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Time Dependence in the Cox Proportional Hazard Model as a Theory Development Opportunity: A Step-by-Step Guide

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Abstract

The Cox proportional hazard model has often been used for survival analysis in organizational research. The Cox model needs to satisfy one critical assumption—time independence—that the effects of independent variables are constant over survival time (also known as the proportional hazard assumption). However, organizational research often encounters time dependence in the Cox model. Organizational studies have traditionally seemed to view time dependence as an empirical nuisance, but we highlight that it is also a theory-development opportunity. Indeed, from our review of AMJ and SMJ papers published in a recent 10-year period, we found that researchers rarely considered time dependence as a theory-development opportunity, and worse, many of them did not test for (or report tests for) time dependence. The purpose of our study is to change this pattern. To this end, we provide a step-by-step guide to facilitate testing for time dependence and using time dependence as a theory development opportunity. We also demonstrate our step-by-step guide with an empirical example.

Keywords

cox proportional hazard model, time dependence, proportional hazard assumption, survival analysis

Survival analysis is an empirical technique for analyzing the antecedents of an event of interest using the time until the event occurrence—e.g., identification of strategic factors related to a risk of the occurrence of an event of interest (e.g., Chakrabarti, 2015; Ortiz-de-Mandojana & Bansal, 2016).

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Many organizational studies have relied on the Cox proportional hazard (PH) model (hereafter, the Cox model) for survival analyses. One of the main reasons for its popularity is that there is no need to specify the shape of the baseline hazard function in advance (Allison, 2014; Kleinbaum & Klein, 2012). However, the Cox model requires the assumption that the effects of the independent variables on the dependent variable are constant over the survival time (Singer & Willett, 2003). This is called the PH assumption (Therneau & Grambsch, 2000). Put differently, the coefficients of the independent variables must remain constant over survival time.

However, organizational researchers often encounter time dependence when using the Cox model (i.e., the PH assumption is violated). Survival time can be measured with any continuous unit of time, such as minutes, hours, days, months, and years, from a starting point to the occurrence of the event of interest, and the choice for the unit of survival time depends on the research design (Kleinbaum & Klein, 2012). In organizational research, the causal relationship between the independent and the dependent variables sometimes changes in predictable ways over the survival time. For example, to test the effects of firm performance on CEO dismissal, CEO tenure (i.e., the number of days or years between the CEO's appointment and the dismissal event) would be a natural choice for the survival time measure (e.g., Shin et al., 2022). However, it is reasonable to expect that the effect of firm performance on CEO dismissal varies over CEO tenure as survival time (i.e., the effect of financial performance is time-dependent) because the board's interpretation of the same financial performance measure may change over CEO tenure, and the board's power vis-à-vis the CEO often changes over CEO tenure (c.f., Finkelstein et al. 2009; Simsek, 2007; Walsh & Seward, 1990). Therefore, the issue of time dependence when using the Cox model is not just an important empirical concern but a theory-driven issue as well.

Nonetheless, it is a common practice in organizational research to assume away time dependence or treat it as an empirical nuisance. To better understand how the Cox model is being used in organizational research, we searched all empirical articles published in two major organizational research journals—*Academy of Management Journal* (AMJ) and *Strategic Management Journal* (SMJ)—from 2012 to 2021 (i.e., 10 years), and found 64 articles that used the Cox model to test hypotheses. We found several common practices that need to be addressed to advance organizational research: (1) Scholars have rarely viewed time dependence as an issue of theoretical interest or capitalized on it as a theory-building opportunity; (2) a majority of the articles using the Cox model did not test for or report tests for time dependence (i.e., test the PH assumption); and (3) even when time dependence was detected (i.e., the PH assumption was violated), most did not explore time-dependent effects of the independent variables.

Our paper aims to change these common practices surrounding the time dependence issue in organizational research. We do so for the following reasons. First, because time dependence means that the nature of a relationship changes over survival time, scholars should consider using time dependence for theory building rather than limiting its importance to an empirical threat. One potential way to do so is to develop *a priori* hypotheses about time dependence—that is, the moderating effect of survival time on the causal relationship between the independent and the dependent variables. Second, even if no theory exists to explain time dependence prior to empirical tests, when time dependence is encountered, scholars can explore its impact and improve theoretical understanding of the phenomena of interest as *a posteriori* analyses. Thus, although scholars may simply avoid using the Cox model when time dependence exists, we recommend instead that they use time dependence in the extended Cox model to test time-dependent theories as well as uncover new phenomena. To this end, we provide a step-by-step guide on how to use the time-dependent effect of independent variables to advance organizational research (e.g., either *a priori* hypothesis development or *a posteriori* analyses). We draw upon the existing methodological literature on the Cox model with time-dependent covariates for guidance (e.g., Kleinbaum & Klein, 2012; Saegusa et al., 2014; Singer & Willett, 2003; Zhang et al., 2018). In addition, we replicate an existing study of CEO dismissal and apply our step-by-step guide to illustrate how the presence of time dependence can deepen theoretical understanding regarding the phenomenon of interest. Lastly, we provide Stata codes for testing time dependence to facilitate future investigations.

The Cox Model and Time Dependence in Organizational Research

Time Dependence in the Cox Model

The Cox model is a regression model designed to estimate the hazard rate, that is, $h(t,\ X)$, determined by covariates after controlling for the effect of survival time (Allison, 2014; Kleinbaum & Klein, 2012; Therneau & Grambsch, 2000). A hazard rate is the instantaneous likelihood of an event's occurrence at time t, given that the event has not occurred prior to time t. For simplicity, if we assume one independent variable and one control variable, the Cox model is estimated using the following equation:

$$\textit{Cox Proportional Hazard Model}: h(t,\ X) = h_0(t) \cdot e^{b_1 x + b_2 z}$$

where bs are regression coefficients, x is a vector of independent variables, z is a vector of control variables, and t is the survival time variable.

Hazard Ratio of x: $\widehat{HR} = e^{b_1}$ *for interpretation of the regression coefficients of x.*

The first part, $h_0(t)$, is the baseline hazard function, and the second part is an exponential expression of a product of the independent variables and their coefficients (Kleinbaum & Klein, 2012). The baseline hazard function is determined by the survival time variable, while the exponential expression represents the effects of the independent and control variables (Therneau & Grambsch, 2000). Because the baseline hazard function can follow any arbitrary shape, the Cox model does not require pre-specification of the baseline hazard function. Put differently, the second part of the equation—that is, the exponential expression—does not use information from the baseline hazard function (or survival time) to estimate the coefficients of the independent variables. Thus, the Cox model assumes that the effects of the independent variables are independent of survival time (Therneau & Grambsch, 2000). As we noted earlier, this time independence of causal effects is called the PH assumption (Allison, 2014; Kleinbaum & Klein, 2012).

However, time dependence is often observed in the Cox model (i.e., PH assumption violation) when independent variables are repeatedly observed in longitudinal (or panel) studies (Fisher & Lin, 1999; Therneau & Grambsch, 2000). In addition, survival time is measured as the time (e.g., minutes, hours, days, weeks, or years) from a starting point to the occurrence of an event of interest, so there exists a potential interaction between the independent variables and survival time. When time dependence exists in the model, survival time effectively becomes a moderating variable on the causal relationships being tested. The Cox model often uses hazard ratios to facilitate the interpretation of regression coefficients, and regression coefficients are converted to hazard ratios using an exponential transformation (Hazard Ratio: $\widehat{HR} = e^{b_x}$) (Kleinbaum & Klein, 2012). A hazard ratio indicates the change in the likelihood of an event's occurrence associated with a one-unit change in the independent variable. If time dependence does exist, the hazard ratios will change over the observed survival time.

It is important to recognize that observed time dependence can be an opportunity to achieve a more comprehensive understanding of a causal relationship between variables of interest and its implication. Positive and negative time-dependent moderation effects theoretically imply that (1) survival time strengthens the main causal effect (i.e., statistically significant main and moderation effects in the same direction), (2) survival time weakens the main causal effect—such effect sometimes appears only when survival time is short (i.e., statistically significant main and moderation effects, but in opposite directions), and (3) the causal effect appears only when survival time is long (i.e., there are only statistically significant moderation effects but no main effect). Unfortunately, prior studies have focused on developing a range of postestimation techniques to check for time dependence in the Cox model, but they have seldom viewed time dependence as an *a priori* or *a posteriori* theory development opportunity. In fact, Allison (2014, p. 42) noted "the possibility that these worries [time dependence] may be exaggerated" because the Cox model is empirically nonrestrictive. However, he additionally stated that time dependence means "an *interaction* between time and one or more explanatory variables" (Allison, 2014, p. 43). Singer and Willett (2003, p. 562) also noted, "Many researchers treat violations of the proportionality assumption as an analytic nuisance". Furthermore, they argued, "violations of the proportionality assumption are often substantively interesting" (Singer & Willett, 2003, p. 562). These studies consistently suggest that time dependence also represents an opportunity (both theoretically and empirically) to explore the interaction between the independent variables and survival time. Building on these studies, we try to change the view that time dependence is a nuisance, highlighting its usefulness as a theory-development opportunity and providing a practical guide for future research.

Addressing Time Dependence in Organizational Research

Table 1 summarizes some exemplary survival time variables from organizational studies that have used the Cox model in AMJ and SMJ between 2012 and 2021 (i.e., 10 years). Although none of the studies listed in Table 1 reported a test for a moderating effect of survival time on their theorized

Table 1. Examples of Survival Time Variables in Organizational Studies.

Authors (Year)	Survival time	Independent variable	Event of interest (Dependent variable)
Bertrand and Lumineau (2016)	The period between a cartel's formation date and its termination date	Age-based experience of cartel members/separation in uncertainty avoidance/power disparity	Cartel termination
Hubbard et al. (2017)	Duration (years) the CEO has been in office	Firm performance/CSR	CEO dismissal
Nadolska and Barkema (2014)	Duration between the acquisition and its divestiture	Top management team's (TMT) experience with acquisitions	Acquisition failure (Divestiture)
Raffiee and Feng (2014)	The amount of time a participant remains in a given paid job prior to starting an entrepreneurial business	Risk aversion	Full time self-employment (Entrepreneurship)
Sharma and Chung (2022)	The period between the month HHGregg electronics retailer closed in a shopping mall (April 2017) and the month a store exited from the mall	Store traits (Size, distance, and relatedness)	Exit (A store exit from a mall)
Xia and Li (2013)	The time between the acquisition date and the divestiture date for each subunit	Mutual dependence/ subsequent acquisition activity by the acquired subunit /subsequent joint ventures by the acquired subunit	Divestiture of an acquired subunit.

main relationship, some of their survival time variables could have potential moderation effects on the main relationship. For example, Raffiee and Feng (2014) examined how an employee's risk aversion (negatively) contributes to entrepreneurship (i.e., starting one's own business). In their study, survival time is the duration between the initial employment date (a paid job) and the start date of one's own business. Although the authors did not theoretically test for time dependence, it is relatively easy to perceive how survival time might function as a moderator. For instance, among professional employees (e.g., attorneys, consultants, and accountants), as job tenure increases, the negative effect of risk aversion on employee entrepreneurship is likely to weaken (i.e., moderation effect of job tenure). Long job tenure is associated with more human capital (e.g., expertise, confidence) as well as social capital (e.g., ties), potentially reducing the perceived level of risk in the entrepreneurship decision (c.f., Jones, Makri & Gomez-Mejia, 2008). Thus, it is possible that the negative effect of risk aversion wanes over job tenure such that the effect exists mostly for short-tenured employees.

Given the vulnerability of the Cox model to time dependence, scholars should pay close attention to the time dependence issue when they use the Cox model. We reviewed the use of the Cox model in organizational studies to understand the current research practices. As noted above, we searched a recent 10-year window (between 2012 and 2021) of AMJ and SMJ papers. We started by searching for keywords (e.g., Cox proportional, Cox model, Cox regression, Cox semiparametric, Cox hazard, Cox specification, survival analysis, survival data, and event history) on the websites of AMJ, SMJ, and Google Scholar. We reviewed each of the identified articles to be sure that each used the Cox model. We found 45 articles from SMJ and 24 articles from AMJ. Later, we dropped 5 papers that did not fit our criteria[1] and kept empirical papers that used the Cox model for the main analysis and robustness checks, resulting in a total of 64 articles. Figure 1 shows that the number of papers using the Cox model increased between 2012 and 2021, confirming the growing appeal of the Cox model. Indeed, in a recent call for papers for the *Journal of Management* special issue (i.e., "Exploring event-oriented approaches to organizational research"), Morgeson et al. (2022, p. 1) noted that "there is a growing acknowledgment of the importance of events in shaping individual

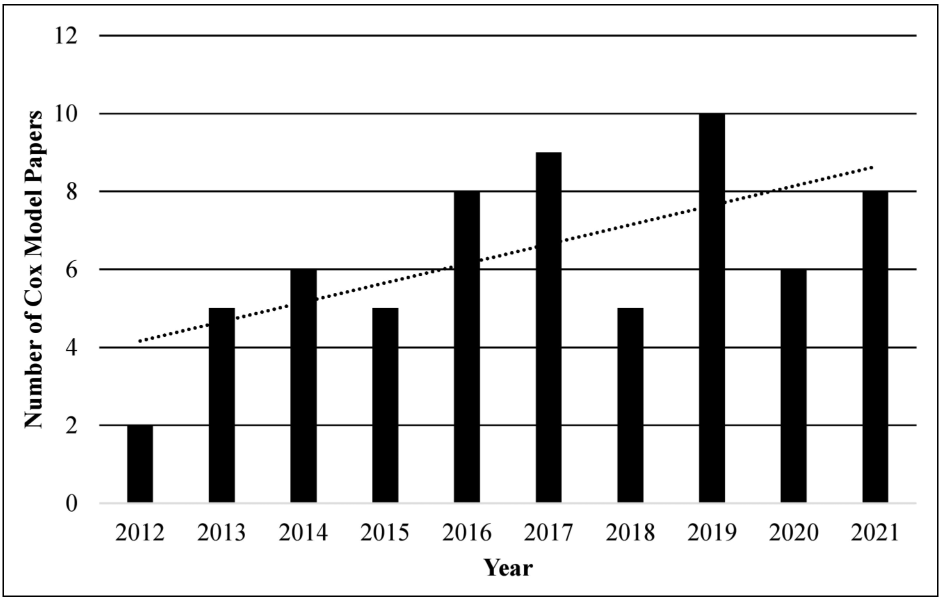

Figure 1. Number of Cox model papers between 2012 and 2021.

and collective behavior" in organizational research. Furthermore, they argued that organizational researchers live in a dynamic era characterized by significant events (e.g., the Covid-19 pandemic) that "break entities (e.g., individuals, teams, organizations, and environments) out of their routines and conventions" (Morgeson et al., 2022, p. 1). Overall, this suggests that the Cox model with time dependence may receive more attention in future organizational studies that explore event-driven phenomena.

We reviewed those 64 articles to determine (1) whether the authors reported and justified the survival time variable, (2) how they tested for time dependence (i.e., PH assumption tests), and (3) how they addressed time dependence when it was detected (i.e., the PH assumption violation). Table 2 summarizes the results of our review. First, we examined whether the studies reported and justified survival time in their Cox model. We found that only 50% of the articles provided information on the variable selected to represent survival time (see Table 2). In other words, 50% of the articles did not describe how survival time was specified. This is a troublesome practice because Cox model results can differ depending on which survival time variable is used to estimate the baseline hazard function. For example, assume that scholars are interested in CEO dismissal events and apply the Cox model. Because CEOs are "at risk" of dismissal as soon as they are appointed, CEO tenure is a natural choice for survival time. CEO tenure can be measured in different scales—either years, months, weeks, or days—depending on the research design (Allison, 2014). When CEO tenure is used to estimate the baseline hazard function, the Cox model controls for right-censoring by using the observed hazard function. However, if the researcher selects calendar year as the measure of survival time instead of CEO tenure, the baseline hazard function will be incorrectly estimated, and in turn, the regression coefficients of the Cox model will not represent the true causal effect of interest. Perhaps equally important, our review of the studies in Table 2 revealed that none of them used survival time for *a priori* and/or *a posteriori* theory-building (e.g., time-dependent moderating hypothesis development or *a posteriori* analysis).

Second, we examined whether the reviewed articles reported tests for time dependence (i.e., PH assumption tests). Unfortunately, a majority (78%) did not report any test of the PH assumption,

Table 2. Use of the Cox Model in Organizational Research.

	Number	Percentage
Survival time	**64**	**100%**
Time variable identification	32	50%
Use time variable for a *priori* and a *posteriori* theory development	0	0%
PH assumption test	**64**	**100%**
Not tested (No report)	50	78%
Tested	14	22%
Goodness of fit approach (e.g., Schoenfeld test)	10	16%
Interaction term with time variable	1	2%
Graphical approach (e.g., Log-log survival curve)	0	0%
No information about a type of test	3	5%
PH assumption violation from test	**14**	**100%**
Not violated	9	64%
Violated	5	36%
Goodness of fit approach (e.g., Schoenfeld test)	5	36%
Graphical approach	0	0%
Addressing PH assumption violation	**5**	**100%**
Alternative survival models (e.g., Exponential, Weibull models)	3	60%
Stratification	2	40%

suggesting that those articles simply assumed time independence or ignored its importance (see Table 2). This practice is troublesome because (as we have already described) the results from the Cox model can be misleading about the association between independent and dependent variables unless the PH assumption is validated. In fact, among the articles (a total of 14) that tested the PH assumption, 36% (5 out of 14) reported that the PH assumption was violated. Given this violation rate in the studies listed in Table 2, we suspect that a significant proportion of the articles that did not test the PH assumption might violate the assumption.

Third, we examined how organizational studies have addressed violations of the PH assumption. Among the articles that reported a violation (a total of five), two used the Cox model with stratification for the variable with time-dependent effects (Greve & Zhang, 2017; Harrison et al., 2018), and three adopted alternative survival models such as a parametric exponential model (Jain, 2016; Jain & Mitchell, 2022) or a discrete-time survival analysis like a complementary log-log model (Guo et al., 2017). Although the stratification and the alternative survival models can be useful as robustness checks, they are not very effective for exploring how a causal relationship varies over survival time. In sum, this evidence suggests that most strategy studies have considered time dependence to be just an empirical nuisance.

In short, our review has several implications. First, it appears that organizational studies often do not clearly state and justify their choices regarding survival time and rarely consider using time dependence for theory building. Second, organizational studies often do not report (or test for) time dependence in their Cox models despite the significant risk of time dependence. Third, even when time dependence is detected, the moderating effect of survival time on the true causal relationship of interest is typically not fully explored. Overall, our review shows that organizational studies are not taking advantage of opportunities to deeply investigate time-dependent causal relationships. We expect that a key reason prior studies have rarely used time dependence as a theory-building opportunity is that scholars are not aware of the methodological approaches that enable the specification and testing of time-contingent causal relationships. To help future researchers better understand and test these relationships, we provide a step-by-step guide for addressing time dependence in the Cox model.

A Step-by-Step Guide for Time Dependence in the Cox Model

Step 1. Choosing and Justifying the Survival Time Variable

The Cox model uses data with survival time—i.e., the time duration for a subject from a starting point to either the occurrence of an event of interest or censoring (Cox, 1972). The Cox model was originally developed and used by medical researchers to examine questions like how long a newborn baby is expected to live. In this case, survival time reflects the interval between birth and death (Cox, 1972). However, the duration depends heavily on the research question and design. Also, survival time can be measured in different scales—years, months, weeks, days, hours, and minutes (Kleinbaum & Klein, 2012). For example, if independent variables are measured annually in a longitudinal or panel data design, survival time can also be measured annually (i.e., years) (Allison, 2014). Thus, an essential concern in selecting a survival time variable is to identify the starting point (when a subject becomes "at risk" of the event). As we report in Table 2, only 50% of the articles we reviewed explained and justified their choice of the survival time variable. Although they typically clarified the event of interest as their dependent variable, most of them did not identify a starting point or provide a clear justification for their choices of survival time variables.

To help future researchers, we highlight some organizational studies as examples that stood out for us in the description and justification of survival time. For instance, Nadolska and Barkema (2014) investigated the survival of acquisitions and considered the divestiture of an acquired unit as a failure event for their survival analysis. In this research setting, they chose the age of the acquisition (i.e., years from the acquisition to the divesture event) as the survival time variable. The starting point of survival time is the date of the acquisition, and it is relevant to the divestiture event because the risk of divestiture does not exist before the acquisition is completed. Also, Sharma and Chung (2022) used a quasi-experiment of the exit of the HHGregg electronics retailer in shopping malls to explore whether the agglomeration benefit of an anchor store disappeared. The failure event was a store exit from the mall and they tracked all remaining stores during the April through December 2017 period. These authors clearly explained the starting point of survival time (April 2017, when the HHGregg electronics retailer closed in shopping malls) and the survival time unit as months by stating "how many months passed before (a store) exited" between April 2017 and December 2017 (Sharma & Chung, 2022, p. 386).

*Step 2. Hypothesis Development for Time Dependence (*a priori *Theory Building)*

After selecting a proper survival time variable, scholars can try to develop a time-dependent hypothesis as an *a priori* theory-building opportunity. Following accepted methodological practice for evaluating moderating effects (Aiken, West & Reno, 1991; Busenbark et al., 2022), we suggest three types of time-dependent moderation that scholars can consider: (1) Statistically significant main and moderation effects in the same direction, (2) statistically significant main and moderation effects in opposite directions, and (3) non-significant main effects coupled with statistically significant moderation effects.

Type 1: Statistically Significant Main and Time-Dependent Moderation Effects in the Same Direction. In this type, the time-dependent moderation effect strengthens the main causal effect. This type occurs when both main and moderating effects are statistically significant and the signs of both coefficients are the same. To explain this moderation type clearly, we provide two graphs with hypothetical scenarios in Figure 2(a). In the left-side plot, the main effect is positive, and it is coupled with a positive time-dependent moderating effect. In the right-side plot, the main effect is negative, and it is coupled with a negative time-dependent moderating effect. We used plots of hazard ratios in Figure 2 because hazard ratios are popular display choices used to interpret associations tested with the Cox model (Allison, 2014; Kleinbaum & Klein, 2012). When the hazard ratio is 1, the regression coefficient is not statistically significant (i.e., HR = 1). However, when the hazard ratio is over 1 or below 1, it indicates positive or negative effects respectively. As the left-side plot of Figure 2(a) shows, the positive main effect (HR > 1) becomes even stronger over time, indicating a positive time-dependent moderating effect. Similarly, the negative main effect (HR < 1) becomes even more negative in the right-side plot of Figure 2(a), indicating a negative time-dependent moderating effect.

Type 2: Statistically Significant Main and Time-Dependent Moderation Effects in Opposite Directions. The second type of time dependence is when the time-dependent moderation effect weakens the main effect. This type occurs when the main and the moderating effects are both statistically significant, but the direction of the effects are opposite. We also provide Figure 2(b) with two scenarios of this type. When the main effect is negative (HR < 1) but coupled with a positive time-dependent moderation effect (see the left-side plot of Figure 2(b)), the hazard ratio increases and is closer to the no-effect hazard ratio of 1 as the survival time is longer. The left-side plot indicates a moderation that weakens the negative main effect. Similarly, when the main effect is positive (HR > 1) but with a negative time-dependent moderation effect (see the right-side plot of Figure 2(b)), the hazard ratio decreases and is close to the null value of HR (when HR = 1). Thus, the positive main effect weakens as the survival time is longer.

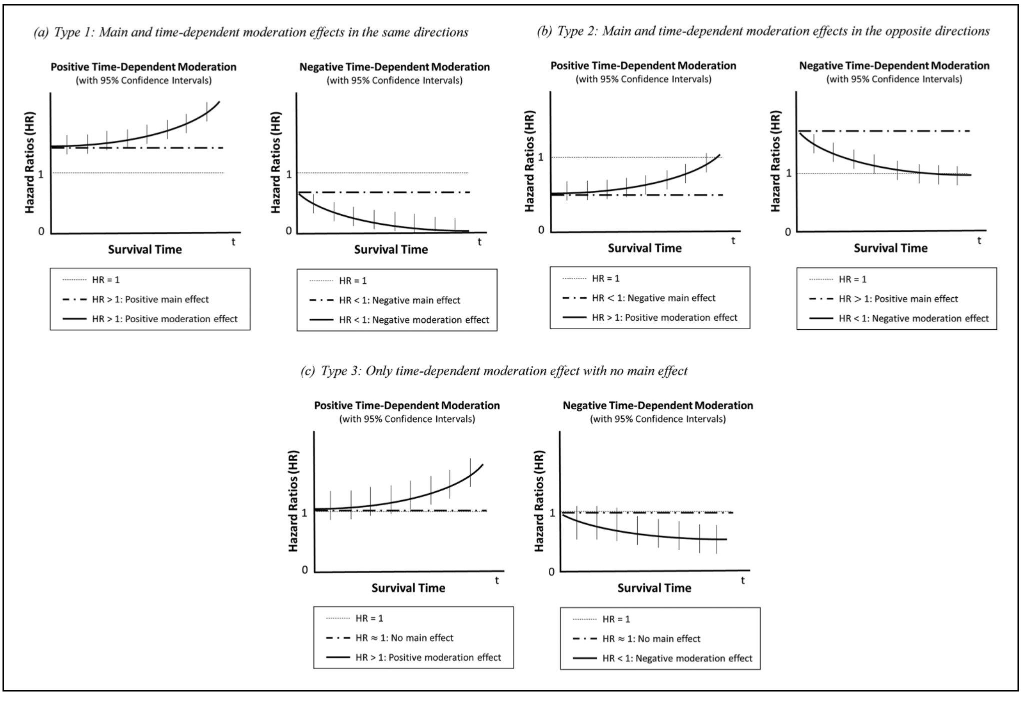

Figure 2. Types of time dependence as a moderating effect. (a) Type 1: Main and time-dependent moderation effects in the same directions. (b) Type 2: Main and time-dependent moderation effects in the opposite directions. (c) Type 3: Only time-dependent moderation effect with no main effect.

Type 3: Statistically Significant Time-Dependent Moderation Effect but No Main Effect. The third type is when the causal effect is manifest only if survival time is longer. This type occurs when the main effect is not statistically significant, but the time-dependent moderating effect is statistically significant. Similarly, we provide Figure 2(c) with two scenarios illustrating a non-significant main effect coupled with positive and negative time-dependent moderation effects, respectively. As Figure 2(c) suggests, the hazard ratio of the main effect starts out close to 1 (HR $\approx$ 1), but the overall hazard ratios increase with positive time dependence in the left-side plot and decrease with negative time dependence in the right-side plot. Because the 95% confidence intervals do not overlap with the line indicating a null hazard ratio (HR = 1) only when survival time is long enough, this implies that the causal effect of the independent variable becomes manifest only when survival time is long.

In short, scholars can consider these three types of potential time-dependent moderation effects if they decide to use time dependence as an *a priori* theory-building opportunity. In particular, these types can provide interesting implications for organizational research when the causal effect of interest may exist only in early (e.g., Figure 2(b)) or late survival times (e.g., Figure 2(c)). If organizational researchers are interested in exploring the time-dependent effect, they can use this step to theorize about different types of time-dependent moderating effects. If scholars want to explore a time-dependent moderation effect as an *a posteriori* theory-building opportunity (e.g., replication studies, mixed models, etc.), they do not need to develop hypotheses and can skip this step.

Step 3. Time Dependence (the PH Assumption) Tests

A traditional way to test for time dependence is a graphical approach (Hess, 1995; Kleinbaum & Klein, 2012; Singer & Willett, 2003). A log-log survival curve is a popular choice for this test. A log-log survival curve is generated by using a natural log transformation of the estimated survival probability across time (Hess, 1995). Most statistical software packages provide a command for generating this plot (e.g., Stata's *stphplot* post-estimation option), so it is relatively easy to use. Scholars usually draw two log-log survival curves over the survival time—one for a treatment group and another for a control group. Then, they check to see whether the two curves are parallel over the survival time. When the curves do not appear to be parallel, the PH assumption is violated.

The use of a graphic approach has two limitations when it is applied to organizational research. First, a graphic approach does not provide any test statistic (e.g., a p-value), so the PH assumption violation must be judged subjectively (Kleinbaum & Klein, 2012). This is troublesome when the survival curves are mostly but not entirely parallel across the survival time. In this case, subjective judgment is required in deciding how parallel is parallel enough (Kleinbaum & Klein, 2012). Second, the independent variables in organizational research are often continuous variables, and it is not clear how to categorize values of continuous variables into meaningful groups (Therneau & Grambsch, 2000). Binary independent variables can be easily split into two groups—treated (coded 1) and control (coded 0) groups, and two log-log survival curves can be drawn separately. This is not the case with continuous variables, and scholars must decide (and transparently explain) how they categorized groups to test the PH assumption. In addition, if scholars use multiple category groups for continuous variables, multiple survival curves will be generated. This can make it even harder to judge whether the multiple survival curves are parallel or not. We believe that this is the main reason that the reviewed organizational research articles in Table 2 seldom used a graphic approach. Therefore, we recommend using a graphic approach only when the independent variables are binary. We also suggest that a graphic approach should be used in combination with other approaches (we will explain some other approaches below) for a robustness check.

An alternative way to test the PH assumption is to use the goodness-of-fit (GOF) testing approach (Kleinbaum & Klein, 2012; Ng'andu, 1997; Therneau & Grambsch, 2000). One key advantage of the GOF approach is that it provides a test statistic, facilitating a clear and objective decision on the PH assumption violation (e.g., a p-value). The most popular GOF approach is a Schoenfeld test (Schoenfeld, 1982; Therneau & Grambsch, 2000) that investigates the effect of survival time on the scaled Schoenfeld residuals for any covariates. When there exists a non-zero relationship (or slope) of survival time on the scaled Schoenfeld residuals (i.e., $p < .05$), it indicates that the PH assumption is violated (Therneau & Grambsch, 2000). Another advantage of the GOF approach is that it provides a simultaneous test statistic for each variable in the Cox model (i.e., a variable-level test) as well as for the overall model (i.e., a global test), so scholars can easily detect a PH assumption violation and find which variables the violation is associated with (Kleinbaum & Klein, 2012; Therneau & Grambsch, 2000). As with the graphic approach, most statistical software packages provide a command for a Schoenfeld test (e.g., Stata *estat phtest* post-estimation option). As we illustrate in Table 2, these benefits explain why a Schoenfeld test (as a GOF test) has been a frequent choice when testing the PH assumption in organizational research. We recommend using a Schoenfeld test (both global- and variable-level tests) for organizational researchers seeking to test the PH assumption.

Step 4. Use of the Extended Cox Model

Once time dependence has been hypothesized and detected from tests of the PH assumption, the next step is to compute the interaction term of the independent variables with the survival time variable and include the interaction term in the Cox model. This is called the extended Cox model (Kleinbaum & Klein, 2012). Because the survival time variable is already included for estimating the baseline hazard function, there is no need to include it as a main effect of survival time in the model. For example, organizational researchers have often studied the effect of firm performance on CEO dismissal (e.g., Hubbard et al., 2017; Shin et al., 2022). They often use CEO tenure as the survival time variable in a Cox model (Hubbard et al., 2017; Shin et al., 2022). If the firm performance variable violates the PH assumption, then one can compute the interaction term of firm performance with CEO tenure and include the interaction term (not the tenure main effect) in the Cox model. When the PH assumption is violated, the interaction term will be statistically significant, meaning that the causal effect of the independent variable is dependent on CEO tenure.

As readers might suspect at this point, the use of an interaction term with the survival time variable provides another alternative for testing the PH assumption. Because the time interaction term has seldom been used in organizational studies, we did not mention this approach in Step 3. In Table 2, we found only one organizational research article that used a survival time interaction term to test the PH assumption. However, if scholars choose to use the interaction term for detecting the PH assumption violation, they can do Steps 3 and 4 of our guide together. Therefore, we suggest that the interaction approach is a good robustness check for the PH assumption if scholars have already tried the graphic or the GOF approach in Step 3.

When scholars include time-dependent interaction terms in the Cox model, they should choose a functional form for the survival time variable. Both a linear (i.e., t) and a log-transformed survival time variable (i.e., $ln(t)$) are potential choices (Kleinbaum & Klein, 2012). The choice of the functional form should be based on the theoretical rationale for the time dependence. If the effect of survival time on the dependent variable is expected to be linear (positive or negative), a linear survival time variable should be used to compute the interaction term. However, if the association is monotonically increasing or decreasing, a log-transformed survival time variable should be chosen. We recommend that organizational researchers review prior studies on the suspected relationship to make an informed decision regarding the functional form of the survival time variable. If scholars cannot find a theoretical justification for the functional form, they can take a post-estimation approach—i.e., check the estimated baseline hazard function and decide on the functional form. Using most statistical software packages, scholars can easily plot the baseline hazard function over the survival time (e.g., Stata's *stcurve, hazard* postestimation option).

Some scholars may wonder if they can use discrete-time survival analysis to test for time dependence. In organizational research, a logit regression model has often been used when the event of interest is observed in discrete time (e.g., Gentry et al., 2021). For example, scholars may not know the exact dates of both CEO appointment and dismissal events, but just check those events at the end of each fiscal year. In this example, researchers would measure CEO tenure (i.e., a survival time variable) in years between appointment and dismissal years. Then, they apply a logit model (with panel data) to test the effect of firm performance on CEO dismissal and include CEO tenure as a control variable. In fact, a logit model has been known as an attractive discrete-time survival analysis option for repeated events (Allison, 2014) that organizational studies often analyze. Notwithstanding these advantages of a logit model, the Cox model is more versatile than a logit model for testing the time-dependent moderation effects. Allison (2014, p. 10) recommended that a logit model include "a set of [survival time] dummy variables" to control for any time-varying hazards, particularly "when the number of time points is small." In this case, researchers should include interaction terms between the independent variable and all of the survival time dummy variables (e.g., yearly dummies) to test for a time-dependent moderation effect. Accordingly, it is relatively hard to theorize, test, and interpret the moderation effect with so many interaction terms. In addition, while a logit regression model is adopted for discrete-time survival analysis, the Cox model can be utilized for both continuous- and discrete-time survival analyses (Allison, 2014). Therefore, we recommend using the extended Cox model if scholars want to test the time-dependent moderation effect.

Step 5. Interpretation of the Time-Dependent Effect (and a Posteriori Theory Building)

The last step is to interpret the time-dependent moderation effect on the causal relationship of interest. Once the extended Cox model is analyzed with both the main effect and the moderating effect of the independent variables with survival time, scholars should interpret the estimated coefficients. The extended Cox model is non-linear, and the causal effects of the independent variables are assumed to be time-dependent, that is, hazard ratios change across the survival time. Thus, for these independent variables, the traditional way of interpreting a hazard ratio (using a single hazard ratio value) is not appropriate. Instead, we recommend computing multiple hazard ratios across survival time or providing a graph of changes in hazard ratios over survival time, as prior methodology studies have suggested for non-linear models in general (see, for example, Hoetker, 2007; Zelner, 2009).

As you can see in the equations below, the extended Cox model includes both the main effect of the independent variable (i.e., x) and the interaction term with the survival time variable (i.e., $x{\cdot}t$) (Kleinbaum & Klein, 2012). Then, the hazard ratios for time dependence can be computed by using the regression coefficients for the main and the interaction terms (i.e., $\widehat{HR} = e^{b_1+b_2t}$). The hazard ratios with time dependence can be interpreted as the change in the likelihood of an event's occurrence associated with a one-unit change in the independent variable over the survival time, other things being equal. Using the hazard ratio function only with the main and the interaction terms, scholars try either (1) to compute the hazard ratios at meaningful values of the survival-time variables (e.g., the mean and the standard deviation from the mean values); or (2) draw a hazard-ratio graph over the survival time. We provide Stata codes in Appendix A for readers who want to apply the extended Cox model and to interpret the hazard ratios across survival time.

$$\text{Extended Cox Model: } h(t,\ X) = h_0(t) \cdot e^{b_1x+b_2x\cdot t+b_3z}$$

$$\text{Hazard Ratio of } x \text{ across } t\text{: } \widehat{HR} = e^{b_1+b_2t}$$

For an *a posteriori* theory-building opportunity, scholars can use the results of the extended Cox model to identify the type of time-dependent moderation effects as we explained in Step 2. Then, scholars can explore this opportunity through replication studies, sensitivity analyses, or an inductive research approach (e.g., developing theory after scientific observation) (see Bonett, 2021; Ethiraj et al., 2016; Turner et al., 2017).

Time Dependence Example: Replication of a CEO Dismissal Study

To demonstrate our step-by-step guide, we elected to replicate a CEO dismissal study because CEO dismissal studies have often used survival analysis (Hubbard et al., 2017; Lee et al., 2020; Shin et al., 2022) and have received a great deal of attention from organizational researchers (Bilgili et al., 2017; Finkelstein et al., 2009). Particularly, we chose a study by Gentry et al. (2021) for the replication. Although the main purpose of Gentry et al. (2021) was to introduce CEO dismissal data and make it publicly available, they also analyzed the effect of firm-market performance on CEO dismissal and (as expected) reported a negative effect. Building on the Gentry et al. (2021) approach, we explain how CEO tenure (i.e., CEO survival time) can change the relationship between firm-market performance and CEO dismissal. The time variable, CEO tenure, refers to the number of days in office since the CEO's appointment. Because CEOs cannot experience a dismissal event before they are appointed and CEO tenure accurately reflects the time that a CEO has been "at risk" of dismissal, CEO tenure is the appropriate survival time measure for our research setting.

Our baseline hypothesis is that firm-level market performance is negatively related to CEO dismissal. The negative link between firm-market performance and CEO dismissal has been confirmed consistently over time (Finkelstein et al., 2009). A large number of CEO dismissal studies are grounded in agency theory, suggesting that CEO dismissal is an effective corporate governance response when a firm performs poorly or its performance is lower than expected. Indeed, research suggests that a board's expectations about firm performance—based on comparisons with industry rivals—is a primary factor in CEO dismissal (Coughlan & Schmidt, 1985; Haleblian & Rajagopalan, 2006; Puffer & Weintrop, 1991; Walsh & Seward, 1990). When the firm's market performance is below rivals', the board may conclude that organizational change is required and dismiss the CEO. The lower the firm's market performance, the more likely it is that the board will fire the CEO. On the flip side, the better the focal firm performs relative to rivals, the more likely the board is to conclude that the CEO should not be dismissed.

Next, we argue that CEO tenure can set the overall tone of how the CEO is assessed, and that CEO tenure will likely reduce the negative impact of firm-market performance on CEO dismissal. First, poor (or lower than expected) market performance signals that the CEO is of low quality and is perhaps inadequate to manage the firm, so the CEO failed to demonstrate ability and quality for the CEO position. When this is combined with a short tenure, the CEO has limited power and social ties within the firm due to the short tenure in office. Put differently, when short-tenured CEOs have lower performance, their boards of directors are more likely to believe that they are not well-suited for the position (e.g., the CEO's hiring was due to adverse selection) (Zhang, 2008). Furthermore, due to the short tenure, the board's power over the CEO is strong, leading to the capacity to remove the CEO promptly. Indeed, Shen and Cannella (2002) found that the likelihood of CEO dismissal is higher in the earlier years than in the later years in office because power contests for the top position are generally observed only early in the CEO's tenure.

In contrast, long-tenured CEOs are likely to have had the opportunity to prove their leadership quality (i.e., having survived for a long time indicates that the CEO has demonstrated quality in the past) as well as achieved social and political power within the firm. Thus, when long-tenured CEOs fail to achieve acceptable market returns, they can divert the blame to others (scapegoat those with less power) and boards of directors have less capacity to sanction the CEOs (Boeker, 1992; Ocasio, 1994). In fact, Ocasio (1994) found that CEO dismissal likelihood decreases over time in office as the strategies and solutions of the CEO become more integrated within the firm and the CEO gains more control over the firm. Also, Fredrickson, Hambrick and Baumrin (1988) suggested that boards' ability to dismiss a CEO varies with the social and political power of the CEO even when the context is one of poor performance. These findings indicate that (longer) CEO tenure is likely to attenuate the negative impact of firm-market performance on CEO dismissal. Taken together, we hypothesize:

> *H1 (Negative main effect)*: Firm-market performance is negatively related to CEO dismissal.
> *H2 (Positive time-dependent moderating effect)*: CEO tenure will attenuate the negative effect of firm-market performance on CEO dismissal such that the negative effect will weaken over CEO tenure.

Methods and Results

For the replication, we contacted the corresponding author of Gentry et al. (2021) and obtained the data that was used for the study. The data covers CEO successions (including dismissals) from S&P 1500 companies between 2000 and 2018. Below, we describe how the authors measured their variables. The dependent variable (or failure event), *CEO dismissal*, is an indicator variable with a value of 1 when the CEO was removed from office. The independent variable for *firm-level market performance* is measured as an industry-adjusted market return, and it is the difference between a firm's total market return and the industry's mean return (i.e., 4-digit SIC) (Wiersema & Zhang, 2011).

CEO tenure was measured as the number of days between the appointment date and the dismissal date or year-end date (i.e., if the CEO was not dismissed during the year). Following the episode-splitting approach described in the survival analysis literature (e.g., Mills, 2011), we split our data into annual episodes (or spells) so that we could update time-varying independent variables and use CEO tenure (in days) as our survival time variable. Since our explanatory variables were updated at the end of each fiscal year, we had annual episodes (or spells) of CEOs if they were in office for several years. When CEOs were appointed during a focal year and remained in office beyond the end of that year, we measured CEO tenure for each episode (or spell) as the number of days between the appointment date and each year-end date. In other words, tenure was captured for each year-end date until the CEO's dismissal. For the last episode year (when the CEO left the position before the end of the last episode year), we measured tenure in days between the CEO's dismissal date and the CEO's appointment date.[2] Figure 3 provides a graphic presentation of this episode splitting for our data.

Lastly, the control variables include *analyst downgrades* (Boivie et al., 2016) (i.e., the number of downgrades investment analysts issued; see Wiersema & Zhang, 2011 for more details), *average analyst recommendations* (i.e., the changes in analyst recommendations that are not explained by firm performance; see Wiersema & Zhang, 2011 for more details), *industry-adjusted ROA* (i.e., the difference between a firm's ROA and the industry's mean ROA (i.e., 4-digit SIC)), *firm size* (i.e., the natural log of sales), *strategic nonconformity* (i.e., the degree to which a firm's strategy is unorthodox) (Geletkanycz & Hambrick, 1997), *board size* (i.e., the number of directors on the board), and *CEO duality* (i.e., whether the CEO also served as the board chair). Year effects were controlled as dummy variables. After we excluded cases with missing values, the final sample had 9,173 firm-year observations and included some 409 CEO dismissal events. Table 3 provides the summary statistics and correlations for all variables used in the study. We do not find high correlations between variables in the data, yet we still tested for potential multicollinearity using an ordinary least squares (OLS) regression. The variance inflation factors were all below 2.14, suggesting that multicollinearity is not likely a concern.

The purpose of this replication is to demonstrate our step-by-step guide to use the extended Cox model for testing time dependence. Thus, while Gentry et al. (2021) applied a random-effects logit model, we tested our hypotheses using the Cox model with robust standard errors.[3] We ran the Cox

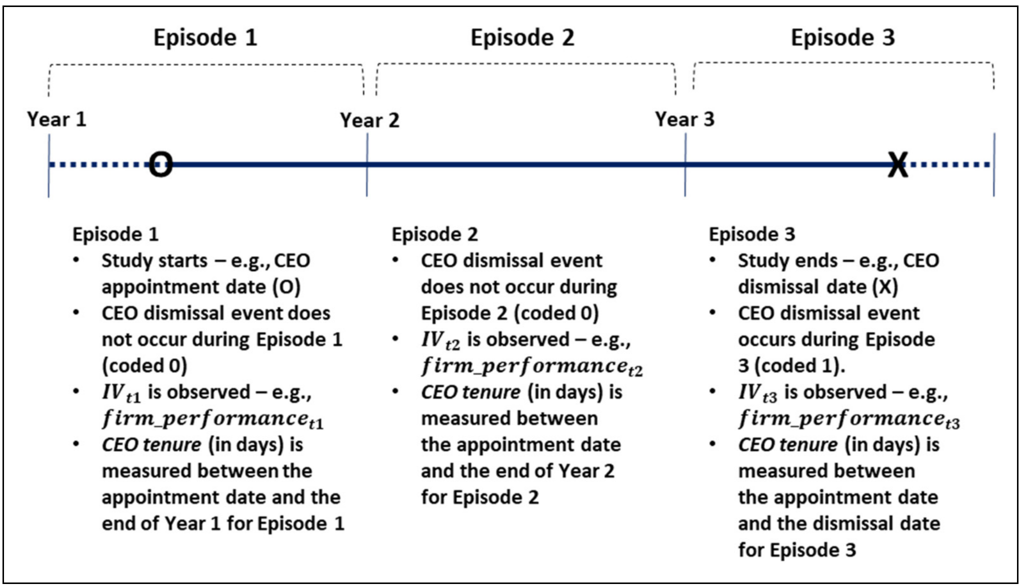

Figure 3. Episode splitting for survival analysis of CEO dismissal.

model with the main independent variable (i.e., firm-market performance) and control variables. Because CEO tenure was already controlled as the survival time variable for the baseline hazard function, it was not included as a main effect variable. Consistent with the Gentry et al. (2021) findings, our replication results using the Cox model showed that firm-market performance (i.e., industry-adjusted market return) has a negative effect on CEO dismissal (Model 1 of Table 4). The coefficient of firm-market performance is −0.016 and it is statistically significant ($p < .001$), supporting the baseline hypothesis (Hypothesis 1). However, when we tested the PH assumption—that is, whether this causal effect was time dependent, the Schoenfeld test (Stata *estat phtest*) indicated that the PH assumption was violated. A global test confirmed the time dependence of the overall Cox model ($\chi^2 = 54.67, p < .01$), and a variable-level test for firm-market performance indicated that its effect also suffered from time dependence ($\chi^2 = 16.15, p < .001$) (see Table 5).[4] This test result means that the effect of the firm-market performance is not constant across time, but rather changes with CEO tenure.

We applied the extended Cox model to test Hypothesis 2 and to better understand how the effect of firm-market performance on CEO dismissal changes over CEO tenure. We computed the interaction between firm-market performance and CEO tenure, and included it in the extended Cox model.[5] Because CEO tenure was already controlled as the survival time variable used to estimate the baseline hazard function, we included only the interaction term (no main effect of CEO tenure). Models 2 and 3 of Table 4 report the results of the extended Cox model. In Model 2, we used the unscaled CEO tenure in days as the survival time and regardless of its significance (p < .001), the interaction coefficient was too small because of a wide range of CEO tenure in days (0–11,000 days). Therefore, we rescaled the CEO tenure to 1,000 days (0–11) and reported the coefficient for the interaction in Model 3. Model 3 shows that the coefficient of the interaction variable is positive and statistically significant ($b = 0.003; p < .001$), confirming Hypothesis 2. The negative main effect of the firm-market performance is made weaker (less negative) as tenure extends. As we explained earlier in our step-by-step guide, if organizational researchers develop an *a priori* hypothesis about time dependence (as we did), the use of an interaction term with the survival time variable is a direct way to test this hypothesis.

Next, we interpreted the time-dependent moderation effect. Because the extended Cox model is by nature nonlinear, scholars should use care in interpreting the nonlinear moderation effects.[6] To better illustrate the moderating effect of CEO tenure, we drew Figure 4 and compared the predicted hazard ratios—the effect of firm-market performance on CEO dismissal—for both the main effect (the dotted line) and the moderation effect (the solid line) (Kleinbaum & Klein, 2012). We used coefficients from Model 2 of Table 4 to compute the hazard ratios, and the solid line suggests the positive time-dependent moderation effect, confirming our Hypothesis 2 (illustrating the Type 2 situation of Figure 2), where the negative main effect weakens over the survival time. Hazard ratios[7] in Figure 4 represent the change in the likelihood of CEO dismissal associated with a one-unit change in firm-market performance. As we explained earlier, firm-market performance was measured as an industry-adjusted market return, stated in percent (%). Then, hazard ratios in Figure 4 can be interpreted as the change in the likelihood of CEO dismissal if firm-market performance rises by a one unit —that is, 1%. A hazard ratio for the negative main effect (the dotted line) is 0.975 ($e^{-0.025}$), which means that a one-unit (i.e., 1%) increase (or decrease) of firm-market performance leads to a 2.5% decrease (or increase) of a CEO dismissal likelihood. It is a meaningful impact because the mean value of firm-market performance is−1.04% and the standard deviation is 41.76% in our samples. If a CEO dismissal likelihood increases by 2.5% for every 1% decrease in the firm-market performance, there exists a dramatic difference in the likelihood of CEO dismissal between highly and poorly performing firms. However, as the figure shows the moderation effect (the solid line), hazard ratios become close to 1 (no effect) as CEO tenure extends. Hazard ratios are 0.977 for 810 days (−1 s.d. of CEO tenure) and 0.989 for 5,202 days (+1 s.d.) in Figure 4. In other words, the change in the likelihood of CEO dismissal decreases from 2.3% for short-tenured (−1 s.d.) to 1.1% for long-tenured CEOs (+1 s.d.), as firm-market performance increases by 1%. When CEO

Table 3. Descriptive Statistics and Correlations.

		Mean	S.D	Min	Max	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1)	CEO dismissal	0.04	0.21	0.00	1.00									
(2)	Firm-market performance	−1.04	41.76	−152.67	339.89	−.10								
(3)	Analyst downgrades	1.78	2.05	0.00	24.00	.10	−0.14							
(4)	Avg analyst recommendation	0.18	0.49	−2.39	1.62	−.08	.03	−.22						
(5)	Industry-adjusted ROA	0.57	1.45	−1.70	21.75	.00	.05	.00	.00					
(6)	Firm size	7.44	1.52	2.62	10.70	.00	−.04	.23	−.20	−.02				
(7)	Strategic nonconformity	2.09	1.21	0.19	7.03	.04	.01	.03	.03	.06	.05			
(8)	Board size	9.52	2.43	5.00	18.00	−.01	−.06	.13	−.21	−.08	.54	−.05		
(9)	CEO duality	0.58	0.49	0.00	1.00	−.05	−.01	.06	−.08	−.01	.23	−.04	.18	
(10)	CEO tenure	3.01	2.20	0.03	11.32	−.02	.01	.00	−.02	.00	−.09	−.06	−.09	.24

Note: N = 9,173. Coefficients above |.02| are all significant at a .05 *p*-value level. The unit of CEO tenure is 1,000 days.

Table 4. Results of the Extended Cox Model.

	Cox model		
	Model 1	Model 2	Model 3
Analyst downgrades	0.109***	0.107***	0.107***
	(0.017)	(0.017)	(0.017)
Average analyst recommendation	−0.625***	−0.638***	−0.638***
	(0.115)	(0.112)	(0.111)
Industry-adjusted ROA	−0.004	−0.007	−0.007
	(0.040)	(0.042)	(0.042)
Firm size	0.065	0.057	0.057
	(0.046)	(0.045)	(0.045)
Strategic nonconformity	0.078**	0.088*	0.088*
	(0.039)	(0.038)	(0.038)
Board size	0.004	0.009	0.009
	(0.024)	(0.024)	(0.024)
CEO duality	−0.294**	−0.325**	−0.325**
	(0.104)	(0.103)	(0.103)
Industry-adjusted market return (H1)	−0.016***	−0.025***	−0.025***
	(0.002)	(0.004)	(0.004)
Industry-adjusted market return x CEO tenure (H2)		0.000***	0.003***
		(0.000)	(0.000)
Log likelihood	−2328.25	−2321.80	−2321.80
Chi-square	282.10	310.08	310.08
Observations	9,173	9,173	9,173

Note: Standard errors in parentheses; $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$; Model 2 has CEO tenure in days; Model 3 has CEO tenure in 1,000 days.

Table 5. Schoenfeld Test for the Cox Model.

Variable-level test	Rho	Chi-square	p-value
Firm-market performance	0.100	16.15	.000
Analyst downgrades	0.067	2.17	.140
Average analyst recommendation	0.026	0.40	.527
Industry-adjusted ROA	0.039	0.92	.338
Firm size	0.089	5.42	.020
Strategic nonconformity	0.037	0.75	.387
Board size	−0.017	0.12	.725
CEO duality	0.043	0.78	.377
Global test		54.67	.001

tenure becomes around 9,000 days, a hazard ratio is approximately 1.000—that is, no effect. We conjecture that while (poor) firm-market performance is a critical factor for CEO dismissal, CEOs with longer tenure have some leverage and power to deflect the blame and avoid dismissal. Thus, the negative effect of firm performance on CEO dismissal is stronger for short-tenured CEOs relative to long-tenured CEOs. The findings with the extended Cox model deepen our understanding of how the causal effect of firm-market performance on CEO dismissal is contingent on CEO tenure, and also provide evidence that survival time can provide new insights even for well-studied relationships.

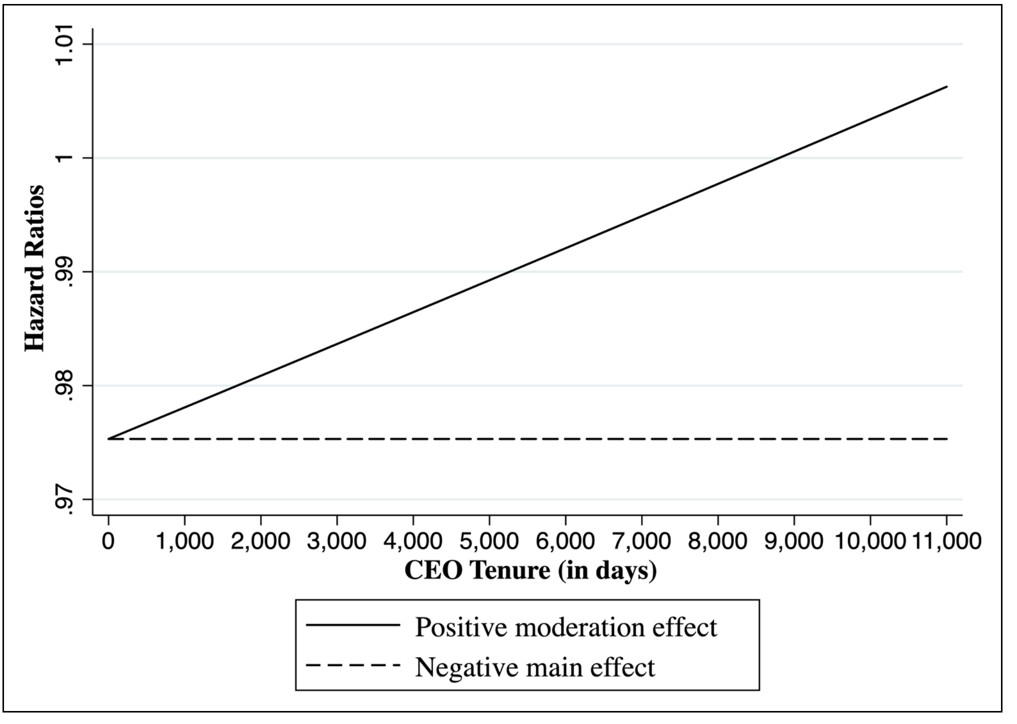

Figure 4. Time-dependent moderation effect over CEO tenure.

The time-dependent moderation effect can provide some insights for future CEO dismissal studies. For example, firm performance has been considered a key governance indicator of poorly performing CEOs (e.g., Finkelstein et al., 2009). However, if this widely accepted governance mechanism mostly applies to newly hired CEOs, what other governance mechanisms should shareholders rely on to monitor long-tenured CEOs? We think that future studies can utilize the extended Cox model to theorize about and explore the time-dependent effects of other governance mechanisms —such as the market for corporate control and boards of directors—over CEO tenure (see also Walsh & Seward, 1990). This can be a way to identify which governance mechanisms are more effective than others for monitoring long-tenured CEOs, because the evidence we have reported suggests that governance mechanisms are not equally effective for short- and long-tenured CEOs.

Conclusion

We aim to provide practical guidance for using time dependence in the Cox model to improve theoretical understanding of the causal relationship between variables of interest. We reviewed 10 years' worth of articles published in AMJ and SMJ to see how researchers have used the Cox model in organizational research and identified some common but troublesome practices. We also used a replication to empirically demonstrate how survival time can affect research conclusions. Along the way, we offered some simple steps that can be taken to address time dependence in the effects of independent variables and to use survival time to further achieve theoretical gains. The step-by-step guidelines we provide can help scholars ensure the transparency of their methodological choices and remind them of potential theory-building opportunities. Lastly, we provide Stata codes (see Appendix) for future scholars who want to use the Cox model to explore time dependence in their data.

Appendix

Stata Code for Time Dependence

<Declare Survival Analysis Data>

stset time_var, id(subject_idvar) failure(failvar==1)

// time_var: survival time variable name

// subject_idvar: subject (firm or individual) id variable name

// failvar: failure event variable name when the event occurrence is coded 1

<Run the Cox Model>

stcox iv_var control_var, nohr

// iv_var: independent variable names

// control_var: control variable names

// nohr: an option to present regression coefficients. If it is not used, the hazard ratios are reported instead.

<PH Assumption Tests after Running the Cox Model>

1. Log-log Plot of Survival

stphplot, by(*var_name*)

// var_name: binary independent variable name. If the independent variable is continuous, a new binary variable should be made for this test. For example, values over the meaning number like the mean is coded 1 and 0 others.

2. Kaplan-Meier and Predicted Survival Plot

stcoxkm, by(var_name)

// var_name: binary independent variable name. See the note above for a continuous variable.

3. Schoenfeld Residuals Test

estat phtest, detail

// detail: an option to present a variable-level test as well as a global test.

<Run the Extended Cox Model for Time Dependence>

stcox iv_var int_iv_time control_var, nohr

// iv_var: independent variable names

// int_iv_time: interaction variable between independent variable (iv_var) and survival time variable (time_var)

// control_var: control variable names

// nohr: an option to present regression coefficients. If it is not used, the hazard ratios are reported instead.

<Interpret the Extended Cox Model for Time Dependence>

1. Hazard Ratio Graph over the Survival Time

*twoway function y=exp(iv_coff + int_coff*x) | function y=exp(iv_coff)*

// manually draw the hazard ratio graph for the moderating effect and the main effect

// iv_coff: regression coefficient of the independent variable

// int_coff: regression coefficient of the interaction term between the independent variable and the survival time variable

2. Hazard Ratio Computation at a Certain Value of the Survival Time

*display exp(*iv_coff + int_coff * t*)* // for $Hazard\ Ratio = e^{(\,iv\_coff\ +\ \mathrm{int}\_coff\ *\ t\,)}$

// manually compute the hazard ratio at a certain value of the survival time

// iv_coff: regression coefficient of the independent variable

// int_coff: regression coefficient of the interaction term between the independent variable and the survival time variable

// *t*: a value of the survival time (e.g., -1 s.d., mean, or +1 s.d. of the survival time)

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Notes

1. We excluded empirical papers that used other survival analysis techniques such as Exponential/Weibull and discrete-time survival models. Those techniques require specification of the baseline hazard function in advance, which is mostly unknown in organizational research. This probably helps to explain the popularity of the Cox model.
2. Alternatively, we tested CEO tenure in years for a survival time variable to compare the results with our main models. The results were consistent, and the statistical significance and the signs of coefficients for the independent variable and time-dependent moderating effects were same.
3. We also successfully replicated the original findings using a random-effects logit model as Gentry et al. (2021) did. Because we obtained the data from the corresponding author, the results were consistent. Thus, we do not report the findings of Gentry et al. (2021).
4. The Schoenfeld test also detected a PH assumption violation for firm size, which is a control variable in our models. To explore whether the PH assumption violation of firm size (control variable) has any impact on the coefficients of firm-market performance (independent variable), we included the interaction term of survival time (i.e., CEO tenure) with firm size in our models as a robustness check. The results were consistent with or without the interaction term.
5. As a robustness check, we also computed a squared term of survival time and a log transformed survival time and tested their moderating effects. However, we did not find any significant results.
6. This problem is quite similar to the one described for logit and probit models (Bowen & Wiersema, 2004; Hoetker, 2007).
7. We computed hazard ratio functions for this graph—i.e., $\widehat{HR} = e^{b_1 + b_2 \cdot Tenure}$. b_1 represents the coefficient of firm-market performance, and b_2 represents the coefficient of the interaction term between firm market performance and CEO tenure.

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