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Interpreting logit regressions with interaction terms: an application to the management turnover literature

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Abstract

Logit and probit models of *turnover*=*f*(*performance*, *firm type*, *firm type***performance*, *controls*) are often used when testing whether turnover is "more sensitive to performance" for different types of firms. Researchers using this specification typically focus on the significance of the interaction term coefficient. If the intent is to show that the likelihood (rather than the odds) of turnover changes by more for one type of firm as performance varies, then this is an inappropriate test. Simulations are used to demonstrate how focusing on this particular coefficient can generate incorrect inferences. I then show how analyzing marginal effects eliminates this inference problem.

JEL classification: C12; C25; G30
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1. Introduction

The impact of organizational performance on management turnover has been a subject of substantial research in accounting, economics, finance, and management for almost 30 years.[1] One particularly active area of turnover research identifies characteristics of the

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[1] Grusky (1963), Sorenson (1974), and McEachern (1975) are some of the earliest examples of research on managerial turnover/tenure/succession. For a complete summary of the early literature, see Kesner and Sebora (1994). A related literature on lower-level labor turnover also exists (e.g., Bishop, 1990).

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manager, organization, or business environment that strengthen or weaken the relationship between turnover and performance. Some of the many characteristics studied are whether there are outside blockholders on the board of directors (James and Soref, 1981), whether the board is insider vs. outsider dominated (Weisbach, 1988; Suchard et al., 2001; Dahya et al., 2002), whether insiders own a significant percentage of shares (Denis et al., 1997), whether directors receive significant incentive compensation (Perry, 1999), and whether the CEO is concurrently Chairman of the Board (Goyal and Park, 2002; Dahya et al., 2002).

The most common method for testing whether turnover is more sensitive to performance for one type of firm is to estimate a logit or probit model, formulated as *turnover=f(performance*, *type*, *type*performance*, *controls*), where *type* is a dichotomous variable representing the particular characteristic that is being studied. For instance, is turnover more sensitive to performance when the board is insider-dominated (*type*=0) or outsider-dominated (*type*=1)? Papers utilizing this methodology then typically test whether the estimated coefficient for the interaction term of *type*performance* is significantly different from zero.

If the intent is to show that changes in performance have a significantly different impact on the *odds*—calculated as likelihood/(1−likelihood)—of turnover for the two types of firms, then this is an appropriate test. If the intent, however, is to show that changes in performance have a significantly different impact on the *likelihood* of turnover, then the commonly used test can lead to incorrect inferences. A better test is to compare differences in the marginal effect of performance on turnover for the two types of firms.

To date, I am aware of 38 academic papers (see Table 1) that estimate either logit or probit models formulated as *turnover=f(performance*, *type*, *type*performance*, *controls*); 28 of these papers are published or are forthcoming in refereed journals.[2] Only five of the 28 accepted papers report differences in the marginal effect of performance on turnover. The remaining 23 focus on the estimated interaction term coefficient.[3]

Focusing on the estimated interaction term coefficient when the objective is to test differences in the relationship between performance and the likelihood of turnover can lead to two types of errors. One possibility is that the true difference in the relationship could be stronger than is indicated by the estimated coefficient, potentially generating type 1 errors. Alternatively, the true difference in the relationship could be weaker than is indicated by the estimated coefficient, potentially generating type 2 errors.

[2] There are additional 16 papers identified in the "*Other*" block of Table 1 that also test the relationship between turnover and performance for two types of firms but that use alternative regression specifications. For example, Kaplan (1994) uses OLS with an interaction term, while Conyon (1998) splits his sample according to various characteristics and runs separate probit regressions on each sample. Many of these specifications vary only slightly from the baseline one discussed in this paper. To minimize confusion, however, I will exclude these papers from subsequent discussion.

[3] It is possible that the intention in these 23 papers is to compare how changes in performance affect the odds of turnover for the two types of firms. However, none of these papers mention the odds of turnover while all mention the likelihood of turnover. Given this, it is likely that tests for a difference in the "sensitivity of turnover to performance" are meant to be tests of whether changes in performance have a differential impact on the likelihood, not the odds, of turnover. To be fair, all of these papers do significantly more than simply estimate the logit or probit regression of *turnover=f(performance*, *type*, *type*performance*, *controls*).

Table 1
List of turnover research

Logit		
Abe (2004)	Defond and Hung (2004)[a]	Hillier et al. (2003)
Allgood and Farrell (2000)[a,b]	Defond and Park (1999)[a]	Huson et al. (2001)[a]
Anderson et al. (2000)[a]	Denis et al. (1997)[a]	Kang and Shivdasani (1995)[a]
Berry et al. (2002)[b]	Engel et al. (2003)[a,b]	McNeil et al. (2004)[a,b]
Boeker (1992)[a]	Fee and Hadlock (2000)[a]	Mikkelson and Partch (1997)[a]
Brickley and Van Horn (2002)[a]	Fee and Hadlock (2004)[a]	Naveen (2003)
Coles et al. (2003)	Firth et al. (2003)	Perry (1999)
Cosh and Hughes (1997)[a]	Fich and Shivdasani (2004)	Scholten (2003)
Crespi et al. (2004)[a]	Goyal and Park (2002)[a]	Suchard et al. (2001)[a]
Dahya et al. (2002)[a]	Hadlock et al. (2002)[a]	Weisbach (1988)[a,b]
Dedman (2003)[a]	Hadlock and Lumer (1997)[a]	Zhao and Lehn (2003)
Probit		
Conyon and Florou (2003)[a,b]	James and Soref (1981)[a]	Zhou (2000)[a]
Farrell and Whidbee (2003)[a]	Volpin (2002)[a]	
Other		
Barro and Barro (1990)[a]	Dahya et al. (1998)[a]	Renneboog (2000)[a]
Bertrand et al. (2003)	Faleye (2003)	Renneboog and Trojanowski (2003)
Bhagat et al. (1999)[a]	Franks et al. (2001)[a]	Salancik and Pfeffer (1980)[a]
Billger and Hallock (in press)[a]	Gibson (2003)[a]	Zajac and Westphal (1996)[a]
Conyon (1998)[a]	Kaplan (1994)[a]	
Conyon and Nicolitsas (1998)[a]	Lausten (2002)[a]	

A shared objective of all research papers listed is to identify factors that strengthen or weaken the relationship between performance and the likelihood of managerial turnover. The papers listed in the Logit and Probit blocks estimate logit and probit regressions, respectively, with interaction terms, e.g., *turnover*=*f*(*performance*, *type*, *type***performance*) where *type* is a dichotomous variable identifying the factor of interest. The papers listed in the Other block use some other methodology to quantify the relationship between *turnover*, *performance*, and *type*. One alternative methodology, for example, is Ordinary Least Squares. Papers with an (a) superscript have been published in a refereed journal. Papers with a (b) superscript report marginal effects in addition to or in place of coefficient estimates.

Assuming that there exists a bias towards publishing results that document significant differences in the relationship between turnover and performance for different types of firms, one might suspect that the 23 published turnover papers lacking analysis of marginal effects would be more prone to type 2 errors. As will be shown later, it is straightforward to sign the direction of any inference bias incurred by focusing on the estimated interaction term coefficient. Doing so suggests that the results of the majority of the 23 papers would likely be strengthened if differences in marginal effects were reported.

While revalidation of existing published research is good news, potential bad news remains. Specifically, it is likely that some valid research is not making it through the publication process because authors or referees are incorrectly focusing on statistically insignificant interaction term coefficients rather than on potentially significant differences in marginal effects. A primary objective of this paper, therefore, is to prevent these type 1 errors from occurring in the future.

In the remainder of the paper, I briefly describe why interactions terms in nonlinear regressions like logit and probit can be misleading. I then use simulations to more fully illustrate the problem of focusing solely on the estimated coefficient for the interaction term and how analyzing marginal effects leads to better inferences. I conclude by discussing the results of existing published papers in the turnover literature in the context of the findings from the simulations.

2. Why are interaction terms potentially misleading?

To understand why interaction terms in a logit or probit model can be misleading, it is helpful to consider a simpler case where the dependent variable is continuous and ordinary least squares is appropriate. In this situation, focusing on the interaction term coefficient in isolation is perfectly reasonable. To illustrate, assume for simplicity that y, x_1, and x_2 are continuous variables with

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_1 x_2 + \varepsilon, \quad \varepsilon \sim N\left(0, \sigma^2\right), \tag{1}$$

so that

$$E[y|x_1, x_2] = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_1 x_2. \tag{2}$$

Then the marginal effects of x_1 and x_2 are

$$\frac{\partial E[y|x_1, x_2]}{\partial x_1} = \beta_1 + \beta_3 x_2, \quad \frac{\partial E[y|x_1, x_2]}{\partial x_2} = \beta_2 + \beta_3 x_1, \tag{3}$$

and the change in the marginal effect of $x_1(x_2)$ as $x_2(x_1)$ varies is given directly by β_3

$$\frac{\partial^2 E[y|x_1, x_2]}{\partial x_1 \partial x_2} = \beta_3. \tag{4}$$

When the observed y is a dichotomous variable, however, estimation is best done using a nonlinear regression technique such as logit or probit where

$$E[y|x_1, x_2] = L(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_1 x_2), \tag{5}$$

and L is the likelihood function.[4] With a logit regression, L is $e^{X\beta}/(1+e^{X\beta})$ and

$$\frac{\partial E[y|x_1, x_2]}{\partial x_1} = (\beta_1 + \beta_3 x_2)\frac{e^{X\beta}}{(1+e^{X\beta})^2}, \quad \frac{\partial E[y|x_1, x_2]}{\partial x_2} = (\beta_2 + \beta_3 x_1)\frac{e^{X\beta}}{(1+e^{X\beta})^2}. \tag{6}$$

As noted by Greene (2003, p. 668), the impact of changes in $x_1(x_2)$ on the expected value of y depends not just on $\beta_1(\beta_2)$ and β_3, as it does in Eq. (3), but on the value of $X\beta$

[4] As seen in Table 1, logit specifications are much more common than probit specifications. The ensuing arguments regarding logit models are easily extended to include other nonlinear models such as probit. See Ai and Norton (2003) for a more general treatment of these issues.

and on the form of the likelihood function. Calculating the change in the marginal effect of $x_1(x_2)$ on the expected value of y as $x_2(x_1)$ changes, we have

$$\frac{\partial^2 E[y|x_1,x_2]}{\partial x_1 \partial x_2} = (\beta_1 + \beta_3 x_2)(\beta_2 + \beta_3 x_1)e^{X\beta}\frac{(1-e^{X\beta})}{(1+e^{X\beta})^3} + \frac{\beta_3 e^{X\beta}}{(1+e^{X\beta})^2}. \tag{7}$$

When one of the independent variables is dichotomous (e.g., if x_2 represents firm type), Eq. (7) is replaced by its discrete equivalent,

$$\left.\frac{\partial E[y|x_1,x_2]}{\partial x_1}\right|_{x_2=1} - \left.\frac{\partial E[y|x_1,x_2]}{\partial x_1}\right|_{x_2=0} = (\beta_1+\beta_3)\frac{e^{\beta_0+\beta_1x_1+\beta_2+\beta_3x_1}}{(1+e^{\beta_0+\beta_1x_1+\beta_2+\beta_3x_1})^2} - (\beta_1)\frac{e^{\beta_0+\beta_1x_1}}{(1+e^{\beta_0+\beta_1x_1})^2}. \tag{8}$$

In most situations, neither Eqs. (7) nor (8) are equal to β_3. Indeed, it is entirely possible for β_3 and the change in the marginal effect of x_1 on y, as x_2 varies, to have different signs. Of equal importance, the statistical significance of the estimated equivalent of Eqs. (7) or (8) is generally not equal to the statistical significance of the estimated β_3 coefficient.

In the context of the turnover literature, focusing solely on the estimated β_3 coefficient could lead to the inference that the marginal effect of performance differs with the type of firm when in reality it does not, or that the marginal effect of performance does not differ with the type of firm when in reality it does. An obvious solution is to calculate and statistically compare the marginal effects of a change in performance on the likelihood of turnover for the two types of firms—this is what is done in the six papers listed in Table 1 that have a "b" superscript. Standard errors for marginal effects and the difference in marginal effects are straightforward to calculate and correctly indicate whether the sensitivity of turnover to performance differs in a statistically significant way for different types of firms.

3. Numerical simulations and analysis

To illustrate the problems inherent in focusing solely on the estimated interaction coefficient, I run simulations where I randomly generate a *Normal* (0,1) performance variable, labeled ROA, for 1000 stylized firms. I then code *turnover* 0 or 1 for each firm using a monotonic function of ROA. The function is parameterized to generate a weak relationship between the likelihood of turnover and performance for half of the firms and a stronger relationship for the other half. As noted earlier, one could think of the firms as being split into those where the board of directors is insider dominated (*type*=0 firms) and those where the board is outsider dominated (*type*=1 firms). Logit regressions of the form *turnover=f*(*performance*, *type*, *type*performance*) are then estimated. This process is repeated 1000 times using new performance numbers but the same turnover function for each iteration to form one trial. Summary statistics are then computed for the estimated coefficients, marginal effects, and differences in marginal effects generated in each iteration. Parameters of the turnover function for the strong-relationship firms are varied, and the trial is repeated two more times to demonstrate how inferences can depend on whether one focuses on the estimated interaction term coefficient or on the difference in marginal effects.

The chosen turnover functions and associated parameters may seem ad hoc. Indeed, they have been specifically chosen to illustrate the inference problems described in the previous section. Bear in mind, however, that researchers are never privy to the mechanism generating the real-world relationship between turnover and performance—only the resulting data are observed. Thus, nothing prevents the inference problems generated by these particular functions from occurring.

3.1. Simulation with constant coefficients but varying marginal effects

In the first set of three trials, I utilize a turnover function and choose parameters such that estimated coefficients for the interaction term of *type*performance* are essentially invariant across the trials. With this function, however, the marginal effect of performance on turnover varies significantly across the three trials for the *type*=1 firms, causing the difference in marginal effects between *type*=0 and *type*=1 firms to vary across the trials.

The function used to generate the likelihood of turnover (τ) is

$$\tau = \frac{e^{a+b(\mathrm{ROA})}}{\left(1 + e^{a+b(\mathrm{ROA})}\right)}. \tag{9}$$

For each observation, *turnover* is coded 1 (0 otherwise) if a randomly generated, uniform [0,1] variable is less than τ.[5]

The parameter b is what generates the strength of the relationship between turnover and performance, while a primarily affects the average likelihood of turnover. For *type*=0 firms (weak relationship between turnover and performance), $b=-0.25$ and $a=-0.75$. For *type*=1 firms (stronger relationship between turnover and performance), $b=-0.55$ while a equals -1.5 for the first trial, -0.75 for the second trial, and 0 for the third trial. The impact of both parameters is shown in Fig. 1 where the likelihood of turnover is plotted against ROA. As can be seen in the figure, increasing the a parameter from -1.5 to -0.75 to 0 shifts the turnover likelihood curve upward while also slightly altering the slope and curvature.

In Table 2A, I report medians for the estimated coefficients and t-statistics from the 1000 logit regressions of *turnover*=*f*(ROA, *type*, *type**ROA) for the three separate trials. I also report the percentage of simulations in each trial where the estimated coefficient for the interaction term of *type**ROA is significant at the 5% and at the 10%

[5] I was first alerted to the pitfalls of focusing on interaction terms in logit regressions when a coauthor insisted on testing whether a turnover model used to motivate a different paper would actually generate reasonable regression results. That turnover model resulted in an equation similar to Eq. (9). Needless to say, the estimated coefficients for the interaction terms were confusing and subsequent analysis revealed the issue addressed in this paper.

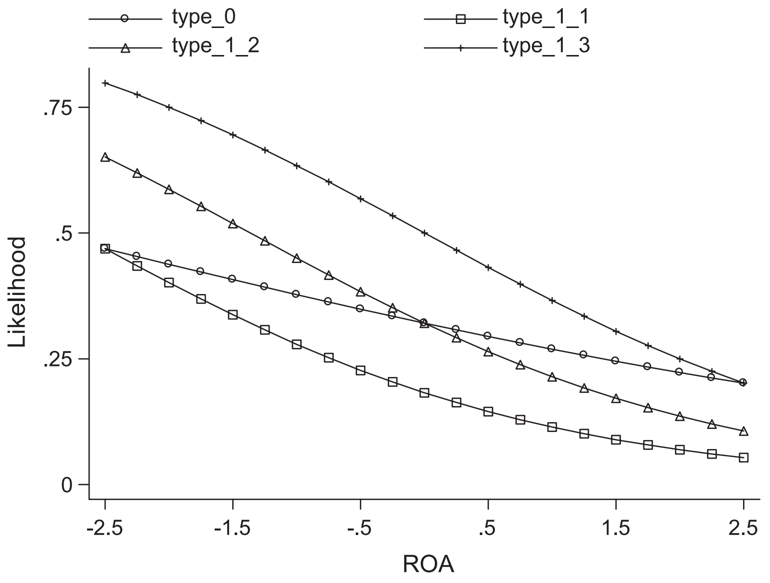

Fig. 1. Turnover likelihood as a function of ROA, simulation set #1. Likelihood of turnover is graphed as a function of ROA where the turnover function is $e^{a+b(\mathrm{ROA})}/(1+e^{a+b(\mathrm{ROA})})$. Type_0 represents a firm where the relationship between turnover and performance is weak, while type_1_1, type_1_2, and type_1_3 represent firms where the relationship is stronger. A more negative b parameter generates a steeper slope and represents a stronger relationship between turnover and performance. A more negative a parameter shifts the curve downward and also alters curvature and slope. Parameters for each sample firm are as follows: type_0: a=−0.75, b=−0.25; type_1_1: a=−1.5, b=−0.55; type_1_2: a=−0.75, b=−0.55; type_1_3: a=0, b=−0.55. The functional form in conjunction with the chosen parameters ensures that estimated coefficients for interaction terms of *type**ROA are essentially invariant across the three different *type*=1 firms, while differences in marginal effects relative to *type*=0 firms vary.

levels. Note that ROA observations for trial one are exactly the same as those for trials two and three.

As expected, estimated coefficients for ROA are exactly the same across the first three trials with a median value of −0.256 and a median t-statistic of 2.599. The

Table 2A
Estimated coefficients for trials 1–4

	ROA	*Type*	*Type**ROA	Pct significant at 5% and 10%
Trial #1, a_1=−1.5	−0.256 (2.599)	−0.741 (4.799)	−0.303 (1.950)	49.1%, 62.0%
Trial #2, a_1=−.75	−0.256 (2.599)	0.005 (0.720)	−0.291 (2.024)	53.7%, 67.2%
Trial #3, a_1=0	−0.256 (2.599)	0.762 (5.661)	−0.296 (2.120)	57.6%, 68.9%
Trial #4	−0.256 (2.599)	0.005 (0.693)	0.008 (0.658)	4.7%, 9.1%

Summary statistics for the estimated coefficients from the first set of trials of 1000 logit regressions of *turnover=f*(ROA, *type*, *type**ROA). See the text for the formulas and parameters used in simulating the data for these trials. Columns one through three present median coefficient estimates (with median t-statistics in parentheses) for each trial of 1000 simulations. The final column gives the percentage of trials where the estimated coefficient for *Type**ROA is statistically significant at either the 5% or 10% level of a two-tailed test.

estimated *type* coefficient, however, varies across the three trials, reflecting the fact that a varies between -1.5 and 0. The coefficient of primary interest is the estimated coefficient for the interaction term of *type**ROA. Its median value is -0.303 (t-statistic=1.950) for trial one, -0.291 (t-statistic=2.024) for trial two, and -0.296 (t-statistic=2.120) for trial three. While there is some variation attributable to the functional form, the interaction coefficient is essentially constant across the three trials.[6]

A fourth trial with $a=-0.75$ and $b=-0.25$ for both types of firms is presented to assess the size of the test. Not surprisingly, when the a and b parameters are equivalent for *type*=0 and *type*=1 firms, the number of estimated interaction coefficients that are significant at the 5% and 10% levels is 4.7% and 9.1%, respectively, consistent with what is expected due to random sampling.

Although each of the estimated interaction coefficients are negative and statistically significant on average, we should not necessarily conclude that the likelihood of turnover increases by a significantly greater amount for *type*=1 firms. The exponentiated value of the estimated ROA coefficient is the multiplicative factor by which the predicted odds of turnover change for *type*=0 firms given a one unit increase in ROA. This is easily verified using the predicted odds calculated using the estimated coefficients. Similarly, the exponentiated value of the estimated coefficient for *type**ROA is the multiplicative factor by which the predicted odds for *type*=1 firms change given a one unit increase in ROA, divided by the equivalent multiplicative factor for *type*=0 firms.[7]

Herein is the root of why the coefficient for the interaction term can be misleading. Assume that, for a given increase in performance, the likelihood of turnover declines from 40% to 30% for *type*=0 firms and from 20% to 10% for *type*=1 firms. Both experience the same absolute change in the likelihood of turnover: 10%. The corresponding ratio of odds, however, is $[(0.1/0.9)/(0.2/0.8)]/[(0.3/0.7)/(0.4/0.6)]=0.6914$. This implies an interaction term coefficient of $\log(0.6914)=-0.369$. With adequate sample size, -0.369 will be significantly different from 0. If interpreted incorrectly, the estimated interaction term coefficient suggests that deteriorating performance will lead to a greater increase in the likelihood of turnover for the *type*=1 firms.

If one wants to compare changes in the likelihood of turnover, a more appropriate measure is the marginal effect. As noted, calculating marginal effects requires calculating the derivative of the likelihood function $[e^{X\beta}/(1+e^{X\beta})]$ with respect to ROA and evaluating

[6] As the a parameter is varied for the *type*=1 curves plotted in Fig. 1, variation in the slope and curvature is effectively offset by changes in the level of each curve. This offsetting effect of level changes is what minimizes the variation in the estimated interaction term coefficients. The a and b parameters have been tweaked to balance this offsetting effect while also ensuring that the median estimated ROA and *type**ROA coefficients are statistically significant at conventional levels, and that the differences in marginal effects are sometimes statistically significant and sometimes insignificant.

[7] Pampel (2000) gives an intuitive and basic discussion of how to correctly interpret results from logit regressions. Jaccard (2001) specifically discusses the use and interpretation of interaction effects in logit regressions.

Table 2B
Marginal effects for trials 1–4

	type=0 firms	*type*=1 firms	Difference	Pct significant at 5% and 10%
Trial #1, a_1=−1.5	−0.055 (2.613)	−0.083 (4.843)	−0.027 (1.057)	14.7%, 25.5%
Trial #2, a_1=−.75	−0.055 (2.613)	−0.121 (5.367)	−0.063 (2.054)	53.9%, 67.6%
Trial #3, a_1=0	−0.055 (2.613)	−0.139 (5.611)	−0.083 (2.538)	71.8%, 82.9%
Trial #4	−0.055 (2.613)	−0.054 (2.556)	0.002 (0.648)	4.8%, 9.0%

Summary statistics for the estimated marginal effect of a change in ROA on the likelihood of turnover for *type*=0 and *type*=1 firms. The data underlying the results here are exactly the same as the data underlying the results in Table2A. Difference is the marginal effect for *type*=1 firms minus the marginal effect for *type*=0 firms. The second value in each cell (in parentheses) is the median z-statistic calculated using the delta method. The final column gives the percentage of trials where the estimated difference in marginal effects is statistically significant at either the 5% or 10% level of a two-tailed test.

the derivative at a particular level of ROA. Standard errors are straightforward to calculate using the delta method (see Greene, 2003, pp. 674–675).[8,9]

Medians for the marginal effect of a change in performance on the likelihood of turnover are presented in Table 2B for both *type*=0 and *type*=1 firms at the 50th percentile of ROA. More importantly, medians for the difference in the two marginal effects are also presented. Median t-statistics are presented for each value.

The median difference in marginal effects are −0.027 (t-statistic=1.057) for trial one, −0.063 (t-statistic=2.054) for trial two, and −0.083 (t-statistic=2.538) for trial three. Results from trial four again show that the size of the test is adequate. In comparison to the estimated coefficients for the interaction term in Panel A, the results for the marginal effect are much more sensitive to changes in the a parameter. Thus, if one were given data generated as in trial one, focusing solely on the interaction coefficient could lead to the conclusion that the likelihood of turnover for *type*=1 firms increases by more than that for *type*=0 firms when performance declines. This conclusion, however, is not supported by the difference in the marginal effects for this particular trial.

3.2. Simulation with varying coefficients but constant marginal effects

In this second set of three trials, I generate the data in such a way that there is little variation in differences in the marginal effects, but estimated coefficients for the

[8] If the estimated coefficient vector $\boldsymbol{\beta}$ has a variance–covariance matrix **V**, and g is a differentiable function, then the variance–covariance matrix of $g(\boldsymbol{\beta})$ is approximated asymptotically by $G'VG$, where G is the derivative of $g()$ with respect to β'. In our case, $g()$ is the derivative of the likelihood function with respect to ROA or the difference in the derivatives for *type*=1 and *type*=0 firms. G is, therefore a column vector with elements that are the derivative of $g()$ with respect to β_0, β_1, β_2, and β_3.

[9] Recent versions of some statistical packages such as Stata® 8.0 have functions that will compute the marginal effect of an individual variable as well as the associated standard error at any point that the user specifies (in Stata® the command is mfx compute). However, these installed functions are generally not flexible enough to account for the fact that the marginal effect of ROA depends on both the estimated ROA and *type**ROA coefficients. Thus, this marginal effect and standard error must still be computed manually.

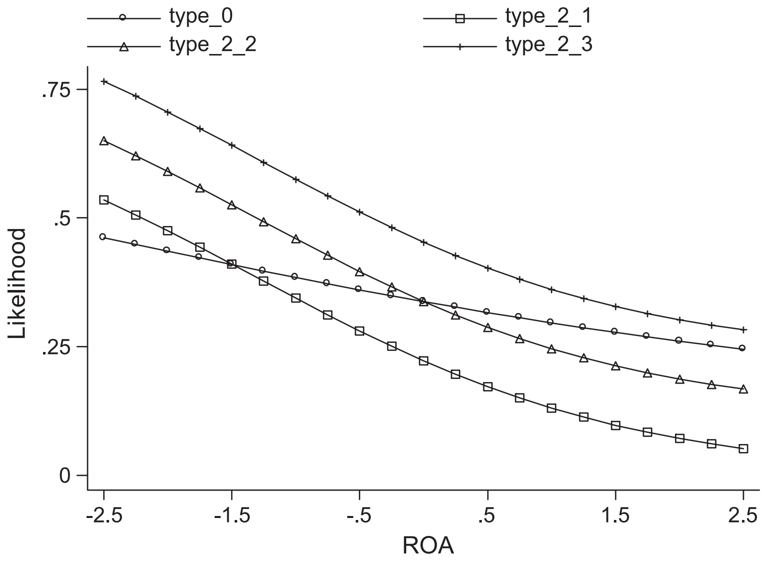

Fig. 2. Turnover likelihood as a function of ROA, simulation set #2. Likelihood of turnover is graphed as a function of ROA where the turnover function is $(a+(e^{-0.9+b(\mathrm{ROA})}/(1+e^{-0.9+b(\mathrm{ROA})})))/(1/3)$. Type_0 represents a firm where the relationship between turnover and performance is weak, while type_2_1, type_2_2, and type_2_3 represent firms where the relationship is stronger. A more negative b parameter generates a steeper slope and represents a stronger relationship between turnover and performance. A more negative a parameter shifts the curve downward but without altering curvature or slope. Parameters for each sample firm are as follows: type_0: a=0.15, b=−0.28; type_2_1: a=0, b=−0.69; type_2_2: a=0.15, b=−0.69; type_2_3: a=0.30, b=−0.69. The functional form in conjunction with the chosen parameters ensures that differences in marginal effects across the three different *type*=1 firms relative to *type*=0 firms are essentially invariant, while estimated coefficients for interaction terms of *type**ROA vary across the three different *type*=1 firms.

interaction term vary significantly. The likelihood of turnover for both types of firms is calculated as

$$\tau = \frac{a + \dfrac{e^{-0.9+b(\mathrm{ROA})}}{\left(1+e^{-0.9+b(\mathrm{ROA})}\right)}}{1.3}. \tag{10}$$

For the *type*=0 firms, b=−0.28 and a=0.15. For the *type*=1 firms, b=−0.69 while a equals 0 for the first trial, 0.15 for the second trial, and 0.30 for the third trial. Again, the greater absolute magnitude of b for the *type*=1 firms is what generates the stronger relationship between turnover and performance. Here, the sole purpose of the a parameter is to shift the likelihood function for the *type*=1 firms; both effects are evident in Fig. 2 where the likelihood of turnover is plotted against ROA.[10]

Table 3A presents the median estimated coefficients from the logit regressions. In each trial, the estimated coefficient for ROA is −0.202 (t-statistic=2.090). As expected, the

[10] The division by 1.3 simply centers each distribution, ensuring that the distribution for the *type*=1 firms is never truncated. This ensures that the residual variances of the *type*=0 and *type*=1 distributions are the same, eliminating the bias that different residual variances would have on the estimated coefficients (Allison, 1999).

Table 3A
Estimated coefficients for trials 5–8

	ROA	*type*	*type**ROA	Pct significant at 5% and 10%
Trial #1, a_1=0	−0.202 (2.090)	−0.599 (4.025)	−0.411 (2.726)	78.4%, 85.7%
Trial #2, a_1=0.15	−0.202 (2.090)	0.0328 (0.706)	−0.273 (1.953)	49.7%, 62.7%
Trial #3, a_1=0.30	−0.202 (2.090)	0.536 (4.032)	−0.235 (1.722)	41.0%, 53.9%
Trial #4	−0.202 (2.090)	0.004 (0.712)	0.008 (0.692)	4.0%, 8.8%

Summary statistics for the estimated coefficients from the second set of trials of 1000 logit regressions of *turnover=f*(ROA, *type*, *type**ROA). See the text for the formulas and parameters used to generate the data for these trials. Columns one through three present median coefficient estimates (with median *t*-statistics in parentheses) for each trial of 1000 simulations. The final column gives the percentage of trials where the estimated coefficient for *type**ROA is statistically significant at either the 5% or 10% level of a two-tailed test.

median estimated coefficient for *type* varies across the trials as the *a* parameter for *type*=1 firms is varied. The coefficient of primary interest is again the coefficient for *type**ROA. The median value for this estimated coefficient is −0.411 (*t*-statistic=2.726) for trial one, −0.273 (*t*-statistic=1.953) in trial two, and −0.235 (*t*-statistic=1.722) in trial three. A fourth trial with a=0.15 and b=−0.28 for both firm types again shows that the size of the test is appropriate.

If inferences are based on the interaction term coefficient, conclusions will obviously depend on which trial is analyzed. Variation in the interaction term coefficient, however, is simply an artifact of differences in the average likelihood of turnover. Unlike the turnover function given by Eq. (9), altering the *a* parameter in Eq. (10) generates parallel shifts in the turnover function with no offsetting effect from a change in slope or curvature.

The true measure of how the likelihood of turnover varies with performance is again given by the marginal effect of performance on turnover, as presented in Table 3B. In this set of trials, despite the fact that the estimated interaction coefficient varies significantly across trials, the difference in estimated marginal effects is relatively constant with values of −0.060 (*t*-statistic=2.088) for trial one, −0.061 (*t*-statistic=1.968) for trial two, and −0.064 (*t*-statistic=1.981) for trial three.[11]

3.3. Commentary

The implication from the two sets of trials is clear: interaction terms in logit (or probit) models do not give a clear indication of whether there are significant differences in the relationship between the likelihood of turnover and performance

[11] Variation in the reported marginal effects reflect the fact that changing the *a* parameter changes the value of ROA at which the marginal effect is maximized. Common practice is to calculate the marginal effect for all of the observations in the sample and take the average (Greene, 2003, p. 876.) If the sample is large enough, however, the Slutsky theorem ensures that evaluating the marginal effect at the sample mean will have the same result. Because it is computationally easier, I report the difference in marginal effects at ROA=0, the average and 50th percentile for the sample.

Table 3B
Marginal effects for trials 5–8

	type=0 firms	*type*=1 firms	Difference	Pct significant at 5% and 10%
Trial #1, a_1=0	−0.045 (2.092)	−0.105 (5.498)	−0.060 (2.088)	55.5%, 66.3%
Trial #2, a_1=0.15	−0.045 (2.092)	−0.107 (4.743)	−0.061 (1.968)	50.4%, 63.3%
Trial #3, a_1=0.30	−0.045 (2.092)	−0.108 (4.557)	−0.064 (1.981)	50.6%, 62.3%
Trial #4	−0.045 (2.092)	−0.045 (2.065)	0.001 (0.685)	4.1%, 8.7%

Summary statistics for the estimated marginal effect of a change in ROA on the likelihood of turnover for *type*=0 and *type*=1 firms. The data underlying the results here are exactly the same as the data underlying the results in Table 3A. Difference is the marginal effect for *type*=1 firms minus the marginal effect for *type*=0 firms. The second value in each cell (in parentheses) is the median z-statistic calculated using the delta method. The final column gives the percentage of trials where the estimated difference in marginal effects is statistically significant at either the 5% or 10% level of a two-tailed test.

across different groups of firms. Marginal effects, however, will appropriately measure this relationship.

As an aside, it is common to include calculations of the implied probability of turnover using the estimated coefficients from the regression to illustrate the economic importance of performance on turnover. For example, in their study of the impact of ownership structure on the relationship between turnover and performance, Denis et al. (1997) provide a table with the implied probability of turnover at the 10th and 90th percentiles of performance for firms split out by existence of an outside blockholder and by insider ownership. If significance statistics for the difference in the implied probability change for the two types of firms were provided, then this would substitute for the marginal effect calculations that I describe. This, however, is not done in any of the papers that do not present marginal effects.[12]

4. Reevaluating existing papers on management turnover

While it might seem that the estimated coefficient for the interaction term of *type**ROA is arbitrarily related to the underlying marginal effects for the two types of firms, there is a consistent and predictable relationship. As long as the distributions of control variables other than *type* and *ROA* (in the simulations there are no additional control variables) are the same for the two types of firms, then the difference in marginal effects between the two types of firms will depend only on the estimated coefficients for *type* and the *type**ROA interaction term. Note that, in both simulation sets, when the estimated coefficient for *type* is positive, the estimated interaction term coefficient suggests a weaker relationship between turnover and performance for *type*=1 relative to *type*=0 firms than is suggested by the difference in marginal effects. Conversely, when

[12] Calculating significance statistics for differences in discrete-implied probability changes is not straightforward. The nonlinearity of the likelihood function distorts normal confidence intervals, necessitating techniques like boot-strapping.

the estimated type coefficient is negative, the estimated interaction term coefficient suggests a stronger relationship between turnover and performance for *type*=1 relative to *type*=0 firms than is suggested by the difference in marginal effects.[13]

Knowing the relationship between the estimated coefficient for *type*, the estimated coefficient for the interaction term, and the marginal effect, we can evaluate whether conclusions for studies lacking analysis of marginal effects would change if marginal effects were included. In Table 4, the 23 published papers that estimate binomial regressions of *turnover*=*f*(*performance*, *type*, *type***performance*) without analyzing marginal effects are listed.[14] In the second column, I describe how the various samples are split into *type*=0 and *type*=1. In the third, fourth, and fifth columns, the sign and statistical significance of the estimated *performance*, *type*, and *type***performance* coefficients are reported. In the sixth column, I state whether analyzing differences in the marginal effect of *performance* on *turnover* would likely increase or reduce the perceived difference between *type*=0 and *type*=1 firms in the relationship between turnover and performance.[15]

In approximately half of the cases, marginal effects would likely indicate a greater differential in the relationship between the likelihood of turnover and performance for *type*=1 vs. *type*=0 firms. Given the manner in which the authors motivate and interpret their respective results, most of the conclusions of these 23 papers would likely be strengthened if differences in marginal effects were analyzed. In only four of the papers (Boeker, 1992; Brickley and Van Horn, 2002; Farrell and Whidbee, 2003; Fee and Hadlock, 2004) does it appear that empirical support for the hypotheses in question would be weakened (but not necessarily to the point that statistical significance would be lost.) In contrast, for 12 of the papers (Crespi et al., 2004; Dahya et al., 2002; Dedman, 2003; Defond and Park, 1999; Denis et al., 1997; Fee and Hadlock, 2000; Goyal and Park, 2002; James and Soref, 1981; Kang and Shivdasani, 1995; Mikkelson and Partch, 1997; Suchard et al., 2001; Zhou, 2000), it appears that the empirical support of the majority of hypotheses would actually be strengthened. For the remainder, analysis of marginal effects would either have limited impact (Anderson et al., 2000; Cosh and Hughes, 1997; Hadlock et al., 2002; Hadlock and Lumer, 1997; Huson et al., 2001) or would strengthen and weaken empirical support for an equal number of hypotheses (Defond and Hung, 2004; Volpin, 2002).

[13] This assumes that turnover is negatively related to performance for both types of firms. This relationship is reversed when the average likelihood of turnover is greater than 50%. For example, if the *a* parameter for *type*=0 in simulation one were 0.75 (instead of −0.75) and 0, 0.75, 1.5 (instead of −1.5, −0.75, 0) for *type*=1, then the difference in marginal effects would be greatest when the estimated *type* coefficient is negative. In all turnover studies of which I am aware, however, the average likelihood of turnover is always well below 50% for all types of firms considered.

[14] The unpublished working papers could also be included. Since they are presumably still evolving, however, they are excluded.

[15] Without having the raw data, my conclusions in column six are rough at best. In many of the analyses, there are multiple control variables and simultaneous interaction terms with several different measures of performance. One common control variable is some measure of manager age. If age affects turnover and age is systematically different between *type*=0 and *type*=1 firms, then this can also bias the estimated coefficient of *type***performance.* These types of interactions are difficult to identify without access to the data.

The potentially bad news is not visible in Table 4. It is possible, however, that some valid research is not seeing the light of day because authors and referees mistakenly focus on a statistically insignificant *type*performance* coefficient (rather than the possibly significant marginal effect) and conclude that the results are not worth pursuing. As a potential example in a paper that was actually published, consider Blackwell et al. (1994). The focus of their paper is on what performance measures (subsidiary or firm specific) influence the turnover of subsidiary bank managers. In Footnote 16, however, they state that logit regressions of turnover on performance (ROA) for subsidiary bank managers and CEOs of comparable stand-alone banks show that "there is a significantly higher turnover among subsidiary bank managers. However, the turnover to performance relation is similar for the two sets of bank managers" (i.e., the coefficient on the interaction term is insignificantly different from zero). It is an open question whether analysis of marginal effects would lead to a different conclusion.[16]

5. Summary

Logit, and to a lesser extent probit, regressions of the form *turnover=f*(*performance*, *type*, *type*performance*) are commonly used in the management turnover literature when trying to show that the likelihood of turnover is more sensitive to changes in performance for one type of firm than for another. For the majority of turnover papers using this methodology, the statistical test is to see whether the estimated coefficient for the interaction term of *type*performance* is significantly different from zero.

I use simulations to demonstrate that the estimated coefficient for the interaction term depends on both the relationship between the likelihood of turnover and performance and on differences in the average likelihood of turnover between the two types of firms being analyzed. Thus, inferences can hinge on a confounding variable that may not be of primary importance.

The solution, also demonstrated by way of simulations, is to separately calculate the marginal effect of a change in performance for the two types of firms. Using the delta method, asymptotic standard errors for these marginal effects can be calculated, enabling the researcher to determine whether there is a statistically significant difference in the relationship between the likelihood of turnover and changes in performance for the two types of firms. The benefit of this method is that it is not affected by differences in the average likelihood of turnover between the two types of firms.

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[16] Using a data set of elderly participation in Medicare HMO's from Mello et al. (2002), Ai and Norton (2003) demonstrate that "not calculating the correct interaction effect would lead to wrong inference in a substantial percentage of the sample."

Table 4
Published literature analysis

Paper	*type*=1	*Performance*	*Type*	*Type* Performance*	Marginal effects: increase or reduce differential?
Anderson et al. (2000)	Firm is diversified	–	+*	+	Reduce
Boeker (1992)	Proportion of insiders on board	–***	–	–**	Reduce
	Board loyalty to incumbent	””	–	–	Reduce
	Insider loyalty to incumbent	””	–	–	Reduce
	Ownership dispersion	””	–	–	Reduce
	CEO ownership	””	–**	–**	Reduce
Brickley and Van Horn (2002)	CEO leads a for-profit hospital	–**	+	+*	Reduce
	Local market concentration high	–**	–*	–	Reduce
Cosh and Hughes (1997)	Significant institutional ownership	–***	–*	–**	Reduce
Crespi et al. (2004)	Dependent bank	–***	–	+**	Increase
	Savings bank	””	–***	+*	Increase
Dahya et al. (2002)	Adopted Cadbury proposals	–***	+	–**	Increase
	Proportion of outsiders on board	–***	+	–*	Increase
	CEO and Chairman are separate	””	–	–	Reduce
	Number of directors	””	–	–	Reduce
Dedman (2003)	Observation is post-Cadbury report	–***	+	–***	Increase
Defond and Hung (2004)	Extensive investor protection laws	–***	+	–	Increase
	Strong law enforcement institutions	–	–***	–**	Reduce
	Stock price is informative	–	–	–**	Reduce
	Earnings are informative	–	+	–	Increase
Defond and Park (1999)	Industry is competitive	–	+***	–*	Increase
	Industry is competitive	–***	+***	+***	Reduce
Farrell and Whidbee (2003)	High dispersion firm forecast error	–***	+	+**	Reduce
	High dispersion industry forecast error	””	+	+	Reduce
Fee and Hadlock (2000)	Competitive market	–***	+*	–	Increase
Denis et al. (1997)	High management ownership	–***	–*	+**	Increase
	Outside blockholder present	–	+	–*	Increase
	Outsiders>60% of board	–**	+	–	Increase

Fee and Hadlock (2004)	CEO (as opposed to other top 5 execs)	–***	–***	–***	Reduce
Goyal and Park (2002)	Incumbent is CEO and Chairman	–***	–***	+***	Increase
Hadlock et al. (2002)	CEO leads a regulated firm	–**	–	–	Reduce
Hadlock and Lumer (1997)	CEO is the founder	–	–	–	Reduce
	CEO Tenure	""	+	+	Reduce
	Insider share holdings 1% to 5%	+*	–	–	Reduce
	Insider share holdings>5%	""	–	–	Reduce
Huson et al. (2001)	Time period is 71–76	–***	+	+*	Reduce
	Time period is 77–82	""	–*	+	Increase
	Time period is 89–94	""	–	+	Increase
James and Soref (1981)	Management controls board	–*	–	+	Increase
Kang and Shivdasani (1995)	Member of keiretsu	–	–**	+	Increase
	Relationship with main bank	""	–*	–**	Reduce
	Presence of outside director	""	+	–	Increase
	Outside blockholder ownership	""	+**	–	Increase
Mikkelson and Partch (1997)	Takeover market is inactive	–***	–	+**	Increase
Suchard et al. (2001)	Nonexecutives>50% of board	–**	+***	–	Increase
	Independents>50% of board	–*	+*	–	Increase
Volpin (2002)	State ownership of firm	–***	+**	–	Increase
	Foreign ownership of firm	""	+	+	Reduce
	Bank ownership of firm	""	+	+*	Reduce
	Manager controls firm	–***	–***	+	Increase
	Manager incentives strong	""	–	–**	Reduce
	Outside blockholder	""	–	+	Increase
	Outside voting syndicate	""	–	–**	Reduce
Zhou (2000)	Firm is large	–*	+**	–	Increase

All papers listed in this table are published. Each estimate logit or probit regressions of *turnover=f*(*performance*, *type*, *type*performance*, *controls*). The *type*=1 column indicates the characteristic on which the data sample is split into *type*=1 (and *type*=0) firms. The + and – entries in the *Performance*, *Type*, and *Type*Performance* columns indicate the sign of the estimated coefficients in each of these studies. When there are double quotes in the *Performance* column, it indicates that the associated *type* split is included in the estimated regression at the same time as the prior *type* split. Thus, the same *performance* term is germane to both *type* splits. The asterisks *, **, *** indicate statistical significance of the estimated coefficients at the 10%, 5%, and 1% levels, respectively. "Increase" and "Reduce" in the final column indicate whether differences in marginal effects would suggest a larger or smaller perceived difference in the relationship between turnover and performance for *type*=1 as compared to *type*=0 firms.

Appendix A. Computational Procedures

The simulation programs described in this paper were written in Stata® 7.0 and rely on the installed uniform pseudo random number generator—a description of the random number generator is provided in the Stata User's Guide. The seed used for each trial was 123456789. Copies of the simulation programs are available from the author on request.

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