AMERICAN PSYCHOLOGICAL ASSOCIATION

Journal of Applied Psychology

ISSN: 0021-9010

2020, Vol. 105, No. 11, 1207–1217
http://dx.doi.org/10.1037/apl0000782

Impact of the COVID-19 Pandemic on Job Search Behavior: An Event Transition Perspective

Lynn A. McFarland
University of South Carolina

Sydney Reeves and W. Benjamin Porr
Harver, New York, New York

Robert E. Ployhart
University of South Carolina

This study examines how job search behavior changed at the onset of the COVID-19 pandemic, the weeks following the event's onset, and if the physical contact required by different jobs moderated these trends. Based on event system theory, we argue that the onset of the pandemic created a strong event because it was highly novel, disruptive, and critical. We test this by examining 16 weeks of job applications for 14 organizations that differ in terms of whether the jobs require employees to work from home or face-to-face. We use Bliese, Adler, and Flynn's (2017) transition framework and discontinuous random coefficient growth curve modeling to test the pandemic's effect on job search behavior both during the event onset and then the weeks following the onset. Importantly, we include a 9-week preonset baseline period to provide more rigorous tests of change. Results show that the onset of the pandemic created an immediate increase in job search behavior (job applications), and this effect endured into the postonset period. Job type moderated these trends, such that the onset and postonset applications were substantially greater for work-from-home jobs (which followed a negatively accelerated curve) compared to face-to-face jobs. These findings advance the job search literature by introducing event system theory and transition frameworks to better understand how and why events uniquely influence job search behavior over time.

Keywords: job search, recruitment, selection, longitudinal

The COVID-19 pandemic is producing unprecedented global health and economic disruptions. Workers and organizations alike are struggling to adapt to "the new normal" (Alter & Villa, 2020; Mull, 2020; Solomon, 2020). Currently, there is more opinion than evidence, especially in terms of understanding how the pandemic is influencing worker preferences. A small but important literature has shown that large-scale macro events (e.g., recessions) can shape jobseeker perceptions (see Bianchi, 2020). However, even this research has focused on reactions to macro events after they occur, rather than understanding the transition created by the introduction of an acute event (Bliese, Adler, & Flynn., 2017). This is especially true for macro events that are unexpected or difficult to predict. Consequently, little is known about how the pandemic shapes job search behavior and what organizations can do about it.

In their comprehensive review of the job search literature, Wanberg, Ali, and Csillag (2020) noted that more research on context (macroeconomic conditions) is needed to provide "deeper and richer insight into the predictors and moderators involved in job search success" (p. 329). Toward this end, the goal of this article is to test whether the onset of the COVID-19 pandemic changed job search behavior (i.e., job applications) over time and, in doing so, advance a broader understanding of events and transitions in job search. First, we integrate event system theory (Morgeson, Mitchell, & Liu, 2015) with the job search literature to better understand and conceptualize how macro events, such as the COVID-19 pandemic, affect job search behavior. Compared to other macro events such as recessions or stock market changes, the pandemic's onset is a macro event of higher novelty, disruption, and criticality. Second, we apply frameworks for studying transitions (Bliese & Lang, 2016; Lang & Bliese, 2009) to distinguish between the transition created at the onset of COVID-19 from the postonset slope. As such, we focus specifically on how the pandemic led to a transition (Bliese et al., 2017) and produced an immediate change in job applications across organizations. The immediate onset period has not been examined in prior job search research, which has instead emphasized the study of processes after an event's occurrence (e.g., job search following job loss). Such an omission is problematic because the immediate conse-

This article was published Online First October 8, 2020.

Lynn A. McFarland, Department of Management, Darla Moore School of Business, University of South Carolina; Sydney Reeves and W. Benjamin Porr, People Science, Harver, New York, New York; Robert E. Ployhart, Department of Management, Darla Moore School of Business, University of South Carolina.

We thank Paul Bliese for his assistance with the analyses and for providing comments on an earlier version of this article.

Correspondence concerning this article should be addressed to Lynn A. McFarland, Department of Management, Darla Moore School of Business, University of South Carolina, 1014 Greene Street, Columbia, SC 29208. E-mail: Lynn.McFarland@moore.sc.edu

quences of an event may differ from effects later in time (Bliese et al., 2017). We disentangle the effects of the event onset on job search behavior from the more commonly studied postevent period to better understand the full consequences of an event. Finally, we theorize that the financial and health-related consequences of the COVID-19 pandemic affect the type of jobs to which applicants apply. We show that the onset of the pandemic produces a sizable shift in job search behavior toward jobs that require less physical contact, and this effect is maintained in subsequent weeks following the onset. The introduction of event system theory into the job search literature, along with the transition modeling framework, offers new ways to theorize and model the impact that events have on job search processes that can be adopted in future research, thus providing implications that endure beyond the COVID-19 pandemic. The findings also have implications for practice, particularly in terms of whether there is value in offering work-from-home opportunities and for understanding the consequences of macro events more generally.

Importantly, we use a longitudinal methodology (discontinuous random coefficient growth curve models [DRCGCM]; Lang & Bliese, 2009; Singer & Willett, 2003) that enables a rigorous test of the effects of the pandemic's onset on job search behavior. Examining the immediate transition caused by the COVID-19 onset event can only be accurately performed when there is a sufficiently long baseline period to observe before the event (Bliese et al., 2017). This study employs a baseline of 9 weeks prior to the pandemic's onset and 6 weeks following the pandemic's onset. DRCGCM leverages these data in a way that enables the decomposition of variance in job applications to preonset, COVID-19 onset, and postonset periods. Therefore, the models test the strength of the pandemic's effect on the onset and postonset duration, relative to prepandemic levels.

Theoretical Foundation

Job search involves psychological processes, behaviors, and contexts surrounding an individual's attempt to find and get a job. Prior research has focused primarily on understanding either individual difference predictors of search activities and outcomes or interventions aimed to enhance job search outcomes (e.g., Kanfer, Wanberg, & Kantrowitz, 2001; Klehe & van Hooft, 2018; Liu, Huang, & Wang, 2014). In contrast, much less research has examined the macro events that shape the manifestation and experience of job search (Wanberg, Ali, et al., 2020). Here, the focus is not on enduring macro conditions (e.g., slowly changing economic conditions) but rather on events that originate at broad economic levels and simultaneously influence multiple organizations and individuals. Event system theory (Morgeson et al., 2015) helps understand the nature of such macro events and when they shape individual and collective responses but, to our knowledge, has not been used to understand macro effects on job search.

Event system theory defines events as "discrete and bounded in space and time" (Morgeson et al., 2015, p. 516). Events differ in their strength and thus lie on a continuum from weak to strong. Events that are more novel (different from prior routines), disruptive (magnitude of change), and critical (demand attention and reprioritization) have stronger influences on outcomes. Events that originate at higher (macro) levels also have broader impact and are more enduring. A macro event has a beginning (i.e., onset) and thus the event creates a temporally defined *transition* period between the introduction of the event and the start of a posttransition period (Bliese et al., 2017). Figure 1 provides an illustration of these *distinct* periods (the figure juxtaposes Bliese et al.'s framework with the pandemic event of interest in this study). The transition period has a specific start and end, but the posttransition

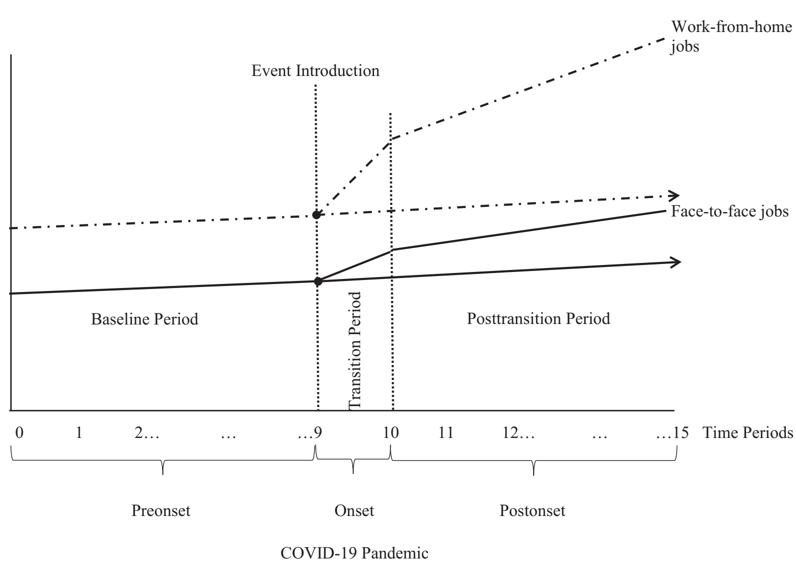

Figure 1. Illustration of baseline, transition, and posttransition periods. The solid line represents face-to-face job applications and the "solid-dot" line represents work-from-home applications. Vertical dotted lines define the transition period. The arrows indicate the slopes that would have been estimated using only the baseline period data.

consequences of the event can endure and change over time. Therefore, it is critical to ensure there are a sufficient number of opportunities to observe behavior *before* and after the transition period. Indeed, Bliese et al. (2017) note that "studies that attempt to determine responses to events or postevent recovery trajectories without . . . [preevent] . . . data are remarkably difficult to interpret" (p. 274).

The introduction of a stronger macro event can thus produce both immediate and long-term changes to behavior, and the effects of predictors may change across these periods. The Great Recession offers one example. This macro event created a period of strong disruption with distinct periods of transition and postrecession recovery, with predictive relationships changing across event onset and postonset periods (e.g., Kim & Ployhart, 2014).

Unfortunately, prior job search research has not adopted such models when examining macro events. As a consequence, prior research has not been able to precisely estimate the variance specific to macro events and their transition periods or disentangle the variance between an event's onset and postonset responses. For example, research has examined the effects of unemployment or job loss events influencing job search (Boswell, Zimmerman, & Swider, 2012; Wanberg, Basbug, van Hooft, & Samtani, 2012). However, this research tends to emphasize postevent reactions, rather than study the transition caused by the event itself. In this sense, there is some understanding of how macro events shape responses after the event is introduced but not research on the experience of the event's introduction (an omission of research more generally; see Bliese et al., 2017; Morgeson et al., 2015). Thus, the field lacks a clear understanding of how macro events produce change in job search behavior, both at the event's onset and subsequently over time.

This is not a criticism of prior research (or the researchers) but rather recognition of the difficulty in studying macro events. Besides the usual challenges associated with collecting longitudinal data, the use of DRCGCM carries additional requirements, such as at least six measurement occasions, at least three measurement occasions before the event onset, and an ability to capture the event's introduction to define the transition period (Bliese et al., 2017; Bliese & Lang, 2016). Such requirements are even more daunting when trying to estimate rare and/or unexpected macro events (e.g., terrorist attacks), as preevent baseline data and event transition data are usually lacking (Bliese et al., 2017).

However, we are able to theorize and test such effects in this study. The COVID-19 pandemic represents a particularly strong macro event because it occurs at a high level (i.e., at the global omnibus level) and is higher in novelty, disruption, and criticality than most macro events, as predicted by event system theory (Morgeson et al., 2015). First, the last event similar to the COVID-19 pandemic was the 1918 flu epidemic; thus, it is highly novel. Second, the pandemic is extremely disruptive as it led entire countries to shut down their businesses, prohibited most travel, and resulted in stay-at-home orders across the nation almost immediately. Third, the pandemic is critical in the sense that it has both financial implications and health consequences. Morgeson et al. (2015) note, "The more critical the event, the more likely it will be seen as salient and require unusual attention and action" (p. 521). Therefore, criticality is particularly important for determining which behaviors are most likely to be affected by an event. In the case of the pandemic, we argue that actions that influence financial well-being and physical health are relevant to employment; thus, this event is likely to influence job search.

When viewed from event system theory, it is clear that the COVID-19 pandemic is similar to, but stronger than, purely economic macro events like recessions. First, recessions are less novel as they occur with some frequency (about every 5–6 years), whereas the COVID-19 pandemic was introduced quickly and unexpectedly. Second, recessions can be reasonably well predicted and tend to be introduced more gradually; thus, recession effects are more likely to unfold over time, and the immediate disruption is usually minimal. Third, while recessions have health consequences in that people may lose access to health care, the COVID-19 pandemic has direct health consequences in terms of hospitalization or death. Thus, the COVID-19 pandemic represents a particularly strong macro event. This fact, combined with the understanding that most prior research on macro events has not examined the immediate effects of an event (i.e., at onset), suggests there is much to learn about how the COVID-19 pandemic may shape job search behavior and how such macro events influence job search more generally.

Context and Hypotheses

Based on job search theory and research (Bianchi, 2020; Wanberg, Ali, et al., 2020) and informed by event system theory (Morgeson et al., 2015), we first consider the extent to which recognition of the COVID-19 pandemic changed job search behavior during the transition period immediately following the event. Event system theory suggests that events originating at a higher level (i.e., omnibus context; Johns, 2006, 2017) are likely to influence behavior across a wider range of contexts. Further, as explained above, the pandemic has higher event strength (i.e., higher novelty, disruptiveness, and criticality; Morgeson et al., 2015) than other macro events and thus should produce immediate consequences. The question then becomes, how will job search behavior change as a result of this strong and far-reaching event? We posit that research examining job search during economic recessions provides some clues. Bianchi (2020) notes that "recessions provoke uncertainty and a loss of control" (p. 121). Individuals tend to respond to such threats by seeking to regain control, and one way this can be accomplished is by proactively applying to new jobs (Bianchi, 2013; Porter et al., 2019; Wanberg, Ali, et al., 2020; Wanberg et al., 2012). Thus, job search research supports the inference that applications will increase under conditions of uncertainty and stress because job search offers a means to cope with these stressors, particularly in the short term (Trope & Liberman, 2010; Wanberg, Kanfer, & Rotundo, 1999).

March 11, 2020, is the day COVID-19 was officially recognized as a global pandemic by the World Health Organization (2020). On this day, the National Basketball Association also officially postponed its season and the U.S. president banned travel from Europe. Further, the response to this event was almost immediate, with business and school closures occurring that same day in many areas of the United States. Therefore, in this study, we examine *preonset* (baseline) job search as the weeks before March 11 and *postonset* job search as the weeks following March 11. The *onset* is the transition period during the week that includes March 11. Given the pandemic's strength (and, in particular, the immediate and severe disruption), the onset period should show a large immediate increase in job applications.

> *Hypothesis 1 (H1):* Formal recognition of COVID-19 as a global pandemic produces an increase in job applications during the onset (transition) period (relative to preonset application rates).

Job search theory and research do not explain precisely how macro events change job search behavior over time. However, event system theory predicts the nature of the posttransition change should depend on event strength as time progresses (Morgeson et al., 2015). For example, a recession may see little change in job search behavior at the onset because the event is not immediately disruptive or critical. As the effects of the recession become more apparent (disruption increases), job search behavior changes drastically. On the other hand, a terrorist attack may be immediately disruptive and critical and thus may quickly change job search behavior, but the effects of this event on job search become less apparent over time (as disruption and criticality decrease). In this way, the differences in event strength are associated with differences in the timing, duration, and magnitude of consequences (Bliese et al., 2017).

We predict that the rate of applications should continue to increase after the onset of the pandemic (postonset period) because the macro context following the pandemic's onset continued to evolve. The pandemic's novelty obviously decreased after the onset transition period. However, as the virus became more widespread, the pandemic's disruption and criticality likely increased.[1] Unemployment rates and layoffs began to rise sharply, and the number of people not able to work increased because of shutdowns. The growing environmental uncertainty during the postonset period likely contributed to greater employment uncertainty and thus more applications (Bianchi, 2013; Porter et al., 2019; Wanberg et al., 2012; Wanberg, van Hooft, et al., 2020).

> *Hypothesis 2 (H2):* Relative to preonset applications, postonset applications will increase over time.

The first two hypotheses test whether the COVID-19 pandemic changed job search behavior. We now seek to provide a more nuanced understanding of these effects by examining if they are consistent across different types of jobs. We hypothesize that the onset of the COVID-19 pandemic should result in increases in job applications to work-from-home jobs, relative to preonset levels. We note above that stronger macroeconomic events prompt uncertainty and loss of control (Bianchi, 2020; Sirola & Pitesa, 2018). The COVID-19 pandemic is stronger than most macro events because it creates threats to economic *and* physical health. Health and safety are not frequently considered in prior research on characteristics influencing job search. However, theory from labor economics suggests that shifts in job search can result from the safety and security offered by an occupation (e.g., Bellante & Link, 1981; Cappelli, 2008).

Event system theory (Morgeson et al., 2015) and Bliese et al. (2017) offer insights regarding why job applications to work-from-home jobs will increase. Criticality is the dimension that pertains to an event's potential to have an influence on "the 'horizon' . . . and may curtail the attainment of important goals such that the 'centrality of the goal at stake in the exchange matters" (Morgeson et al., 2015, p. 521). The pandemic event specifically makes face-to-face jobs unsafe, from both a financial perspective (face-to-face jobs are most likely to be lost during the pandemic because of business closures) and a health perspective (face-to-face jobs are more likely to result in one getting sick; Rudolph et al., in press). Therefore, work-from-home jobs are a better alternative at the pandemic's onset, leading to the prediction that applications to work-from-home jobs will increase.

> *Hypothesis 3 (H3):* Relative to preonset application rates, organizations offering work-from-home jobs will experience an increase in applications during the onset of the COVID-19 pandemic (transition period) compared to organizations offering face-to-face jobs.

Likewise, postonset, jobseekers will apply to work-from-home jobs at an increasing rate relative to preonset levels. H3 argues that work-from-home jobs offer the greatest means to increase control and reduce uncertainty caused by the pandemic's simultaneous impact on economics and health. Further, time increases the disruption and criticality associated with the event, thus increasing event strength. Specifically, as the health (e.g., the virus becomes more widespread and individuals begin to see the effects of the virus on people close to them) and economic (e.g., the loss of face-to-face jobs in the community increases) environments worsen, the desire for work-from-home jobs will increase in an attempt to offset the potential negative consequences associated with the virus (e.g., Rudolph et al., in press). Thus, as the pandemic spreads in the postonset period, workers should increasingly apply to work-from-home jobs relative to preonset levels.

> *Hypothesis 4 (H4):* Relative to preonset application rates, organizations offering work-from-home jobs will experience a postonset increase in applications compared to organizations offering face-to-face jobs.

Method

Sample and Procedure

The data in this sample are based on 14 organizations that were clients of a global talent acquisition vendor (University of South Carolina IRB Pro00100146; "Job Search Change as a Result of a Disruptive Event"). This is the first publication from a larger data set. Four of the organizations offer work-from-home jobs, while the remaining 10 organizations offer traditional face-to-face jobs (see Table 1). The organizations represent a fairly diverse range of industries. Eight of the firms hired nationally, with the remainder focused on regional hiring (e.g., Southwest, Northeast). Six of the firms hired in urban areas, two in suburban areas, and the rest a mix of both.[2] The vendor tracks the number of applications to each organization on a daily basis (no demographic data were collected during the application stage). We cluster the data weekly as a means to balance having a large number of repeated observations versus having so many that the models run into convergence problems (see Ployhart & Vandenberg, 2010). Thus, the pandemic onset occurs the week of March 9,

[1] The fact that the pandemic's strength (i.e., novelty, disruption, and criticality) theoretically changes between onset and postonset periods is yet another reason why onset and postonset periods should be disentangled.

[2] Geographic location and urban/suburban status are unrelated to changes in job application trends (results available upon request).

Table 1
Characteristics of Organizations in Sample

Variable	$M_{\text{weekly applications}}$	$SD_{\text{weekly applications}}$	Roles	Industry
Face-to-face organizations				
1.	176.69	69.02	Customer service	Information technology & services
2.	158.06	30.36	Customer service and sales	Retail
3.	8.44	5.76	Finance and sales	Financial services
4.	11.31	9.46	Food preparation and management	Hospitality
5.	29.88	10.28	Research and management	Biotechnology
6.	12.56	9.04	Sales	Real estate
7.	88.44	72.36	Customer service and maintenance	Hospitality
8.	26.88	8.11	Sales and management	Transportation
9.	1,017.75	570.30	Customer service and technician	Consumer goods
10.	64.25	32.56	Research and management	Food and beverage
Subtotal	159.43	81.73		
Work-from-home organizations				
11.	1,334.88	1,929.53	Sales	Insurance
12.	3,705.56	4,296.80	Customer service and sales	Consumer services
13.	3,171.25	1,594.22	Customer service and sales	Outsourcing
14.	1,953.75	1,660.33	Customer service and sales	Outsourcing
Subtotal	2,541.36	2,370.22		

with data collection starting January 6 and ending the week of April 20. All 14 organizations, each with 16 weeks of data and all job applications in this window, are included in the analyses.

To provide further insights into the change in job applications, we also examined weekly mean selection test performance. Each firm uses a battery of cognitive, noncognitive, and situational judgment assessments. The specific constructs measured and the weighting of the different scores are specific to each firm as determined by a job analysis and validation study. The vendor converts applicant scores into a percentage from zero to 100 (100% indicates perfect fit).

Analytic Approach

A strength of this study's design is the multiple waves of data and, importantly, 9 weeks of preonset baseline data (see Table 2). DRCGCMs are ideally suited for this situation (Bliese et al., 2017) because they enable one to test whether the pandemic's onset and postonset slope differ relative to the preonset slope, as a means to estimate how much the pandemic *changed* job search application behavior relative to the baseline period. Further, these models enable us to test whether differences observed in the onset and postonset slopes are (at least in part) explained by job type (face-to-face vs. work-from-home). We followed the approach described by Bliese, Lang, and colleagues (Bliese et al., 2017; Bliese & Lang, 2016; Lang & Bliese, 2009) and used in research seeking to examine discontinuous trends (e.g., the Great Recession; Kim & Ployhart, 2014). DRCGCMs are extensions of the basic growth curve model (Singer & Willett, 2003) and similar to regression discontinuity designs used in economics (Imbens & Lemieux, 2008).

The DRCGCM regresses the outcome (vector of each firm's weekly job applications) onto a set of growth terms. These terms are

Table 2
Discontinuous Random Coefficient Growth Curve Model Terms

Time period	Date (month /day/year)	Intercept	Preonset slope	Pandemic onset event	Postonset slope	Postonset slope^2
Preonset	1/6/2020	1	0	0	0	0
	1/13/2020	1	1	0	0	0
	1/20/2020	1	2	0	0	0
	1/27/2020	1	3	0	0	0
	2/3/2020	1	4	0	0	0
	2/10/2020	1	5	0	0	0
	2/17/2020	1	6	0	0	0
	2/24/2020	1	7	0	0	0
	3/2/2020	1	8	0	0	0
Pandemic onset	3/9/2020	1	9	0	0	0
Postonset	3/16/2020	1	10	1	0	0
	3/23/2020	1	11	1	1	1
	3/30/2020	1	12	1	2	4
	4/6/2020	1	13	1	3	9
	4/13/2020	1	14	1	4	16
	4/20/2020	1	15	1	5	25

Note. The week of 3/9/2020 was when the pandemic onset occurred (with the pandemic specifically recognized on March 11, 2020).

structured so that they model specific forms of hypothesized change and thus disentangle different forms of variance (see Table 2). The preonset term captures the linear baseline slope. The pandemic onset term is coded zero (before the event) and 1 (after the event), thus estimating how applications changed the week of March 9. As the unit for "time" in our study is 1 week, we specify the transition period to be the shortest period possible to provide the most precise estimate of the event variance (Bliese & Lang, 2016). Longer periods of time would confound the onset variance with the postonset variance. We consider the possibility of nonlinear (quadratic or negatively accelerated) change in the postonset period by using two terms: postonset and postonset squared (e.g., Lang & Bliese, 2009). The postonset terms use zeros before and during the pandemic's onset so that change is modeled only after the transition period. The intercept is a constant of 1s to estimate the start period.

Just as dummy codes or effects coding enable different contrasts in the general linear model, the terms in Table 2 work together to uniquely estimate preonset, onset, and postonset variance as shown in Figure 1. H1 is supported by a significant pandemic onset term, H2 is supported by significant postonset terms, H3 is supported by significant pandemic onset by job type interaction, and H4 is supported by a significant postonset by job type interaction and postonset^2 by job type interaction (both terms must be significant for full support; one significant term is indicative of partial support). SAS (Version 9.4) proc mixed with restricted maximum likelihood is used for the analyses. H tests are based on Type I sequential sums of squares, which means that the coefficients are tested sequentially based on the order they enter the model. Order of entry is important when using polynomials, so one should test the lower-order terms before adding higher-order terms (Bliese & Ployhart, 2002). Pseudo-R^2 is estimated using Xu (2003).

DRCGCMs allow the estimation of variance components or the amount of between-firm variability in each term in Table 2. Allowing the growth terms to vary across firms, including the intercept (initial status), enables us to model how the pandemic has influenced application rates across firms and helps reduce concerns about preexisting between-firm differences (see Bliese & Lang, 2016; Bliese, Schepker, Essman, & Ployhart, 2020). This allows one to disentangle the variance associated with the preonset, onset, and postonset periods (see Bliese et al., 2017; Bliese & Lang, 2016; Lang & Bliese, 2009). Statistical tests for variance components are low power because variance components cannot fall below zero (Bliese & Ployhart, 2002), so one-tailed tests are used according to common practice (Littell, Milliken, Stroup, & Wolfinger, 1996). But perhaps the most important benefit of using DRCGCMs is that pandemic onset effect and postonset slope are compared relative to preonset slopes (i.e., baseline levels). For example, the onset by job type interaction is tested relative to what would have been predicted given the baseline data.

Results

Hypothesis Tests

Descriptive statistics are in Table 3. Model 1 (see Table 4), an unconditional model that only contains the growth terms, shows H1 is supported. The average number of applications in Week 1 was 878.52 (i.e., the intercept). Applications declined 59.39 (on average) per week before the pandemic. When the pandemic hit

Table 3
Descriptive Statistics

Variable	*M*	*SD*	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1. Week 0	1,082.4	2,202.9	—																
2. Week 1	827.4	1,051.9	0.72**	—															
3. Week 2	737.1	974.2	0.38	0.87***	—														
4. Week 3	608.6	896.6	0.31	0.72**	0.94***	—													
5. Week 4	508.4	686.3	0.4	0.85***	0.97***	0.92***	—												
6. Week 5	488.3	649.3	0.61*	0.86***	0.88***	0.84***	0.94***	—											
7. Week 6	467.1	634.0	0.39	0.79***	0.93***	0.91***	0.98***	0.96***	—										
8. Week 7	476.9	624.5	0.32	0.87***	0.9***	0.7**	0.9***	0.79***	0.83***	—									
9. Week 8	384.1	495.7	0.34	0.84***	0.97***	0.87***	0.99***	0.92***	0.97***	0.94***	—								
10. Week 9	532.6	812.3	0.3	0.72**	0.94***	0.99***	0.9***	0.8***	0.87***	0.71**	0.85***	—							
11. Week 10	1,011.1	2,084.0	0.27	0.53	0.75**	0.89***	0.67**	0.58*	0.63*	0.41	0.58*	0.92***	—						
12. Week 11	1,241.1	2,162.8	0.37	0.78***	0.82***	0.68**	0.81***	0.67**	0.72**	0.86***	0.78***	0.74**	0.58*	—					
13. Week 12	1,540.1	3,424.0	0.18	0.66**	0.63*	0.38	0.6*	0.41	0.48	0.84***	0.63*	0.45	0.24	0.9***	—				
14. Week 13	1,081.3	2,271.5	0.21	0.68**	0.71**	0.5	0.72**	0.55*	0.63*	0.87***	0.73**	0.55*	0.32	0.95***	0.97***	—			
15. Week 14	1,522.1	3,850.1	0.1	0.59*	0.56*	0.3	0.52	0.31	0.39	0.79***	0.56*	0.37	0.18	0.84***	0.99***	0.93***	—		
16. Week 15	931.0	2,034.0	0.16	0.66*	0.66*	0.42	0.64*	0.45	0.52	0.86***	0.67**	0.49	0.27	0.91***	1***	0.98***	0.99***	—	
17. Job type	0.3	0.5	0.69**	0.88***	0.79***	0.7**	0.75**	0.71**	0.66**	0.71**	0.68**	0.75**	0.69**	0.89***	0.7**	0.73**	0.62*	0.69**	—

Note. n = 14 organizations. Job type is coded 0 = face-to-face (n = 10); 1 = work-from-home (n = 4).
* $p < .05$. ** $p < .01$. *** $p < .001$.

Table 4
Discontinuous Random Coefficient Growth Curve Models of Weekly Application Rates

	Model 1 (unconditional model)			Model 2 (job type main effect)			Model 3 (job type interactions)		
Variable	Coefficient	*SE* [95% CI]	Type I (sequential) *F* test	Coefficient	*SE* [95% CI]	Type I (sequential) *F* test	Coefficient	*SE* [95% CI]	Type I (sequential) *F* test
Intercept	878.52	291.46 [248.85, 1,508.20]		396.37	171.71 [22.24, 770.50]		231.32	188.93 [−180.32, 642.96]	
Preonset slope	−59.39	28.80 [−116.16, −2.61]	$F_{(1, 206)} = .22$	−59.39	30.71 [−119.93, 1.16]	$F_{(1, 206)} = .24$	−5.37	36.86 [−78.04, 67.30]	$F_{(1, 202)} = 1.40$
Pandemic onset	(H1) 726.99	438.22 [−136.98, 1,590.95]	$F_{(1, 206)} = 3.89^{*}$	726.99	314.11 [107.70, 1346.28]	$F_{(1, 206)} = 6.33^{*}$	−55.13	417.05 [−877.47, 767.20]	$F_{(1, 202)} = 9.86^{**}$
Postonset slope	(H2) 374.86	345.37 [−306.06, 1,055.78]	$F_{(1, 206)} = .04$	374.86	341.98 [−299.38, 1,049.10]	$F_{(1, 206)} = .04$	−31.46	254.68 [−533.64, 470.72]	$F_{(1, 202)} = .28$
Postonset slope^2	−63.19	45.16 [−152.21, 25.84]	$F_{(1, 206)} = 1.96$	−63.19	53.41 [−168.48, 42.11]	$F_{(1, 206)} = 1.40$	5.39	53.03 [−99.17, 109.95]	$F_{(1, 202)} = 1.99$
Job type				1,687.54	227.42 [1,192.04, 2,183.04]	$F_{(1, 12)} = 55.06^{***}$	2,265.22	353.46 [1,495.11, 3,035.34]	$F_{(1, 12)} = 39.15^{***}$
Job Type × Preonset Slope							−189.06	68.95 [−325.01, −53.11]	$F_{(1, 202)} = 6.20^{*}$
Job Type × Pandemic Onset							(H3) 2,737.42	780.23 [1,198.98, 4,275.87]	$F_{(1, 202)} = 28.65^{***}$
Job Type × Postonset Slope							(H4) 1,422.11	476.47 [482.63, 2,361.60]	$F_{(1, 202)} = .80$
Job Type × Postonset Slope^2							(H4) −240.04	99.21 [−435.65, −44.42]	$F_{(1, 206)} = 5.85^{*}$
	Coefficient	*SE* [95% CI]	*z* test (one-tailed)	Coefficient	*SE* [95% CI]	*z* test (one-tailed)	Coefficient	*SE* [95% CI]	*z* test (one-tailed)
Variance components									
Intercept	886,975	706,018 [290,482, 11,122,530]	$z = 1.26$	26,499	59,369 [3,501.52, 8.908E11]	$z = .45$	53,696	81,915 [9,974.60, 1.6359E8]	$z = .66$
Preonset slope	1,001.70	4,014.45 [91.00, 5.688E27]	$z = .25$	1,724.06	1,809.27 [448.26, 93,857]	$z = .95$	2,942.42	2,820.76 [826.95, 90,048]	$z = 1.04$
Pandemic onset	1,561,095	878,704 [659,467, 7,170,651]	$z = 1.78^{*}$	161,363	217,752 [33,519, 90,751,106]	$z = .74$	608,600	498,326 [194,863, 8,561,060]	$z = 1.22$
Postonset slope	1,023,260	[a]		937,506	905,728 [261,752, 30,014,198]	$z = 1.04$	[b]		
Postonset slope^2	5,101.58	6,564.43 [1,106.43, 1,664,809]	$z = .78$	14,564	22,099 [2,178.669, 40,804,554]	$z = .66$	4,607.08	2,656.93 [1,914.51, 22,286]	$z = 1.73^{*}$
Error	875,222	164,459 [624,930, 1,313,751]	$z = 5.32^{***}$	947,125	[a]	$z = .0$	877,826	94,449 [718,574, 1,096,886]	$z = 9.29^{***}$
−2LLR		3,723.1			3,697.3			3,635.3	
df		11			12			15	
Intraclass correlation		$.74^{***}$							
Pseudo-R^2		.047			.053			.069	

Note. $n = 224$ (16 repeated observations nested within 14 organizations). Job type 0 = face-to-face; 1 = work-from-home. Confidence intervals are based on estimates where order of entry does not matter. The z tests for variance components are one-tailed according to standard practice (Littell, Milliken, Stroup, & Wolfinger, 1996). Hypothesis tests use Type I sequential sums of squares, which test each coefficient based on order of entry in the model (e.g., the second variable is tested after inclusion of the first). H = hypothesis; LLR = log-likelihood ratio.
[a] SAS set this value to zero to reach convergence. [b] This component created convergence problems and is not estimated.
$^{*} p < .05$. $^{**} p < .01$. $^{***} p < .001$.

(week of Marth 9), applications jumped a statistically significant 726.99 relative to expected preonset levels. The variance component for the pandemic onset (u = 1,561,095) is statistically significant, suggesting there are between-firm differences in the effect of the pandemic onset. In contrast, H2 is not supported, as neither the postonset slopes nor their variance components were statistically significant. Altogether, Model 1 suggests the onset of the pandemic produces a large mean increase in applications during the onset of the pandemic, and this transition effect continues through the postonset period. The pandemic's onset effect is so strong that it largely determines the shape of the postonset period.

H3 predicted that, relative to expected preonset trends, organizations offering work-from-home jobs will experience an increase in applications during the onset of the COVID-19 pandemic compared to organizations offering face-to-face jobs. Model 3 (see Table 4) shows H3 is supported. Organizations that offer work-from-home jobs see a significant increase of 2,737.42 more applications during the onset of the pandemic than organizations offering face-to-face jobs (relative to preonset levels). Further, the variance component for the pandemic onset term is no longer statistically significant, indicating that job type (face-to-face vs. work-from-home) accounts for the explainable variance. H4 is marginally supported, as the quadratic term (postonset slope^2) is significant but the linear postonset slope is not (there was also difficulty getting an estimate for the slope's variance component, which is common when modeling such trends; Ployhart & Vandenberg, 2010). This means that work-from-home jobs exhibit a modest negatively accelerated increase in applications. Figure 2 illustrates Model 3.[3]

Supplemental Analyses

We report a number of supplemental analyses to evaluate the robustness of the findings and consider alternative explanations. First, one might question whether unemployment rates are causing the increase in job applications. To test this possibility, we modeled weekly unemployment claims as a time-varying predictor in the DRCGCMs along with the existing terms. The results found that unemployment claims did not significantly predict job applications (p = .17), while the significant effects for the pandemic onset and job type still held. Indeed, the unemployment claims rate was relatively steady and did not rise until after the pandemic's onset, which argues against unemployment causing the onset effect (lagging the unemployment–application relationships by 1- or 2-week intervals made no difference). Further, hypothesis tests suggest that only work-from-home jobs saw a significant increase in the pandemic onset and postonset periods. If unemployment was the primary explanation for the increase in job applications, one would expect there to be at least some meaningful increase in applications to face-to-face jobs, but this is not the case. Second, we tested for the possibility of cyclical hiring trends by comparing 2020 data to a subset of the organizations that were clients during the same weeks (January–April) in 2019. No significant onset was found in the same time period in 2019, and the pattern of applications differed from 2020, suggesting cyclical effects are not present.

Third, we consider whether changes in the quality of applicants over time might account for the differences in application rates. We used the same models used to test the hypotheses but with candidate test scores as the outcome. The results found no significant changes in applicant quality over time and no significant differences between job types. The mean candidate fit was essentially unchanged over time and not an explanation of the changes in job applications. Fourth, we examine if changes in job openings affect applications. Based on a survey of the client project managers, one work-from-home organization and four face-to-face organizations indicated increased job openings, two face-to-face organizations indicated decreased job openings, and the rest were unchanged. Including job openings as a variable in the model (coded 1 = increased openings, 0 = no change, −1 = decreased openings) does not change support for any of the hypotheses. Thus, volume in applications did not change because of job openings.

Finally, given that work-from-home jobs have a larger number of job applications at all time periods, one may question whether the comparison between the two groups is fair. Applying the DRCGCM to only the face-to-face organizations found no significant change for the preonset, onset, or postonset periods—essentially a flat line over time. In contrast, applying the models on only the work-from-home firms produced a trajectory similar to the hypothesis tests and found significant effects for the pandemic onset. Thus, the job application rates are not affected by changes in applicant supply (unemployment rates), changes in applicant quality (test scores), or changes in demand (job openings). All of these results are available upon request.

Discussion

The COVID-19 pandemic is unprecedented in terms of speed and global impact. We sought to advance practice in ways that help organizations understand the crisis created by COVID-19 while simultaneously advancing job search theory in ways that generalize beyond the crisis. By applying a rigorous DRCGCM approach, we found (a) the COVID-19 pandemic's onset led to a large immediate increase in job applications, (b) this increase occurred primarily due to a stronger increase in applications to work-from-home jobs, and (c) most of the impact occurred during the pandemic's onset, as the postonset period showed a modest negatively accelerated increase in applications for work-from-home jobs. The longitudinal baseline and modeling approach used in this study offer reasonably strong evidence that it was the introduction of the COVID-19 pandemic that created this disruption in job applications. Supplemental analyses reinforce this interpretation, as neither unemployment claims nor candidate quality scores account for the change in applications.

[3] Although the diversity of organizations in this study helps ensure findings are not industry specific, it could also create difficulties in making comparisons across firms or jobs. To evaluate this possibility, we ran analyses that limited the organizations to jobs that focused only on customer service or sales (Organizations 1, 2, 6, and 11–14 in Table 1) and analyses that excluded organizations with jobs that were not focused primarily on customer service or sales job (i.e., excluding Organizations 4, 5, and 10 in Table 1). We compared these results to each other and the effects reported above. The effect sizes were highly similar across models, and support for all hypothesis tests was the same except for H4, which approached but did not reach statistical significance (perhaps because this analysis used only 3 of the 10 face-to-face organizations). Analyses are available upon request.

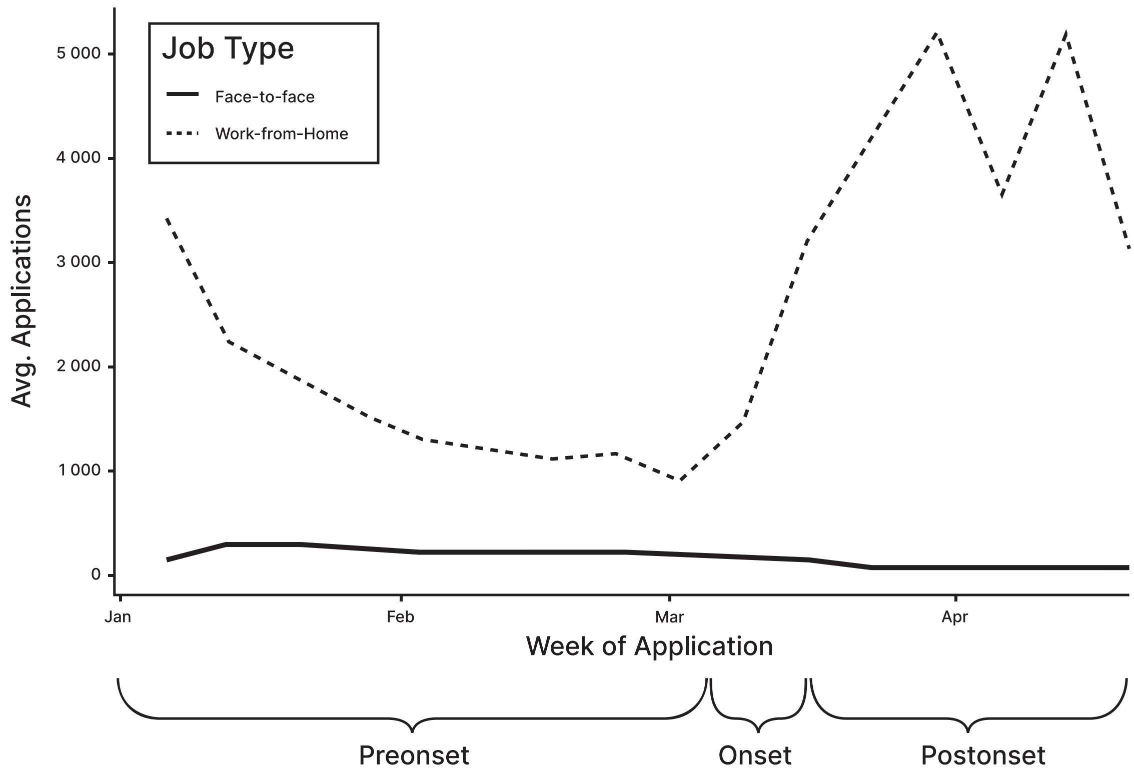

Figure 2. Average number of applicants over time by job type.

This research offers important implications for job search theory and for directing future research, especially given that context has not played a central role in the job search literature (Boswell et al., 2012; Wanberg et al., 2012). First, we introduce event system theory and transition frameworks as a means to conceptualize, theorize, and analyze job search. Job search is punctuated by many acute events, including college graduation, job acceptance, and job loss. A nascent area of research is starting to recognize that macro events may also influence search, such that job search during times of hardship and uncertainty contributes to a loss of control or increased gratitude (Bianchi, 2020; Peterson & Seligman, 2003). Yet in prior research, the event itself is rarely given careful theoretical attention, and the transition period associated with the event is usually ignored or confounded with the posttransition period.

The approach used in this study thus offers new ways to think about events that punctuate job search—macro or otherwise. Not all events have the same consequences. The effects of an event are largely determined by event strength, which lies on a continuum. Research should apply event system theory to compare and contrast the strength of different events (e.g., compare the novelty, disruption, and criticality of furloughs, expected job loss, unexpected job loss, layoffs) to determine how they create different transition and posttransition reactions (see Halbesleben, Wheeler, & Paustian-Underdahl, 2013, for one example).[4] Failing to appropriately understand events can lead to inconsistent or even contradictory findings. For example, the effectiveness of interventions used to facilitate job search during times of economic recession may differ from the effectiveness during times of economic prosperity (Liu et al., 2014). Conceptualizing job search events along a continuum of event strength, as proposed by Morgeson et al. (2015), should help improve the understanding and reporting of context in job search articles, which in turn could improve meta-analyses and the ability to identify contextual moderators of predictive relationships (Wanberg, Ali, et al., 2020).

A second theoretical implication involves consideration of how outcomes and the predictors of such outcomes may change across event preonset, onset, and postonset periods. Our study found a slow decline in job applications to work-from-home jobs, but this changed abruptly and significantly once the pandemic onset occurred, suggesting the predictors of job application behavior (i.e., job type) changed over time. Future research should examine if the predictors of job search behavior change across preonset, onset, and postonset periods for different types of events (varying on strength). Such relationships cannot be examined without sufficient baseline data and the application of models capable of testing discontinuity and change (Bliese et al., 2017). Thus, this study's approach may be used to better understand how the strength of events, macro and micro, influence the predictors of job search over time.

[4] We compared the effects of the COVID-19 onset to other macro events occurring in 2020 (Brexit) and 2019 (Trump impeachment). Theoretically, these other events are weaker than the COVID-19 onset because they are both less disruptive and critical for employment. Consistent with event system theory predictions, neither of these other events created a significant onset effect. We thank an anonymous reviewer for this suggestion.

Our study also offers some important practical implications. First, event system theory and the transitions framework introduced here can help firms understand events in new ways and thus provide a greater ability to strategically anticipate or respond to macro events. Reeves, Whitaker, and Ketels (2019) argue that environmental complexity and uncertainty appear to be more frequent. If firms try to understand the wide variety of potential macro events without an organizing framework, then strategies will need to be based on each event (e.g., responses for terrorist attacks, health crises, economic crises, and all the variations within these). This is obviously an unwieldy and impractical approach, especially for events that are strong but infrequent or difficult to predict. On the other hand, organizations could apply event system theory to understand these events in terms of their key underlying features: novelty, disruption, and criticality. It is likely that many seemingly different events are actually similar in terms of their strength, and hence the organizational responses can be similar as well. This provides a simpler and more flexible approach to strategic planning.

Second, recognizing that the onset transition is different from the postonset period helps firms better react to change. For example, it may seem apparent that people will apply to work-from-home jobs when a pandemic begins. However, the difficult question facing managers is whether these effects are strong enough and last long enough to justify investing in work-from-home opportunities. Strategy is about making choices about where to invest and where not to invest. Should firms make more work-from-home opportunities, recognizing that doing so will require significant resource investments (e.g., hardware, infrastructure), training (performance management), and cultural change? If one believed the increase in work-from-home jobs was driven by unemployment, a firm may decide not to make such investments, believing the demand will subside as unemployment decreases. Our study shows this is not the case. Thus, event system theory and the transition approach provide a way for firms to make better strategic decisions and can be used as a tool to improve strategic planning and forecasting.

Of course, this study has potential limitations that need to be addressed in future research. First, we were not able to measure the psychological reactions or experience of the pandemic's onset period. We theorized that the onset created uncertainty that led to increased applications, but such explanatory processes need to be tested in future research. Consistent with such expectations, a follow-up survey administered to a nationally representative sample of U.S. workers in late March found that 82% of job seekers were more anxious about their current job search than they would be normally ($z = 5.76$; $p < .001$), and 74% indicated they needed additional job search support ($z = 6.97$; $p < .001$; results available upon request). Future research thus needs to consider how the perceptions and experiences observed shortly after the pandemic's onset continue as the pandemic evolves. Second, we modeled the transition period as the week during which the COVID-19 virus was recognized as a pandemic. This is consistent with similar approaches using DRCGCM and provides the most rigorous test of the onset (Bliese & Lang, 2016), but theoretical work is needed to more precisely define when a transition point ends. Third, in the weeks following the onset, many locations have reopened their economies and so the effects observed here may (or may not) generalize to later time periods. There may also be differences across geographic regions, and although we did not find any effects due to the geographic location of hiring (national vs. regional) or population type (urban/suburban), future research should explore this further.

One century ago, the *Journal of Applied Psychology* was born at a time when applied psychology was desperately needed: World War I was waging and the 1918 flu pandemic was beginning. It began from a desire to apply the best of psychological science to better human work conditions (Hall, Baird, & Geissler, 1917). We have sought to follow this tradition by seeking to understand the effects of COVID-19 (and event strength more broadly) on job search behavior, to help individuals and organizations better adapt to a changing world.

References

Alter, C., & Villa, L. (2020, March). "You must act now": How states and cities have responded to the coronavirus pandemic. *Time*. Retrieved from https://time.com/5803334/coronavirus-pandemic-local-governments/

Bellante, D., & Link, A. N. (1981). Are public sector workers more risk averse than private sector workers? *Industrial & Labor Relations Review, 34,* 408–412. http://dx.doi.org/10.1177/001979398103400307

Bianchi, E. C. (2013). The bright side of bad times: The affective advantages of entering the workforce in a recession. *Administrative Science Quarterly, 58,* 587–623. http://dx.doi.org/10.1177/0001839213509590

Bianchi, E. C. (2020). How the economy shapes the way we think about ourselves and others. *Current Opinion in Psychology, 32,* 120–123. http://dx.doi.org/10.1016/j.copsyc.2019.07.007

Bliese, P. D., Adler, A. B., & Flynn, P. J. (2017). Transition processes: A review and synthesis integrating methods and theory. *Annual Review of Organizational Psychology and Organizational Behavior, 4,* 263–286. http://dx.doi.org/10.1146/annurev-orgpsych-032516-113213

Bliese, P. D., & Lang, J. W. B. (2016). Understanding relative and absolute change in discontinuous growth models: Coding alternatives and implications for hypothesis testing. *Organizational Research Methods, 19,* 562–592. http://dx.doi.org/10.1177/1094428116633502

Bliese, P. D., & Ployhart, R. E. (2002). Growth modeling using random coefficient models: Model building, testing, and illustrations. *Organizational Research Methods, 5,* 362–387. http://dx.doi.org/10.1177/109442802237116

Bliese, P. D., Schepker, D. J., Essman, S. M., & Ployhart, R. E. (2020). Bridging methodological divides between macro- and micro research: Endogeneity and methods for panel data. *Journal of Management, 46,* 70–99. http://dx.doi.org/10.1177/0149206319868016

Boswell, W. R., Zimmerman, R. D., & Swider, B. W. (2012). Employee job search: Toward an understanding of search context and search objectives. *Journal of Management, 38,* 129–163. http://dx.doi.org/10.1177/0149206311421829

Cappelli, P. (2008). *Talent on demand: Managing talent in an age of uncertainty*. Cambridge, MA: Harvard Business School Publishing.

Halbesleben, J. R., Wheeler, A. R., & Paustian-Underdahl, S. C. (2013). The impact of furloughs on emotional exhaustion, self-rated performance, and recovery experiences. *Journal of Applied Psychology, 98,* 492–503. http://dx.doi.org/10.1037/a0032242

Hall, G. S., Baird, J. W., & Geissler, L. R. (1917). Foreword. *Journal of Applied Psychology, 1,* 5–7. http://dx.doi.org/10.1037/h0065981

Imbens, G., & Lemieux, T. (2008). Regression discontinuity designs: A guide to practice. *Journal of Econometrics, 142,* 615–635. http://dx.doi.org/10.1016/j.jeconom.2007.05.001

Johns, G. (2006). The essential impact of context on organizational behavior. *Academy of Management Review, 31,* 386–408. http://dx.doi.org/10.5465/amr.2006.20208687

Johns, G. (2017). Reflections on the 2016 Decade Award: Incorporating context in organizational research. *Academy of Management Review, 42,* 577–595. http://dx.doi.org/10.5465/amr.2017.0044

Kanfer, R., Wanberg, C. R., & Kantrowitz, T. M. (2001). Job search and employment: A personality-motivational analysis and meta-analytic review. *Journal of Applied Psychology, 86,* 837–855. http://dx.doi.org/10.1037/0021-9010.86.5.837

Kim, Y., & Ployhart, R. E. (2014). The effects of staffing and training on firm productivity and profit growth before, during, and after the Great Recession. *Journal of Applied Psychology, 99,* 361–389. http://dx.doi.org/10.1037/a0035408

Klehe, U., & van Hooft, E. (2018). *The Oxford handbook of job loss and job search*. New York, NY: Oxford University Press.

Lang, J. W. B., & Bliese, P. D. (2009). General mental ability and two types of adaptation to unforeseen change: Applying discontinuous growth models to the task-change paradigm. *Journal of Applied Psychology, 94,* 411–428. http://dx.doi.org/10.1037/a0013803

Littell, R. C., Milliken, G. A., Stroup, W. W., & Wolfinger, R. D. (1996). *SAS system for mixed models*. Cary, NC: SAS Institute.

Liu, S., Huang, J. L., & Wang, M. (2014). Effectiveness of job search interventions: A meta-analytic review. *Psychological Bulletin, 140,* 1009–1041. http://dx.doi.org/10.1037/a0035923

Morgeson, F. P., Mitchell, T. R., & Liu, D. (2015). Event system theory: An event-oriented approach to the organizational sciences. *Academy of Management Review, 40,* 515–537. http://dx.doi.org/10.5465/amr.2012.0099

Mull, A. (2020, March). The Coronavirus customer-service crisis: When the public panics, service workers are the first to deal with it. *The Atlantic*. Retrieved from https://www.theatlantic.com/health/archive/2020/03/customer-service-workers-are-charge-pandemic/607801/

Peterson, C., & Seligman, M. E. P. (2003). Character strengths before and after September 11. *Psychological Science, 14,* 381–384. http://dx.doi.org/10.1111/1467-9280.24482

Ployhart, R. E., & Vandenberg, R. J. (2010). Longitudinal research: The theory, design, and analysis of change. *Journal of Management, 36,* 94–120. http://dx.doi.org/10.1177/0149206309352110

Porter, C. M., Posthuma, R. A., Maertz, C. P., Joplin, J. R. W., Rigby, J., Gordon, M., & Graves, K. (2019). On-the-job and off-the-job embeddedness differentially influence relationships between informal job search and turnover. *Journal of Applied Psychology, 104,* 678–689. http://dx.doi.org/10.1037/apl0000375

Reeves, M., Whitaker, K., & Ketels, C. (2019, April). Companies need to prepare for the next economic downturn. *Harvard Business Review*. Retrieved from https://hbr.org/2019/04/companies-need-to-prepare-for-the-next-economic-downturn

Rudolph, C., Allan, B., Clark, M., Hertel, G., Hirschi, A., Kunze, F., . . . Zacher, H. (in press). Pandemics: Implications for research and practice industrial and organizational psychology. *Industrial and Organizational Psychology: Perspectives on Science and Practice*.

Singer, J. D., & Willett, J. B. (2003). *Applied longitudinal data analysis: Modeling change and event occurrence*. New York, NY: Oxford University Press. http://dx.doi.org/10.1093/acprof:oso/9780195152968.001.0001

Sirola, N., & Pitesa, M. (2018). The macroeconomic environment and the psychology of work evaluation. *Organizational Behavior and Human Decision Processes, 144,* 11–24. http://dx.doi.org/10.1016/j.obhdp.2017.09.003

Solomon, A. (2020, April 9). When the pandemic leaves us alone, anxious, and depressed. *New York Times*. Retrieved from https://www.nytimes.com/2020/04/09/opinion/sunday/coronavirus-depression-anxiety.html

Trope, Y., & Liberman, N. (2010). Construal-level theory of psychological distance. *Psychological Review, 117,* 440–463. http://dx.doi.org/10.1037/a0018963

Wanberg, C. R., Ali, A. A., & Csillag, B. (2020). Job seeking: The process and experience of looking for a job. *Annual Review of Organizational Psychology and Organizational Behavior, 7,* 315–337. http://dx.doi.org/10.1146/annurev-orgpsych-012119-044939

Wanberg, C., Basbug, G., van Hooft, E. A. J., & Samtani, A. (2012). Navigating the black hole: Explicating layers of job search context and adaptational responses. *Personnel Psychology, 65,* 887–926. http://dx.doi.org/10.1111/peps.12005

Wanberg, C. R., Kanfer, R., & Rotundo, M. (1999). Unemployed individuals: Motives, job-search competencies, and job-search constraints as predictors of job seeking and reemployment. *Journal of Applied Psychology, 84,* 897–910. http://dx.doi.org/10.1037/0021-9010.84.6.897

Wanberg, C. R., van Hooft, E. A. J., Dossinger, K., van Vianen, A. E. M., & Klehe, U. C. (2020). How strong is my safety net? Perceived unemployment insurance generosity and implications for job search, mental health, and reemployment. *Journal of Applied Psychology, 105,* 209–229. http://dx.doi.org/10.1037/apl0000435

World Health Organization. (2020). Who Director-General's opening remarks at the media briefing on COVID-19 - 11 March 2020. Retrieved from https://www.who.int/dg/speeches/detail/who-director-general-s-opening-remarks-at-the-media-briefing-on-covid-19---11-march-2020

Xu, R. (2003). Measuring explained variation in linear mixed effects models. *Statistics in Medicine, 22,* 3527–3541. http://dx.doi.org/10.1002/sim.1572

Received May 20, 2020
Revision received July 30, 2020
Accepted July 31, 2020 ■