e.g., Kanazawa, 2006; Lynn & Vanhanen, 2002; Meisenberg, 2012). In the current study we examine nonlinear models of wealth using pay as a dependent variable. We suggest that the effect of intelligence on pay is not uniform (as would be suggested by a linear effect), and we examine two nonlinear hypotheses regarding this effect. First, we examine an interactive hypothesis about the effect of intelligence on pay: the higher the mental requirement of the occupation (i.e., the higher the occupational complexity), the stronger the effect of intelligence on pay (*H1*). This hypothesis suggests an interaction between intelligence and occupational complexity in the determination

of pay. Second, we examine a curvilinear hypothesis about the effect of intelligence on pay: the effect of intelligence on pay is concave — it is stronger when intelligence is low than when it is high (*H2*).

As we discuss below, the rationale for these two hypotheses is based on evidence regarding non-linear effects of intelligence on performance. Since in many contemporary economies pay is related to performance, we expect that in such economies the nonlinear effects of intelligence on performance will be manifested in nonlinear effects of intelligence on pay. Note that in this respect the rationale underlying our argument regarding the *nonlinear* effects of intelligence on pay is not different from the rationale underlying the *linear* effect of intelligence on pay: intelligence is a good predictor of pay because it is a good predictor of performance (e.g., Gottfredson, 2002), and because performance is rewarded by pay (e.g., Herrnstein & Murray, 1994).

In the following paragraphs we first elaborate on the conceptualization of pay as an indicator of performance, and then proceed to develop the two hypotheses regarding the nonlinear effects of intelligence on *pay* based on the literature about the nonlinear effects of intelligence on *performance*. We subsequently test these hypotheses using a large nationally representative American sample.

1.1. Pay as an indicator of performance

One novel aspect of the present study is its reliance on the view, adopted from economics, that pay is an indicator of performance. This is a somewhat unusual indicator of performance in the applied psychology literature that commonly use either output (e.g., number of units produced or services provided, level of quality achieved) or supervisory evaluation ratings (of behaviors, approach or output) as indicators of performance.[1] However, although pay is not often used in the applied psychology as an indicator for performance, there is much literature suggesting that in most work environments pay is strongly related to performance (Baker, Jensen, & Murphy, 1988; Bonner & Sprinkle, 2002; Prendergast, 1999) despite the finding that this relationship may be weaker when it relates to performance quality as opposed to performance quantity (Jenkins, Mitra, Gupta, & Shaw, 1998). Thus, for example, on the basis of 77 empirical studies, Heneman (1990) found that performance ratings were positively and usually significantly related to pay increases. Although there are some experimental studies showing that under certain situations there may be weak, and even negative, relationships between pay and performance (Gneezy & Rustichini, 2000; Heyman & Ariely, 2004) these studies were usually conducted in situations that do not represent typical work environments.

In sharp contrast to that, pay is the single most common measure of performance in economics. From an economic perspective, pay is a universal measure for performance because it expresses the utility obtained from one's work as measured by the market (Lazear, 2000). It enables comparing the performance of people in different occupations, whose 'raw' performance is measured in different units, by scaling them on a common scale representing the benefit that their employer obtains from their work. The logic behind this view of the relationship between pay and performance is that in equilibrium there is no reason to assume that people will not be paid according to their performance. To see why this is the case, consider person A who is paid less than the utility her employer obtains from her performance. A is likely to seek and be hired by another employer who will be willing to pay according to the utility he might gain from her performance. Similarly, consider person B who is paid more than the utility his employer obtains from his performance. B is likely to be laid off and be re-hired only by an employer who is willing to pay (less) according to the utility gained from B's performance. As a result, over time pay reflects employees' performance, namely the utility they bring to their employers.

1.2. Occupational complexity as a moderator of the relationship between intelligence and performance

Intelligence is more crucial for performing complex as opposed to simple occupations. Therefore, it is natural to expect that the higher the complexity of the occupation, the higher the validity of intelligence in predicting performance. This expectation is supported by Hunter and Hunter (1984), who present two sets of relevant correlations. One set, obtained from studies conducted by the United State Employment Service, shows correlations of .56, .58, .51, .40, and .23 between intelligence and job performance for five occupational families arranged by *decreasing* order of complexity. The other set, obtained from re-analysis of data collected by Ghishelli (1973), likewise arranged by decreasing order of complexity, shows correlations of .53, .54, .61, .42, .48, .46, .37, .28, and .27. Thus, despite the small number of correlations and the rough pattern of the results, the trend in these data is consistent with the expected positive relationship between the complexity of the occupation and the validity of intelligence as a predictor of performance (see also Hulsheger, Gunter, & Stumpp, 2007, for a recent replication). These findings regarding the relationship between intelligence and performance provide support to our hypothesis about the interaction between intelligence and occupational complexity with regard to pay (*H1*).

1.3. Concave relationships between intelligence and performance

The relationship between intelligence and performance is concave if the higher the intelligence, the lower its effect on performance. Such a relationship is consistent with the Spearman view of intelligence, which distinguishes between General Mental Ability (GMA, or g) and specific abilities, where GMA is a major determinant of specific abilities — each specific ability is related both to a factor common to all abilities (GMA) and to a unique factor that characterizes this ability. These specific factors are particularly relevant to job performance since general ability may be invested in specific experiences and crystallizes to specific abilities, which may add to the prediction of performance (Cattell, 1987). Indeed, even studies that argue for the central role of GMA in predicting performance note that specific abilities contribute a significant, though small, amount to the prediction of job performance. Thus, for example, even when stating that there is not "much more than g" in predicting job performance, Ree, Earles, and Teachour (1994) stated that specific factors "added to the accuracy of prediction, but only by a small amount" (p. 520). Similarly, in reviewing the literature about the predictive power of cognitive ability, Kuncel, Hezlett, and Ones (2004) say, "We believe that the ability determinants of creative work are mainly composed of g, related specific abilities, and acquired domain specific knowledge" (p. 153).

Spearman's view also proposes that the higher a person's level of intelligence, the weaker its effect of GMA on specific abilities, indicating a concave relationship between GMA and specific *abilities*. This latter proposal, known in the intelligence literature as "Spearman's law of diminishing returns", is explained as a result of the fact that "High-g persons have more diversified abilities, with more of the total variance in their abilities existing in non-g factors" (Jensen, 1998, p. 585). A relevant example for this law is the threshold theory of creativity which suggests that the relationship between GMA and creativity is weaker in higher than in lower levels of intelligence (Guilford, 1967).

Within the context of the current paper, Spearman's law of diminishing returns is important because it suggests that – if performance depends to some extent on specific abilities

---

[1] We are aware of only one study in the applied psychology literature that used pay to measure performance (Hunter, Schmidt, & Judiesch, 1990), but even there pay was considered to be an appropriate measure only among non-salaried workers (this study, however, focused on the estimation of the ratio of the standard deviation of output to mean output, and did not involve an examination of the relationship between ability and performance per se).

(Gustafsson & Balke, 1993; Humphreys, 1981) – the relationship between GMA and performance is concave.[2] Thus, using creativity as an example for a specific ability that may affect performance, the threshold theory of creativity predicts that the relationship between GMA and performance will be concave because GMA has a stronger effect on creativity in lower than higher levels of GMA.

There were some attempts in the applied psychology literature to examine for curvilinear relationships – particularly concave ones – between GMA and performance (Coward & Sackett, 1990; Ghiselli & Kahneman, 1962; Hawk, 1970; Tiffin & Vincent, 1960), but all of them reported negative results. However, only Coward and Sackett (1990) and Hawk (1970) relied on sufficiently large samples that allowed for reliable conclusions; and only the former used a powerful statistical method. Coward and Sackett (1990) compared the linear validity of GMA to the validity of a squared polynomial of GMA (i.e., they compare the validity of GMA to the validity of GMA + GMA^2). Hawk (1970), on the other hand, relied on the less powerful *r* versus *eta* test that compares the validity of the linear correlation to the validity of the nonlinear *eta* measure of association (Guion, 1965; McNemanr, 1962. See Coward & Sackett, 1990, for a comparison between the two methods).

But even Coward and Sackett's (1990) study lacks in power. They calculated both linear and nonlinear validity coefficients for samples of workers in various occupations, tested in each sample whether the nonlinear validity is significantly higher than the linear validity, and examined whether the number of samples in which the nonlinear validity significantly exceeded the linear validity is higher than what would be expected by chance. This method could suffer from lack of power because it is possible that a consistent 'true' pattern of nonlinearity was not significantly detected in the individual samples due to their small sizes (although the total number of participants in their study was 36,614, the average sample size was 210). A test that takes into account *non-significant*, yet consistent, deviations from nonlinearity in individual samples may be more powerful in detecting nonlinear relationships between ability and performance. Indeed, Coward and Sackett did report that a close look at their data revealed indications for a nonlinear–concave-relationship between GMA and performance: "we do note that the sign of the regression weights for the polynomial term was negative more often than positive… note that a negative regression weight indicates a decreasing slope as predictor scores increase" (p. 299). This finding regarding the concave relationship between GMA and *performance* is consistent with the hypothesis that the relationship between GMA and *pay* is concave (*H2*).

Finally, we note that there is voluminous literature suggesting that although specific abilities contribute significantly to the prediction performance, their contribution is rather small. As our hypothesized concave relationship between

GMA and pay is based on the effect of GMA on specific abilities, we should also expect the concave effect of GMA to have a small, though significant, contribution on pay. Nevertheless, it is important to emphasize that because of the robustness of linear models, small differences in model fit may be associated with substantial differences in process. Thus, for example, a linear model often provides a considerable fit to the data even if the underlying process is nonlinear (Dawes & Corrigan, 1974). Furthermore, the empirical evidence for the importance of GMA in the determination of performance critically depends on the statistical methods by which GMA is estimated, and a number of scholars argued that different methods of estimating GMA may lead to different results regarding the effects of specific abilities on performance. Thus, even small incremental variance associated with concave effects of GMA is relevant to a better understanding of the effect of GMA on performance, and the extent by which this effect is mediated by specific abilities. We also note that findings suggesting that there is not 'much more than g' in the prediction of performance (Ree et al., 1994; Schmidt & Hunter, 2004) are not inconsistent with our Spearmanian model of GMA, which implies that specific abilities mediate the effect of GMA on performance, as such findings focus on the maximum amount of variance that can be attributed to GMA, attributing the shared variance between GMA and specific abilities to the former and not to the latter, rather than on a process analysis of the relationship between GMA and specific abilities on performance (see Lang, Kersting, Hulsheger, & Lang, 2010).

2. Method

2.1. Data

The data were taken from the National Longitudinal Survey of Youth (NLSY), conducted with a probability sample of 12,686 persons born between 1957 and 1964. The interviews are administered annually, and aimed primarily to assess the labor market experience of the participants (see the NLS user guide, 1995, for details). The 4591 participants who reported working more than 35 h per week at the time of the 1993 survey, who did not have missing values on the variables of interest, and whose values on these variables did not deviate more than 2.5 standard deviations from the mean were included in the study.

2.2. Measures

2.2.1. GMA

The measure for GMA is derived from participants' test scores in the Armed Forces Qualifying Test (AFQT). This test was administered to groups of five to ten participants of the NLSY during the period June through October 1980; respondents were compensated, and the overall completion rate was 94%. The GMA score in the NLSY is the sum of the standardized scores of four tests: arithmetic reasoning, reading comprehension, word knowledge and mathematics knowledge. Since this score is correlated with age (*r* = .21), it was standardized within each age group to obtain an age-independent measure of GMA.

---

[2] Note that findings suggesting that there is not 'much more than g' in the prediction of performance (e.g., Ree et al., 1994; Schmidt & Hunter, 2004) are not inconsistent with our Spearmanian model of intelligence which implies that specific abilities mediate the effect of intelligence on performance, since such findings focus on the maximum amount of variance that can be attributed to g, attributing the shared variance between intelligence and specific abilities to the former and not to the latter, rather than on a process analysis of the relationship between intelligence and specific abilities on performance.

2.2.2. Occupation

The NLSY includes an occupational code, which was derived from participants' open-ended descriptions of their jobs. This information was categorized by the NLSY staff into 591 occupational categories using the 3-digit Census classification.

2.2.3. Occupational complexity

A measure of occupational complexity is available for each of the 3-digit census bureau occupations. It was derived by Roos and Treiman (1980) from the 4th edition of the *Dictionary of Occupational Titles*. It is a summary index of the following occupational characteristics, evaluated by objective observers: complexity with regard to data, the degree to which the work is abstract and creative, the degree to which it requires verbal and numerical aptitudes, and the required educational and vocational preparation.

2.2.4. Pay

Following the convention of using a logarithmic transformation of pay in pay models (e.g., Ehrenberg & Smith, 1988), our measure for pay is the logarithm of the hourly rate of pay, obtained by dividing the monthly income of each participant by the number of hours he or she worked during the month (a logarithmic transformation is used in empirical work on pay mainly because the distribution of pay, but not of the logarithm of pay, is strongly skewed to the right).

3. Results

3.1. Within occupations correlational analysis

We begin with a correlational analysis (validity analysis) that allows for presenting our main findings in terms of validity coefficients. In doing that we adopted the analytical method used by Hunter and Hunter (1984). We calculated the validity of GMA for each occupation, and then examined the relationship between these validities and occupational complexity.

First, to examine the moderating effect of occupational complexity, we calculated the validity of GMA *within* each of the 84 occupations in the sample which were represented by more than 15 participants. This was done by calculating the within-occupation correlations (or validities) between GMA and pay. Subsequently, we calculated the correlation between these (untransformed) validity coefficients and the complexity indices of the 84 occupations. Consistent with *H1*, this correlation was significantly positive, $r = .33$, $p < .002$, indicating that the higher the complexity of the occupation, the higher the validity of GMA. Note that this moderating effect of occupational complexity was not driven by non-salaried workers; the correlation between occupational complexity and the validity of GMA remained almost the same when the analysis was limited to salaried workers.

Second, to examine the curvilinear relationship between GMA and pay, we calculated the *average* within-occupation correlation between GMA *squared* and pay, controlling for the linear effect of GMA (a Fisher r to Z transformation was employed before averaging the correlations). The average correlation (omitting occupation that had less than 15 people in the database) was $-.07$ ($p < .02$, with a standard error of .02), indicating that the relationship between GMA and pay is concave. This result is consistent with our re-analysis of Coward and Sackett's (1990) data and supports our second hypothesis.

3.2. Regression analysis

We supplement the correlational analysis with a regression analysis. Using this method, we could examine the entire sample, including those in less popular occupations. The appropriate model to detect curvilinear and interactive effects of GMA and complexity is the regression of the logarithm of pay on the linear and quadratic terms of GMA and complexity together with the interaction between GMA and complexity. The reason for including the quadratic effect of complexity in addition to the quadratic effect of GMA is that when interaction is estimated in the presence of multicollinearity, the two quadratic terms of the components of the interaction must be estimated as well (see Cortina, 1994; Ganzach, 1998; Lubinski & Humphreys, 1990). The results of this model – after standardization of the independent variables to allow for meaningful interpretation of main effects (see Cohen & Cohen, 1983, pp.324–325) – are given in the second column (labeled the "Full model") of Table 1. It is clear from

Table 1
Pay as a function of GMA, occupational complexity, their interaction and their curvilinear effects.

	Full model	Partial model I	Partial model II	Partial model III	Fixed effects model
GMA	.146*** (.007)	.143*** (.007)	.141*** (.007)	.093*** (.015)	.134*** (.007)
Occupational complexity (OC)	.151*** (.007)	.073*** (.003)	.091*** (.012)	.072*** (.003)	
GMA × OC	.052*** (.008)			.010** (.003)	.038*** (.008)
GMA²	−.031*** (.008)	−.010 (.006)			−.032*** (.008)
OC²	−.029*** (.007)		−.002 (.001)		
R²	.270	.263	.263	.264	

Pay is expressed in terms of the natural logarithm of the hourly rate of pay. GMA and OC are standardized. A comparison of the partial models to the full model suggests that the pattern of negative quadratic effects and a positive interaction effect is associated with reciprocal suppression.
*** $p < .0001$.
** $p < .0005$.

these results that there is a highly significant negative quadratic effect of GMA on pay as well a highly significant positive interaction between GMA and complexity.

Fig. 1 depicts the effects of GMA on pay for low (one standard deviation below the mean) and for high (one standard deviation above the mean) levels of occupational complexity. Consistent with the two hypotheses, it is clear from this figure that the effect of GMA on pay was stronger at the higher level of occupational complexity than at the lower level. It is also clear that the effect of GMA on pay was concave for both levels of complexity.

These two effects can also be stated in terms of returns on GMA. The quadratic effect of GMA represents a marginally decreasing return on GMA when occupational complexity is kept constant. The interaction effect between complexity and GMA represents an increasing return on GMA when complexity increases (the results also indicate that the curvilinear effect of complexity on pay is significant, for which we do not have a clear substantive interpretation).

Our regression analysis is particularly interesting as the pattern of negative quadratic effects and a positive interaction effect is associated – given that GMA and complexity are highly correlated – with reciprocal suppression; that is, with a situation in which the (true) curvilinear and interactive effects can be detected when examined jointly, but *not* when examined separately (Ganzach, 1997). Table 1 presents the three relevant partial models. It is clear from partial model I that the curvilinear effect of GMA would not have been detected had it not been jointly estimated with the interaction with complexity (similarly, the curvilinear effect of occupational complexity would not be have been detected had it not been jointly estimated with the interaction with GMA; see partial model II). Additionally, it is clear from partial model III that the interaction of GMA and complexity would have appeared much weaker unless jointly estimated with the curvilinear effects (the interaction coefficient is five times larger in the full model than in partial model III).
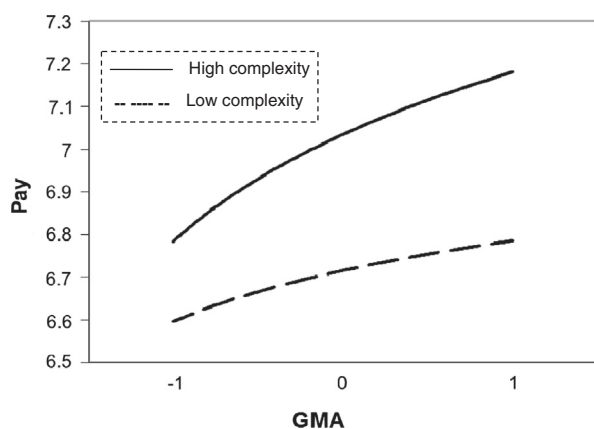
3.3. Additional analyses

We conducted two additional analyses to examine for possible alternative explanations. First, to control for the average salary of the various occupations, as well as all other aspects of the occupations, we conducted a fixed effects regression by including a dummy for each occupation. The estimates of the effects of GMA, the curvilinear effect of GMA and the interaction between GMA and job complexity are given in the last column of Table 1, and it is clear that the estimates of the effects obtained in this fixed effects regression are very similar to the estimates obtained in model I (the effects of occupational complexity cannot be estimated in such a model since they are fixed within occupation).

Second, one possible explanation for the concave relationship between GMA and pay is range restriction due to compensation pay banding. It is possible that when one reaches the ceiling of the occupation pay band, one has substantial difficulty getting higher pay regardless of performance. To examine for this possibility, we performed a fixed effects regression, regressing the hourly rate of pay on the occupations' dummies, and plotted the histogram of the residuals of this regression in Fig. 2a. This histogram represents the distribution of raw pay controlling for occupation (i.e., the representative distribution of pay within occupations). It is clear from the figure that, if anything, this distribution is skewed to the right, which suggests a possible floor, rather than a ceiling, effect.[3]

Finally, Fig. 2b presents the histogram of the residuals of a fixed effects regression regressing the *logarithm* of the hourly rate of pay – the dependent variable in our analyses above – on the occupation dummies. The histogram of the residuals of this regression is plotted in Fig. 2b. It is clear from this figure that the distribution of the residuals of the logarithm of the hourly rate of pay, the pay measure used in our analyses, is approximately normally distributed. Thus range restriction, whether a ceiling or a floor effect, is not likely to explain the concave effect of GMA on pay observed in our analyses.

4. Discussion

This study shows that there are important nonlinear elements in the effect of GMA on pay. First, the (positive) effect of GMA on pay increases with increasing occupational complexity. Second, keeping occupational complexity constant, the relationship between GMA and pay is concave. Bearing in mind the close association between pay and performance, this pattern of nonlinear relationships is consistent with a previous data reported by Hunter and Hunter (1984) regarding the interaction between occupational complexity and performance, and with our re-analysis of Coward and Sackett's (1990) data which discovered concave relationship between GMA and performance.

An interesting aspect of the pattern of a negative quadratic effect of GMA and a positive interaction effect between GMA and occupational complexity is the suppression effect discussed above. Thus, it is clear that in order to detect the accurate

Fig. 1. The concave effect of GMA and its interaction with occupational complexity in determining pay. Pay is expressed in terms of the logarithm of the hourly rate of pay. GMA is expressed in terms of standard deviations. Note that the slope of the curves represents the validity of GMA as a function of the level of GMA in high versus low levels of job complexity.

---

[3] Note that a concave effect of intelligence may be consistent with a ceiling effect but not with a floor effect.

a

b
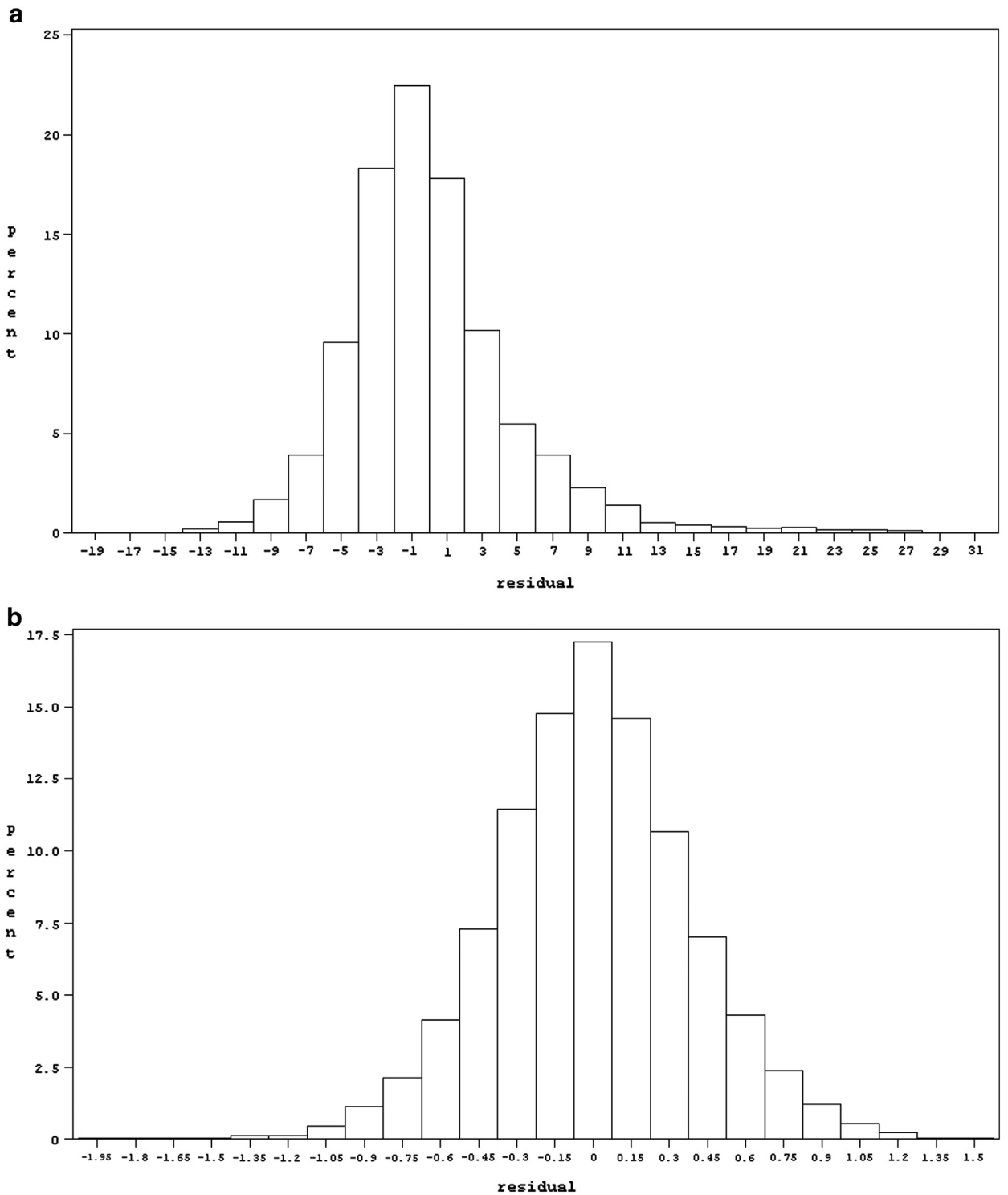
Fig. 2. *a*. The distribution of residuals obtained from regressing hourly rate of pay on the occupations' dummies. *b*. The distribution of residuals obtained from regressing the logarithm of hourly rate of pay on the occupations' dummies.

relationship between GMA and pay, a relationship that includes a curvilinear–concave-element, it is necessary to introduce the interaction between GMA and occupational complexity.

Further insight into the meaning of the suppression effect can be gained by considering the nonlinear effects on pay of an increase in GMA. On the one hand, an increase in GMA

leads to higher occupational complexity, which in turn leads to an increase in the monetary return on GMA (an effect associated with the interaction between complexity and GMA). On the other hand, an increase in GMA leads to a decrease in the monetary return on GMA (associated with the negative quadratic effect of GMA). Thus, there are two opposing consequences to increase in GMA, each associated with a different nonlinear effect.

Viewing pay as a measure of performance suggests clear substantive explanations for the quadratic and interactive effects of GMA on pay. The interactive effect is associated with the higher importance of GMA for performance of – and therefore compensation for –complex as opposed to simple occupations. The quadratic effect is associated with a cutoff above which an increase in mental ability does not add to job performance, and therefore does not add to pay.

References

Anonymous (1995). *NLS User Guide.* Center for Human Resource Research, The Ohio State University.

Baker, G. P., Jensen, M. C., & Murphy, K. J. (1988). Compensation and incentives: Practice vs. theory. *Journal of Finance, 43*, 593–616.

Bonner, S. E., & Sprinkle, G. B. (2002). The effects of monetary incentives on effort and task performance: Theories, evidence, and a framework for research. *Accounting, Organizations and Society, 27*, 303–345.

Cattell, R. (1987). *Intelligence: Its Structure, Growth and Action.* New York: Elsevier Science.

Cohen, J., & Cohen, P. (1983). *Applied Multiple Regression/Correlation Analysis for the Behavioral Science.* Hillsdale, NJ: Lawrence Erlbaum.

Cortina, J. M. (1994). Interaction, nonlinearity, and multicollinearity: Implications for multiple regression. *Journal of Management, 19*, 915–922.

Coward, W. M., & Sackett, P. R. (1990). Linearity of ability–performance relationships: A reconfirmation. *Journal of Applied Psychology, 75*, 297–300.

Dawes, R. M., & Corrigan, B. (1974). Linear models in decision making. *Psychological Bulletin, 81*, 95.

Ehrenberg, R. G., & Smith, R. S. (1988). *Modern Labor Economics.* Boston: Scott, Firesman & Company.

Ganzach, Y. (1997). Misleading interaction and curvilinear terms. *Psychological Methods, 3*, 235–247.

Ganzach, Y. (1998). Nonlinearity, multicollinearity and the probability of type II error in detecting interaction. *Journal of Management, 24*, 615–622.

Ganzach, Y. (2011). A dynamic analysis of the effects of intelligence and socioeconomic background on wages. *Intelligence, 39*, 120–129.

Ghishelli, E. E. (1973). The validity of aptitude tests in personnel selection. *Personnel Psychology, 26*, 461–477.

Ghishelli, E. E., & Kahneman, D. (1962). Validity and non-linear heteroscedastic models. *Personnel Psychology, 15*, 1–11.

Gneezy, U., & Rustichini, A. (2000). Pay enough or don't pay at all. *Quarterly Journal of Economics, 65*, 791–810.

Gottfredson, L. S. (2002). Where and why g matters: Not a mystery. *Human Performance, 15*, 25–46.

Guilford, J. P. (1967). *The nature of human intelligence.*

Guion, R. M. (1965). *Personnel Testing.* New York: McGraw-Hill.

Gustafsson, J. E., & Balke, G. (1993). General and specific abilities as predictors of school achievement. *Multivariate Behavioral Research, 28*, 407–434.

Hawk, J. (1970). Linearity of criterion–GATB aptitude relationships. *Measurement and Evaluation Guidance, 2*, 249–251.

Heneman, R. L. (1990). Merit pay research. In G. Ferris, & K. Rowland (Eds.), *Research in Personnel and Human Resource Management (pp. 203–263).* Greenwich CT: JAI Press.

Herrnstein, R. J., & Murray, C. (1994). *The Bell Curve: Intelligence and Class Structure in American Life.* New York: The Free Press.

Heyman, J., & Ariely, D. (2004). Effort for payment: A tale of two markets. *Psychological Science, 15*, 787–793.

Hulsheger, U. R., Gunter, W. M., & Stumpp, T. (2007). Validity of general mental ability for the prediction of job performance and training success in Germany: A meta-analysis. *International Journal of Selection and Assessment, 15*, 3–18.

Humphreys, L. G. (1981). The primary mental ability. In M. P. Friedman, J. R. Das, & N. O'Connor (Eds.), *Intelligence and Learning (pp. 87–102).* New York: Plenum.

Hunter, J. E., & Hunter, R. F. (1984). Validity and utility of alternative predictors of job performance. *Journal of Applied Psychology, 96*, 72–98.

Hunter, J. E., Schmidt, F. L., & Judiesch, M. K. (1990). Individual differences in output variability as a function of job complexity. *Journal of Applied Psychology, 75*, 28–42.

Jenkins, G. D., Jr., Mitra, A., Gupta, N., & Shaw, J. D. (1998). Are financial incentives related to performance? A meta-analytic review of empirical research. *Journal of Applied Psychology, 83*, 777.

Jensen, A. (1998). *The g Factor.* Wetporst, Connecticut: Prageger.

Kanazawa, S. (2006). IQ and the wealth of states. *Intelligence, 34*, 593–600.

Kuncel, N. R., Hezlett, S. A., & Ones, D. S. (2004). Academic performance, career potential, creativity, and job performance: Can one construct predict them all? *Journal of Personality and Social Psychology, 86*, 148–161.

Lang, J. W. B., Kersting, M., Hulsheger, U. R., & Lang, J. (2010). General mental ability, narrower cognitive abilities, and job performance: The perspective of the nested-factors model of cognitive abilities. *Personnel Psychology, 63*, 595–640.

Lazear, E. P. (2000). Performance pay and productivity. *American Economic Review, 90*, 1346–1361.

Lubinski, D., & Humphreys, L. G. (1990). Assessing spurious "moderator effects": Illustrated substantively with the hypothesized ("synergistic") relation between spatial and mathematical ability. *Psychological Bulletin, 107*, 385–393.

Lynn, R., & Vanhanen, T. (2002). *IQ and the Wealth of Nations.* Westport: Praeger.

McNemanr, Q. (1962). *Psychological Statistics* (3rd ed.)New York: Wiley.

Meisenberg, G. (2012). National IQ and economic outcomes. *Personality and Individual Differences, 53*, 103–107.

Ng, T. W. H., Eby, L. T., Sorensen, K. L., & Feldman, D. C. (2005). Predictors of objective and subjective career success: A meta-analysis. *Personnel Psychology, 58*, 367–408.

Prendergast, C. (1999). The provision of incentives in firms. *Journal of Economic Literature, 27*, 7–63.

Ree, M., Earles, J., & Teachour, M. S. (1994). Predicting job performance: Not much more than g. *Journal of Applied Psychology, 79*, 518–524.

Roos, P. A., & Treiman, D. J. (1980). Worker functions and worker traits in the 1970 U.S. census. In A. R. Miller, D. J. Treiman, P. S. Cain, & P. A. Roos (Eds.), *Work jobs and occupation: A critical review of the Dictionary of Occupational Titles (45–92).* Washington, DC: National Academy Press.

Schmidt, F. L., & Hunter, J. E. (2004). General mental ability in the world of work: occupational attainment and job performance. *Journal of Personality and Social Psychology, 86*, 162–173.

Tiffin, J., & Vincent, N. L. (1960). Comparison of empirical and theoretical expectations. *Personnel Psychology, 13*, 59–64.